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Large Model-Driven Technology Transfer: Value Conduction, Policy Optimization and Empirical Exploration

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Abstract: Addressing the challenges in the commercