Exploration of the Double Helix Integration Model for Technological Innovation and Industrial Innovation Driven by Large-Scale AI Models

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Abstract: In the era of digital economy, large AI models, as a pivotal engine of new quality productive forces, are spearheading a new wave of scientific and technological revolution alongside industrial transformation. However, achieving deep synergy between technological innovation and industrial innovation remains challenging. This paper focuses on the dual-helix integration model driven by large AI models, clarifies the essence of this model for technological and industrial innovation, and establishes an enterprise-led collaborative innovation system integrating industry, academia, research, and application. The goal is to achieve seamless convergence and mutually reinforcing spiral advancement between innovation chains and industrial chains. The study further analyzes the driving mechanisms and challenges of large models in propelling technological innovation. In terms of mechanisms, large models are reconstructing the entire chain of technological innovation by transforming innovative thinking from "fragmented knowledge accumulation" to "cross-domain knowledge integration and application," from "linear trial-and-error iteration" to "predictive innovation simulation," from "individual experience-driven" to "collaborative ideation," and from "professional threshold limitations" to "democratized innovation thinking." Furthermore, they optimize the industrial ecosystem across four dimensions: industrial chain collaboration, entity capability reinvention, resource allocation efficiency, and innovation mechanism restructuring. Adhere to the principle that AI large models use data, knowledge, and scenarios as bonds to form a bidirectional iterative closed loop of "technological breakthrough - industrial application - data feedback - technological refinement" between the scientific innovation chain and industrial innovation chain. It is recommended to propose from four aspects: building a super ecosystem integrating industry, academia, and research; empowering small and medium-sized enterprises and underdeveloped regions; constructing a multi-level capital market; and improving ethical governance and security frameworks. This provides support for implementing the double helix integration model and fostering new quality productivity.

Keywords: Large AI Models; Technological Innovation; Industrial Innovation; Dual-Helix Integration Model; Case Studies

1. Overview of the Integration Model Between Large AI Models and the Double Helix

1.1 The Current Development Status of Large AI Models

To effectively advance the "AI+" initiative [1], promote extensive and deep integration of artificial intelligence with all sectors and fields of the economy and society, thereby reshaping human production and lifestyle, driving revolutionary improvements in productivity and profound transformations in production relations, and accelerating the formation of a new intelligent economy and society characterized by human-machine collaboration, cross-domain integration, and co-creation and sharing, it is imperative to vigorously develop next-generation artificial intelligence, accelerate the pace of scientific discovery, strengthen AI's cross-disciplinary driving effects, and facilitate multidisciplinary convergence and development.

Developing new quality productive forces is both an inherent requirement and a key focal point for advancing high-quality development. It is essential to continuously prioritize innovation as the central task, thereby accelerating the growth of these new quality productive forces. Those who capitalize on the opportunities presented by emerging economic sectors, such as big data and artificial intelligence, will be in tune with the pulse of our era. In the digital economy, artificial intelligence-characterized by large-scale models, big data, and substantial computing power-has emerged as a pivotal engine for new quality productive forces. The onset of the AI technological revolution, coupled with its deep integration into the economy and society, has provided significant momentum for the development of new quality productive forces, offering a critical pathway to comprehensively empower China's high-quality economic development [2]. Vigorously promoting the comprehensive and in-depth integration of artificial intelligence into the real economy can leverage AI as a pivotal engine for new quality productive forces, thereby injecting sustained momentum into high-quality economic development. The official document of 2025 clearly states the need to fully implement the new development philosophy, adhere to a people-centered development approach, and fully capitalize on China's advantages, such as abundant data resources, a complete industrial system, and vast application scenarios. By strengthening forward-looking planning, systematic layout, sector-specific policies, open sharing, and secure controllability, with a focus on key areas such as technology, industry, consumption, people's livelihoods, governance, and global cooperation, the "AI+" initiative will be effectively advanced. This will give rise to a range of new infrastructures, technological systems, industrial ecosystems, and employment opportunities, thereby accelerating the cultivation and development of new quality productive forces. The benefits of AI development will be shared by all, serving the modernization of China [3].

The early exploration of artificial intelligence can be traced back to the mid-20th century [4]. The debate between the Symbolism and Connectionism schools laid the groundwork for subsequent technological approaches. Artificial intelligence constitutes the science and engineering of creating intelligent machines and computer programs, and it is closely related to the analogous task of using computers to understand human intelligence. However, AI is not necessarily confined to methods that are biologically observable-a relatively comprehensive summary that remains valid to this day. Although related research continued, no unified definition emerged. Recently, the UK updated its definition of artificial intelligence, describing it as the capability of computers or computer-controlled robots to perform tasks typically associated with human cognitive processes. While the academic and technological communities have yet to reach a consensus on the concept of artificial intelligence, it is not difficult to discern their common ground: the shared understanding that AI relies on computers to accomplish tasks related to human intelligence.

As a key driving force leading the new round of scientific and technological revolution and industrial transformation, artificial intelligence is profoundly reshaping global economic development models and the course of human civilization. In recent years, China has witnessed robust development in artificial intelligence. According to data released by the Ministry of Industry and Information Technology, the scale of China's core AI industry continues to expand, with the number of related enterprises exceeding 4,500. There are now over 200 generative AI service models available to the public, boasting more than 600 million registered users. The construction of digital workshops and smart factories has accelerated, while intelligent infrastructure continues to be strengthened. This has laid a solid foundation for AI to empower new industrialization. Large models represent an advanced form and core vehicle of artificial intelligence. They establish an intelligent 'data-knowledge-decision' closed loop in industrial sectors, thereby expanding both the depth and breadth of AI applications in these domains. In this context, it is crucial to clarify the obstacles and challenges faced by industrial AI large models, particularly concerning datasets, computing power, and technological development. Additionally, identifying corresponding countermeasures is essential for advancing AI-enabled new industrialization. Over the past few years, large AI models have transitioned from theoretical conception to practical infrastructure. In 2017, the Transformer architecture replaced recurrent structures with self-attention mechanisms, laying the groundwork for parallel training. Subsequently, the computing power of specialized chips, such as GPUs and TPUs, has experienced exponential growth, making the training of models with hundreds of billions of parameters commonplace. Innovations in mixed-precision computing, distributed frameworks, and algorithms-such as sparsity and mixture-of-experts—have significantly reduced training cycles from months to weeks. However, energy consumption still reaches levels equivalent to the annual electricity usage of hundreds of households, highlighting persistent bottlenecks in computing power and energy efficiency. At the data level, TB-scale multilingual corpora, after undergoing adversarial cleaning and knowledge graph enhancement, can support models in achieving cross-domain generalization. Privacy compliance has become a mandatory constraint for data utilization. The model ecosystem demonstrates a trend of simultaneous development in both general-purpose and vertical domains, with GPT-4 showcasing cross-task general intelligence, while MathGPT, Tencent MIYING, and Spark Cognitive achieve in-depth advancements in education, healthcare, and speech scenarios. In 2023, the scale of China's large model-related industry has exceeded 200 billion yuan. Parameter inflation, surging energy consumption, and copyright disputes have exposed ethical and institutional gaps amid rapid technological advancement. Industry standards and governance frameworks urgently require synchronous improvement. Despite numerous challenges, large AI models have preliminarily established their status as new infrastructure, and their developmental trajectory will continue to influence the processes of technological innovation and industrial transformation.

1.2 The Connotation of the Dual-Helix Integration Model of Technological Innovation and Industrial Innovation

Scientific and technological innovation represents the primary productive force, while industrial innovation serves as the cornerstone of the national economy. It is essential to vigorously promote the deep integration of technological innovation and industrial innovation to foster the development of new quality productive forces. Advancing this integration is pivotal for both the growth of new quality productive forces and the broader framework of Chinese modernization. Currently, as a new wave of technological revolution and industrial transformation unfolds, the boundaries between scientific/technological innovation and industrial innovation are increasingly blurring, with their interconnectedness becoming more pronounced. To address significant national strategic needs, systematically enhancing the synergy between scientific/technological and industrial innovation has emerged as a crucial strategy for securing a leading position in technological competition, gaining the initiative in future development, and achieving high-level self-reliance and strength in science and technology.

The dual-spiral integration model of technological and industrial innovation refers to the convergence of all stages of technological innovation and all dimensions of industrial innovation, thereby forming an enterprise-led collaborative innovation system that integrates industry, academia, research, and application [5]. Enterprises play a crucial role in technological innovation, serving as fundamental carriers of modern industrial systems and as microeconomic entities within market economies, effectively acting as bridges that connect technology, industry, and the economy. In recent years, China has actively implemented an innovation-driven development strategy. Fueled by relevant policies, an increasing number of enterprises have emerged as key players in R&D investment, project organization, and the commercialization of scientific and technological achievements. Through practical engagement, these enterprises continuously seek solutions to address the disconnect between technology and the economy, thereby enhancing the quality of economic development [6]. However, despite these advancements, a disconnect persists between the innovation chain and the industrial chain, indicating that the dominant role of enterprises in technological innovation still requires further strengthening.

1.3 Research Background and Significance

The essence of integrating technological innovation with industrial innovation lies in establishing a virtuous cycle between knowledge production and the creation of social wealth, thereby enhancing overall societal prosperity and well-being. This integration primarily manifests through the seamless connection between the innovation chain and the industrial chain. On one hand, driving industrial innovation through technological innovation requires aligning industrial chains with innovation chains, extending and upgrading industrial chains through research and development (R&D) and technology transfer. On the other hand, promoting technological innovation via industrial innovation necessitates deploying innovation chains around industrial chains, utilizing the needs of industrial development as drivers to advance innovation chains by addressing key technical challenges within industrial chains. Through tight integration, concerted efforts, coordinated interaction, and mutual reinforcement, the innovation chain and industrial chain achieve a dual-spiral ascension, propelling high-quality economic and social development.

1.3.1 Technological innovation guides the direction of industrial innovation and serves as its "catalyst"

Science and technology form the foundation of a nation's strength, with innovation acting as the primary driving force for development. Scientific and technological innovation serves as an inexhaustible source of prosperity for a country. Leading industrial innovation through advancements in science and technology is essential for promoting high-quality economic and social development in China. However, technological innovation is a challenging endeavor that requires the courage to overcome scientific challenges and reach new heights. First, robust basic research is the cornerstone of a modern industrial system, as fundamental scientific studies provide the groundwork for industrial innovation [7]. While interconnected, basic research and innovation remain distinct; the former serves as the wellspring for the latter. Although characterized by long cycles, high risks, and substantial investments, basic research holds immense developmental potential, enhances industrial capacity, and exerts a powerful economic impact. Once breakthroughs are achieved, such innovations can become the decisive force driving a new round of industrial transformation. Second, winning the battle in core technologies is key to translating scientific and technological innovations into industrial applications. Core technologies serve as the fundamental force for building a modern industrial system and accelerating industrial upgrading. We should give full play to the significant advantage of concentrating resources to accomplish major tasks, strengthen national strategic scientific and technological capabilities, and achieve breakthroughs in a number of key generic technologies, cutting-edge technologies, modern engineering technologies, and disruptive technologies. A sound and robust scientific and technological system will underpin industrial innovation and development, create channels for the close integration of science and technology, education, industry, and finance, ensure the supply of core technologies at the source, and support and guide new business forms and models to generate new momentum for development. Furthermore, research institutions and universities provide intellectual support for industrial development. To achieve a virtuous interaction between independent technological innovation and self-reliant talent cultivation, education must further play its leading and foundational supporting role. Technological innovation relies on talent, and talent cultivation depends on education. Education, technology, and talent are mutually supportive and indispensable, and it is essential to focus on education, technology, and talent simultaneously.

1.3.2 Industrial innovation serves as the "main arena" for realizing the value of scientific and technological achievements

Industrial innovation refers to innovation driven by the new technological revolution and global competitive landscape, aligned with national development and competitiveness objectives. It encompasses building a modern industrial system, transforming and upgrading existing industries, and innovating industrial development models [8]. Industrial innovation provides market demand and application scenarios for technological innovation, while facilitating the iterative advancement of science and technology. Through industrial innovation, new industries, business forms, and models can achieve rapid development. Strategic emerging industries and future industries, exemplified by cloud computing, artificial intelligence, and the Internet of Things, represent a critical arena for technological innovation. By embracing the application of digital, networked, and intelligent technologies, these industries can profoundly transform industrial ecosystems and production-operation models. They foster globally competitive emerging industrial clusters, drive significant changes in traditional production methods, and establish high-end, intelligent, and environmentally sustainable production models. Industrial innovation enhances the quality and efficiency of factor supply, thereby propelling the sustained and rapid development of new quality productive forces. Currently, new industries driven by the latest technological revolution are emerging rapidly; digital and intelligent technologies are swiftly penetrating traditional sectors, and innovations in industrial development models are accelerating. Accelerating industrial innovation and achieving the integrated development of technological and industrial innovation is an essential strategy for China to establish new competitive advantages in the new era [9].

Overall, existing studies have primarily focused on analyzing the impact of technological innovation on high-tech industrial innovation, with limited research discussing the integration mechanism between the two, failing to effectively drive their deep convergence. The intensifying international competition landscape has heightened the urgency of such research. The United States maintains a leading position in patent applications for fundamental algorithms, while China holds advantages in application scenario innovation. This differentiated competitive dynamic necessitates that research on the dual-helix integration model must be grounded in national conditions, distill practical experience, and form a distinctive path of innovative development.

2 Mechanisms and Challenges of AI Large Models in Driving Technological Innovation

2.1 The Transformation of Large Models on Technological Innovation Thinking

The multilateral development finance system addresses global mismatches in development financing through centralized fundraising and targeted allocation. By leveraging institutions such as the World Bank, the Asian Development Bank (ADB), and the African Development Bank (AfDB), it pools funds through member contributions and international bond issuances to provide low-interest loans, grants, and other forms of support for high-risk, long-cycle sectors in developing countries, including infrastructure, agriculture, and education. In fiscal year 2024, the World Bank allocated $93 billion to developing nations, with 60% directed toward low-income countries to alleviate financing challenges. This policy-driven system incorporates binding conditions, such as environmental protection and poverty reduction, to mobilize private capital. Through risk-sharing instruments, it channels private investment into renewable energy projects in the Asia-Pacific region, thereby promoting capital reallocation toward green sectors and optimizing resource distribution. In traditional scientific research activities, human thinking is often constrained by cognitive boundaries and knowledge structures. The emergence of large AI models has transformed this constrained scenario. By processing and analyzing massive datasets, these models can uncover underlying patterns that may elude human detection. For instance, in drug discovery, certain synergistic effects of compound combinations might be overlooked by researchers, whereas large models can predict potential new drug combinations based on historical databases. This capability breaks through the cognitive inertia of researchers, liberating innovation activities from being confined solely to empirical accumulation and trial-and-error processes [10]. As the core vehicle of next-generation artificial intelligence technology, large language models are evolving from "tool assistance" to "cognitive reshaping," systematically transforming the fundamental logic, methodologies, and even cognitive patterns of scientific innovation. This transformation goes beyond mere efficiency improvement; it fundamentally restructures innovators' end-to-end thinking processes, encompassing problem identification, knowledge integration, solution generation, and iterative validation.

2.1.1 From "fragmented knowledge accumulation" to "cross-domain knowledge integration and application": breaking the "cognitive barriers" to innovation

Under the traditional paradigm of scientific and technological innovation, the cognitive boundaries of innovators are largely confined by the limits of their individual knowledge reserves. This constraint becomes particularly pronounced in interdisciplinary innovation scenarios, where innovators from different academic fields tend to delve deeply into their respective specialized domains, forming relatively independent knowledge systems. They often lack both profound understanding and rapid assimilation capabilities regarding the foundational theories, technical principles, and practical details of other disciplines. The fragmentation of this knowledge system compels innovation actors to invest substantial time and effort in acquiring cross-disciplinary knowledge-often referred to as "knowledge remediation"-to achieve preliminary integration of different academic domains. More critically, such knowledge fragmentation may hinder innovators from discerning potential logical connections between disciplines, thereby impeding timely identification of interdisciplinary opportunities. This phenomenon constrains both the efficiency and breakthrough potential of interdisciplinary innovation, ultimately creating "cognitive barriers" during the innovation process [11].

As a key carrier of next-generation artificial intelligence technology, large language models possess the capability to conduct deep learning and integrate massive cross-domain data. Their data sources include academic papers in the natural sciences, technical documentation in engineering fields, and various empirical data accumulated through industrial practices. By performing structured processing and correlation analysis on these diverse datasets, large language models can effectively dismantle the "knowledge silos" between different disciplines and establish interdisciplinary knowledge association networks. In this network, theoretical systems, technical methodologies, and practical cases from various disciplines are organically interconnected to form a systematic knowledge repository, providing comprehensive knowledge integration services for innovation entities. In specific innovation practices, when confronted with innovation demands that require multidisciplinary knowledge integration, the large model can swiftly retrieve core knowledge from relevant disciplines based on the established interdisciplinary knowledge association network, conducting multi-dimensional correlation analysis and synthesis. This knowledge integration capability enables innovators to bypass the inefficient traditional processes of retrieving, organizing, and sequentially learning interdisciplinary materials, allowing them to directly focus on combining cross-domain knowledge and innovative applications. It facilitates a shift in innovative thinking-from relying solely on individual knowledge breadth to leveraging systematic knowledge integration. This transformation not only enhances the efficiency of interdisciplinary innovation but also fundamentally lowers the cognitive barriers to such innovation. Consequently, it creates opportunities for more innovators to engage in interdisciplinary innovation practices and drives technological advancement across broader domains.

2.1.2 From "linear trial-and-error iteration" to "predictive innovation deduction": compressing the "cost of trial and error" in innovation

The data-driven predictive capabilities of large models have shifted scientific and technological innovation thinking from "passive trial-and-error" to "active deduction," establishing a new paradigm of thought. This capability stems from the deep mining and integration of multi-source data, including historical experimental data, simulation models, and industrial cases. Through structured processing and pattern recognition, it establishes correlative mappings between innovative solutions and outcomes, enabling the preemptive simulation and evaluation of a solution's feasibility, effectiveness, and risks.

This capability plays a pivotal role throughout the entire innovation process: For complex multi-parameter tasks, it can accurately predict outcome performance under different parameter combinations and identify optimization directions. During the solution screening phase, it quantitatively assesses potential and risks to prioritize high-value, low-risk options, thereby reducing ineffective experiments and optimizing resource allocation. Throughout the iteration process, it refines models by incorporating experimental results to enhance precision and avoid inefficient exploration. This "prediction-first" paradigm shift breaks the traditional innovation model's heavy reliance on experimental resources, establishing a new "data-driven pre-screening" approach. Under conventional methods, resources are consumed through repeated trial-and-error processes, resulting in prolonged cycles and high costs. By leveraging large models to pre-screen solutions and mitigate risks, unnecessary experiments are significantly reduced, substantially shortening innovation cycles and lowering costs. This provides robust support for efficient scientific and technological innovation [12].

2.1.3 From "individual experience-driven" to "collaborative thinking co-creation": expanding

collective wisdom for innovation

The large model employs a dual-wheel mechanism of "real-time knowledge synchronization" and "multi-role cognitive adaptation" to create a systematic "collaborative innovation thinking network," fundamentally optimizing group collaboration patterns in technological innovation. In the realm of "real-time knowledge synchronization," the large model functions as the central component of a "collective knowledge hub." It facilitates the real-time aggregation, structured processing, and global distribution of dispersed innovation elements-such as research data, design proposals, and technical documentation-across various teams and stages. This ensures that all innovation participants operate on a unified information foundation, effectively mitigating cognitive biases and efficiency losses caused by information asymmetry or delayed updates in traditional collaboration. Consequently, it establishes a foundation for collective cognitive synergy.

In terms of multi-role cognitive adaptation, large language models can accurately identify the core demands and knowledge requirements of various roles within the technological innovation system. Decision-makers prioritize the strategic value and risk assessment of innovative solutions; engineers focus on the technical feasibility and detailed optimization of implementation, while marketing personnel emphasize the exploration of application scenarios and market compatibility for innovative outcomes. Accordingly, through customized knowledge output, large language models provide role-specific information support tailored to each position's responsibilities. This framework generates risk-reward assessments of solutions for decision-makers, supplies engineers with actionable technical parameters for implementation, and offers scenario-based application forecasts for marketing teams. By enabling all stakeholders to contribute their domain expertise from a shared cognitive foundation, it achieves precise alignment between individual insights and collective objectives. Such a collaborative innovation network demonstrates remarkable efficacy in cross-organizational and cross-regional contexts. It can eliminate communication barriers caused by geographical space and language systems, achieving cognitive synchronization and thought linkage among globally dispersed teams. This transforms innovative collaboration from the traditional division-of-labor execution model into an end-to-end collective ideation model. Such paradigm shift reconstructs the thought-driven logic of technological innovation, evolving the process from an individual-dominated paradigm reliant on core personal expertise to a group-synergy paradigm integrating multi-agent, cross-domain wisdom. This unleashes cross-organizational resource integration capabilities and trans-regional thought linkage efficacy, injecting stronger collaborative creativity into the technological innovation ecosystem.

2.1.4 From professional threshold restrictions to inclusive innovation thinking: breaking participation barriers in technological and industrial innovation

In the traditional science and technology innovation system, especially where small and medium-sized enterprises (SMEs) serve as key components of the industrial ecosystem, their insufficient innovation capacity can hinder the diffusion of innovation within the industry. This makes it difficult to translate scientific and technological achievements into practical drivers for industrial upgrading, resulting in a "participation gap" between scientific/technological innovation and industrial innovation.

Large language models (LLMs) facilitate the democratization of innovative thinking capabilities through a synergistic mechanism of "natural language interaction + professional competency encapsulation," fundamentally dismantling the aforementioned barriers. The core logic resides in modularizing and contextualizing complex professional tools and theoretical models in scientific innovation. By utilizing natural language as a low-threshold interaction interface, theoretical analysis and tool operations-traditionally necessitating specialized training—are transformed into directive-based cognitive activities. At the technological innovation level, this mechanism empowers non-professional groups to engage in preliminary innovation ideation and solution development based on their own needs, without requiring an in-depth mastery of professional knowledge systems. Consequently, it broadens the scope of participants in technological innovation. At the industrial innovation level, it offers low-cost innovation support for resource-constrained market entities, such as

SMEs and startup teams. Without substantial investments in hiring professionals or acquiring high-end tools, these entities can leverage large models to conduct innovation activities, including technology improvements and product optimizations tailored to industrial needs, thereby reducing both startup costs and the risks associated with trial-and-error in industrial innovation. This transformation does not replace the core value of professional innovators; rather, it achieves the integration of participants in technological and industrial innovation by reconstructing the pathways to innovative thinking. From the perspective of technological innovation, the inclusion of diverse entities breaks the traditional closed nature of innovation, fostering cross-domain and scenario-based ideas, thereby providing a broader range of creative sources for breakthroughs in core technologies. From the standpoint of industrial innovation, activating the innovation capabilities of groups such as small and medium-sized enterprises accelerates the rapid diffusion of innovation across all segments of the industrial chain. This facilitates the transformation of scientific and technological achievements into end products and industrial services, speeding up the overall technological iteration and model upgrading within industries. Ultimately, the democratization of innovative thinking fosters a synergistic ecosystem where professional innovators lead core breakthroughs while mass innovators drive the proliferation of applications. This transformation shifts scientific and technological innovation from being niche-driven to widely accessible and upgrades industrial innovation from isolated breakthroughs to comprehensive activation. Such a shift lays the foundational groundwork for the deep integration of scientific-technological innovation and industrial innovation.

The transformation of large AI models in scientific and technological innovation thinking does not fundamentally replace the dominant role of human cognition. Instead, by functioning as technology-enabled platforms, these models construct more systematic cognitive frameworks and provide richer thinking tools for innovators through five core pathways: knowledge integration, predictive deduction, collaborative creation, problem discovery, and barrier reduction. The core value of this transformation is reflected not only in enhancing the efficiency of knowledge integration during technological innovation but also in optimizing the achievement transformation chain within industrial innovation scenarios. This transformation effectively addresses the inherent challenges of traditional innovation models-such as the fragmentation of information between technological and industrial innovation, inefficient trial-and-error processes, poor collaboration, missed opportunities, and excessively high barriers-thereby enabling innovators to concentrate more on the higher-order cognitive abilities unique to humanity. Consequently, this alignment fosters a precise connection between technological innovation and industrial innovation.

2.2 The Challenges of Deep Integration Between Large Models and Sci-Tech Innovation Scenarios

The deep integration of large models with scientific and technological innovation scenarios is, in essence, a co-evolution of intelligent paradigms and research paradigms. By constructing domain-specific models, end-to-end intelligent platforms, interpretable reasoning frameworks, real-time experimental ecosystems, and collaborative innovation mechanisms, large models are transitioning from auxiliary tools to co-researchers in scientific discovery. However, this integration process also faces numerous challenges. How to achieve synergistic progress between the two has become a focal point for both academia and industry [13].

2.2.1 Data Quality and Privacy Issues: The Dual Barriers from "Usable" to "Trustworthy"

Throughout the entire lifecycle of scientific research data, inherent issues at each stage impose significant constraints on the application of large models. During the data collection phase, the pervasive 'native defects' of research data present challenges. In the data integration phase, cross-domain data heterogeneity and ambiguous data ownership create dual barriers. Interdisciplinary and inter-institutional data, essential for technological innovation, are governed by different entities, resulting in discrepancies in format standards and 'semantic barriers' due to term ambiguities across fields. If large models fail to accurately identify these discrepancies, data integration risks devolving into a superficial exercise or a chaotic patchwork, exacerbating the issue of 'data silos.' During the data utilization phase, the conflict between privacy protection and data exploitation becomes increasingly pronounced. The leakage of personal sensitive information and research-sensitive data in scientific research can trigger both privacy security risks and strategic security risks, which conflict with the need for cross-border data flow in international research collaboration, thereby impeding the progress of joint global research efforts.

2.2.2 Interpretability and trustworthiness of models: bridging the cognitive gap from "black box" to transparency

In the context of technological innovation, the 'black-box nature' of large models sharply conflicts with the core requirements of scientific research-namely, 'traceable logic and verifiable results.' This contradiction exists not only at the technical level but also extends to research paradigms and academic norms. From an explanatory perspective, large language models fundamentally rely on 'correlational learning' from massive datasets, generating outputs by identifying statistical patterns without the ability to distinguish between causal and correlational relationships. Since the essence of technological innovation lies in exploring causal mechanisms, treating such 'correlational outputs' as definitive research conclusions may lead to pseudo-innovation [14]. Furthermore, the multi-step reasoning of large models in complex research tasks lacks interpretability. Researchers are unable to trace the logical trade-offs made among multiple factors during the reasoning process, nor can they ascertain whether critical parameters have been overlooked. This significantly undermines the academic credibility of conclusions derived from models. From the perspective of validation criteria, the performance evaluation of large models relies on statistical metrics such as accuracy and recall rates. However, scientific research prioritizes extreme cases significantly more than general scenarios, while the training data for large models predominantly originates from conventional scenarios. This insufficient coverage of extreme cases leads to performance failures in critical research contexts, making it challenging to meet the rigorous demands of scientific inquiry. From the standpoint of establishing trust, the 'unreproducibility' of large models conflicts with the core academic norm of 'reproducible results.' The training process is heavily influenced by factors such as computing environments, random seeds, and data batches; even with identical model architectures and datasets, different teams may yield divergent outcomes. Furthermore, the vast parameter scale of large models exacerbates this irreproducibility, making it difficult to validate research conclusions generated with their assistance through peer review. This situation creates a crisis of trust and poses a significant barrier to integrating large models into the scientific research ecosystem.

2.2.3 Insufficient domain-specific adaptability: The capability gap from "general-purpose" to "vertical"

In the context of technological innovation, there exists a significant capability gap between the generalizability of large models and the demand for specialized depth in specific scenarios. This gap does not arise merely from an insufficient volume of knowledge; rather, it reflects a systemic mismatch across three dimensions: knowledge representation, reasoning logic, and domain-specific tools. General-purpose large models leverage vast amounts of internet data to establish cross-domain foundational knowledge. However, the specialized expertise required for technological innovation-encompassing complex mathematical derivations, physics concepts, and tacit experiential knowledge-constitutes an extremely small proportion of publicly available online data, making effective parsing challenging. Consequently, this results in poor performance in specialized research tasks due to insufficient knowledge depth. From the perspective of task complexity, innovation-driven scenarios predominantly involve multi-step, cross-modal, and dynamically adjusted complex tasks with feedback loops between subtasks at various stages. The lack of deep multimodal information integration and collaborative reasoning capabilities complicates meeting the complexity demands of scientific research. Regarding tool interoperability, technological innovation heavily relies on specialized toolchains, which serve both as research infrastructure and extensions of scientific logic. Misuse of these tools can lead to biased research conclusions, further exposing the inadequacy of general-purpose large models in adapting to vertical domains [15].

3. The Path of Industrial Innovation Driven by Large AI Models

From the perspective of large model

development, innovation-driven approaches mainly encompass two modes: technology push and demand pull. The technology push approach spans the entire spectrum from fundamental science to practical applications, where breakthroughs in technology itself establish the groundwork for engineering implementation. Conversely, the demand pull approach fosters a feedback loop from application scenarios to engineering technology and technical science, propelling research on core technologies and facilitating major engineering breakthroughs through innovation in key scenarios. Scenario-driven innovation has emerged as a crucial pathway for large model development, holding significant potential for future applications in fields such as industrial innovation and construction.

3.1 Large Models Drive Intelligent Upgrading of Traditional Industries

Against the backdrop of rapid technological advancement, large models have emerged as a pivotal force driving the intelligent transformation of traditional industries, leveraging their robust capabilities in data analysis, learning, and prediction [16]. Persistent challenges faced by traditional industries-such as efficiency plateaus, sluggish innovation cycles, and suboptimal resource allocation-have been effectively addressed through large model technologies. This has enabled substantive breakthroughs across multiple dimensions, including production, management, and innovation. In terms of production processes, large models can deeply analyze multi-source data from manufacturing equipment operations to achieve precise fault prediction and maintenance, thereby reducing production downtime. Additionally, these models can construct predictive frameworks based on production and quality inspection data, allowing for real-time adjustments to production parameters, which in turn lowers defect rates. For process-oriented industries such as energy and chemicals, large models optimize production pathways by learning material properties, reaction conditions, and operational parameters, ultimately achieving objectives related to energy conservation, emission reduction, and cost control. At the management decision-making level, large models can integrate financial, human resources, and supply chain data from enterprise resource planning systems. By incorporating market demand, raw material supply, and equipment capacity, these models can formulate optimal production plans that enhance resource utilization and mitigate inventory risks [17]. In supply chain management processes, large models facilitate real-time tracking of procurement, production, and distribution data across all stages. They can predict potential disruption risks and develop corresponding contingency strategies to ensure supply chain stability. The technology behind large models presents an unprecedented opportunity for the intelligent upgrading of traditional industries. Although certain challenges may arise, continuous technological advancement and refinement will enable large models to assume an increasingly pivotal role in traditional sectors. They will drive high-quality and sustainable development, injecting new vitality into traditional industries during this new wave of technological revolution and industrial transformation.

3.2 Large Models Promote the Optimization of Industrial Ecosystems

The core value of an industrial ecosystem lies in maximizing overall efficiency through the dynamic synergy among all entities across the industrial chain, interdisciplinary resources, and innovation factors. By leveraging capabilities in cross-domain knowledge integration, multi-agent collaborative empowerment, and intelligent resource allocation, large models facilitate the transformation of industrial ecosystems from fragmentation to collaborative symbiosis, and from resource-driven to data- and intelligence-driven frameworks. This transformation is achieved through four dimensions: industrial chain collaboration, entity capability reshaping, resource allocation efficiency, and innovation mechanism restructuring, ultimately fostering a more resilient and vibrant ecological landscape.

From the perspective of industrial chain collaboration, large models break down the coordination barriers caused by information silos in traditional industrial ecosystems, establishing an end-to-end data circulation and decision-making linkage mechanism. Vertically, they integrate upstream raw material supply, midstream production, and downstream market demand data, achieving dynamic matching of demand, production, and supply through real-time analysis and prediction, thereby shortening the industrial chain response cycle. Horizontally, they connect related sectors such as manufacturing, logistics, finance, and services to form a cross-industry value network, reducing transaction costs and risks in cross-industry collaboration. From the perspective of reshaping the capabilities of ecosystem participants, large models empower entities of varying scales and types within the ecosystem to complement each other's competencies, narrowing capability gaps to foster inclusive innovation. For small and medium-sized enterprises (SMEs), they lower the barrier to intelligent transformation through encapsulated technical capabilities, enabling optimization of production processes and customer demand analysis without the need to establish complex algorithm teams in-house. For service-oriented entities such as logistics providers, research institutions, and financial organizations, these models drive the transition of service models from standardized to customized approaches, thereby enhancing the ecosystem's service support framework. From the perspective of resource allocation efficiency, large models enable precise matching and efficient reuse of core resources such as data, computing power, and technology within the industrial ecosystem, reducing idle resource waste. At the data level, standardized interfaces and semantic understanding frameworks facilitate "available but invisible" sharing of decentralized data. At the computing power level, they support elastic scheduling and the construction of shared computing power pools. At the technological level, they establish a technology transfer platform to accelerate the transformation of research outcomes into industrial applications. From the dimension of innovation mechanism restructuring, large models drive the transformation of industrial innovation models from linear and unidirectional to networked collaboration, activating cross-domain and multi-agent innovation vitality. On one hand, they promote cross-domain innovation integration, breaking industrial boundary constraints and fostering new industrial forms and formats. On the other hand, they advance user-participatory innovation, converting user demands into front-end innovation drivers, thereby forming a closed loop of demand, innovation, production, and feedback to align innovation more closely with actual market needs.

4. Implementation Strategies and Case Studies of the Dual Helix Integration Model

4.1 Implementation Strategies for the Dual Helix Integration Model

The integrated and mutually reinforcing development of technological innovation and industrial innovation serves as the dual engines for fostering new quality productive forces. The key lies in establishing a virtuous cycle where technological innovation better empowers industrial innovation, and industrial innovation in turn further stimulates technological innovation. The essence of this integration is to create a positive feedback loop between knowledge production and social wealth creation, thereby enhancing overall societal prosperity and well-being. The path of integration is primarily manifested in the seamless connection between the innovation chain and the industrial chain. On one hand, driving industrial innovation through technological innovation necessitates arranging the industrial chain around the innovation chain, thereby extending and upgrading the industrial chain through technology R&D and transformation of achievements. On the other hand, promoting technological innovation via industrial innovation requires aligning the innovation chain with the industrial chain, utilizing the demands of industrial development as the driving force to advance the innovation chain by addressing key technological challenges within the industrial chain. Through tight integration, aligned efforts, coordinated interactions, and mutual reinforcement, the innovation chain and industrial chain achieve a spiral escalation, fostering high-quality economic and social development [18].

4.2 The Dual Helix Integration Model: A Case Study of City Commercial Banks

The dual-helix integration of technological innovation and industrial innovation essentially involves constructing a closed-loop mechanism of "technology empowerment - scenario feedback - collaborative iteration" through large-scale AI models. One helix is the technological innovation chain, which focuses on breakthroughs in large model R&D, scenario adaptation, and capability evolution, covering core aspects such as algorithm optimization for financial sector-specific large models, multimodal data processing, and risk decision logic restructuring. The other helix is the industrial innovation chain, leveraging the role of city commercial banks in serving local economies to drive digital transformation of regional industries, innovation in financing models, and optimization of supply chain collaboration. The two are intertwined like a DNA double helix, with large models serving as the "hydrogen bonds" to achieve deep integration. Technological innovation provides intelligent tools and decision-making support for industrial innovation, while industrial innovation offers real-world application scenarios and data feedback for technological innovation. Ultimately, this forms a spiraling upward cycle of "technological breakthroughs - industrial implementation - data feedback - technological refinement" [19]. As illustrated in Figure 1.

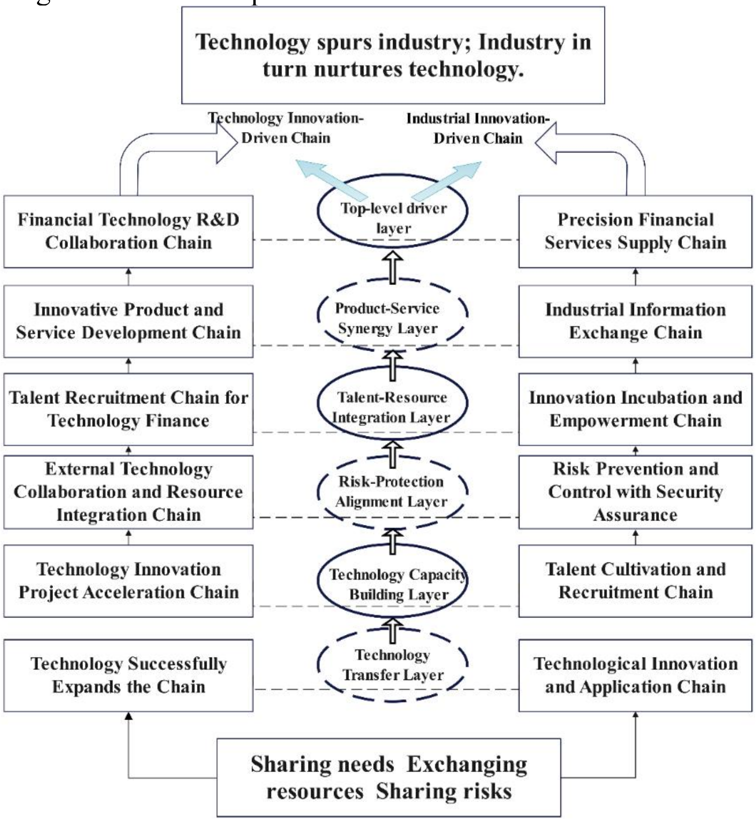

Figure 1. The Dual Helix Model of Deep Integration Between Technological Innovation and Industrial Innovation in City Commercial Banks

As a hub connecting local sci-tech innovation resources with industrial ecosystems, city commercial banks' unique positioning determines the practical path for dual-helix integration [20]. On one hand, compared with large state-owned banks, city commercial banks are closer to local SMEs and micro-enterprises, enabling them to precisely identify pain points in industrial innovation. On the other hand, relative to local technology firms, city commercial banks possess financial licensing advantages and accumulated data-such as corporate account transactions, credit records, and settlement data-which can be integrated with industrial data through large models to provide scenario-based validation fields for technological innovation, thereby preventing disconnection between R&D and industrial needs.

5. Research Findings and Policy Implications

Large AI models do not unilaterally drive technological or industrial innovation; rather, they function as a nexus that integrates data, knowledge, and application scenarios to synergistically enhance the efficient operation of a "dual-helix structure." It is essential to move beyond the conventional linear logic of technology transfer and to strengthen systematic research on the constituent elements, operational mechanisms, and institutional frameworks within this dual-helix paradigm. This approach will foster the development of new models, mechanisms, and policies that align with practical requirements. The technological innovation chain focuses on breakthroughs in large model development, which includes algorithm optimization, domain adaptation, and multimodal interaction. These advancements provide industrial innovation with intelligent toolkits and cognitive reference systems. Conversely, the industrial innovation chain is driven by real-world industry demands, utilizing practices such as production optimization, product iteration, and business model innovation to offer technological innovation platforms for scenario validation and data feedback. Through large models, both parties achieve technological breakthroughs, scenario implementation, data feedback, and iterative optimization, forming a virtuous upward spiral. This process addresses the challenges of traditional innovation, where research and development are often disconnected from industrial needs, and data silos impede collaboration. Ultimately, it creates a bidirectional iterative loop in which technology empowers industries, and industries, in turn, contribute to technological advancement.

5.1 Directly "Translate" Scientific Research Achievements into Industrial Momentum, Building A Regional-Level "Industry-University-Research" Super Ecosystem

The science and technology innovation platform must establish an integrated support system encompassing "talent cultivation, technology transformation, and business implementation" through cross-domain resource integration and an ecological collaboration network in education. This involves creating a new engineering curriculum system that incorporates "design thinking, engineering thinking, and business thinking," alongside promoting project-based credit transfers with universities to nurture talents in science and technology innovation. On the technology front, it is essential to develop laboratory clusters and cross-domain R&D networks to reduce the technology R&D cycle. At the industrial level, leveraging regional industrial advantages, an innovation agglomeration circle, a gradient financial support system, and a benchmark enterprise leadership mechanism should be established to expedite market validation and incubation. This approach will effectively promote the integration of the innovation chain, industrial chain, capital chain, and talent chain, fostering a positive cycle where education empowers talents, talents convert achievements, and achievements feedback into the ecosystem, thereby driving the advancement of regional hard technology industries.

5.2 Empower Small and Medium-Sized Enterprises and Underprivileged Regions to Alleviate "Uneven Resource Allocation"

To support the intelligent transformation of small and medium-sized enterprises (SMEs), it is essential to implement a subsidy program for large model applications. This program would provide financial assistance to enterprises purchasing large model services. Additionally, establishing a large model service marketplace would integrate resources from third-party service providers, offering low-cost customized solutions tailored for SMEs. Furthermore, strengthening the cultivation of interdisciplinary talent is crucial; this can be achieved by introducing "AI + major" interdisciplinary programs in universities and establishing university-enterprise joint training bases to produce professionals proficient in both technology and industry. It is also important to provide fiscal support for talent training programs in central and western regions and to conduct AI technology outreach activities, which would enhance the technical application capabilities of local enterprises. Moreover, optimizing financial support policies is necessary; financial institutions should be encouraged to develop large model empowerment loans that offer low-interest loans to SMEs participating in dual-spiral integration. Finally, establishing a large model innovation risk compensation fund would help to partially cover bad debts incurred by financial institutions due to enterprise innovation failures, thereby reducing financing risks.

5.3 Building a Multi-Level Capital "Interchange": Precisely Empowering the Integrated Innovation of Technology and Industry

Building a multi-tiered capital market is fundamental to addressing the financing needs of integrated sci-tech and industrial innovation. This necessitates the vigorous development of direct financing mechanisms and the revitalization of the M&A and restructuring market to create a capital service system that encompasses the entire innovation cycle and aligns with the complete industrial chain. First, it is crucial to optimize the architecture of the multi-tiered capital market system, enhance service coverage and precision, and promote coordinated synergy among the Main Board, ChiNext, STAR Market, and Beijing Stock Exchange. This will form an integrated framework that supports the convergence of sci-tech and industrial innovation. After years of development, China's capital market has established a multi-tiered structure characterized by differentiated yet complementary functions, with clearly defined roles for each sector. The Main Board should leverage its advantage of aggregating large-cap blue-chip stocks to provide continuous financing and M&A restructuring support for large, mature technology enterprises, thereby assisting them in driving deep integration between traditional industries and technological innovation through effective capital operations. The ChiNext, STAR Market, and Beijing Stock Exchange, as primary platforms for technological innovation, must continuously enhance their institutional advantages. They should deepen the reform of the registration-based IPO system, focusing on information disclosure, and specifically target 'hard-tech' enterprises. This strategy aims to attract more sci-tech innovators with proprietary core technologies and leading industry positions to list and raise capital. Furthermore, the New Third Board needs to emphasize its role as a 'nursery' and 'incubator.' It should improve its tiered management mechanism and trading system, enhance market liquidity, and provide a foundational platform for standardized development and equity financing for early-stage sci-tech enterprises. Concurrently, efforts should be made to strengthen market coordination among regional equity markets, the New Third Board, the Beijing Stock Exchange, the STAR Market, and the ChiNext. This includes improving the mechanism for enterprise board transfers and establishing seamless capital upgrade channels for technology innovation enterprises at various development stages. Such measures will ensure comprehensive capital service coverage and provide more efficient capital support for the integration of technological and industrial innovation.

5.4 Enhance Ethical Oversight and Safety Frameworks to Prevent "Innovation-Related Risks and Hidden Dangers"

An ethical review mechanism for large models should be established, including the formation of an ethics committee comprising representatives from government bodies, research institutions, enterprises, and the public. This committee will conduct pre-review assessments of the research, development, and application of large models. The Ethical Guidelines for Large Models have been issued, explicitly prohibiting the use of such models for unfair competitive practices. A dynamic regulatory framework should be implemented, adopting the regulatory sandbox approach to enable pilot supervision of integrated applications of emerging large models-such as "AI+finance" and " AI+healthcare " to evaluate innovation-related risks within a controlled environment. A dedicated large model security monitoring platform should be established to enable real-time oversight of model decision-making behaviors, ensuring timely alerts and effective responses to anomalous activities. Intellectual property rights protection must be strengthened by refining the rules governing the ownership of outputs generated by large models and intensifying enforcement against infringement. Furthermore, a patent pool for large models should be developed to promote cross-licensing of core technology patents, reduce patent licensing costs for small and medium-sized enterprises, and facilitate broader technological collaboration and sharing.

The dual-spiral integration of technological innovation and industrial advancement, driven by large artificial intelligence models, represents a pivotal pathway for fostering high-quality economic development. By establishing a comprehensive policy framework that ensures seamless data flow, technological interoperability, ecosystem synergy, balanced resource allocation, and effective risk management, the enabling potential of large AI models can be fully realized. This facilitates the removal of innovation barriers and achieves a mutually reinforcing dynamic between technological capabilities and industrial competitiveness, thereby providing robust support for the ongoing technological revolution and industrial transformation. Going forward, it is essential to continuously refine policy mechanisms, dynamically address emerging challenges in the integration process, and advance the dual-spiral model toward deeper and broader domains.

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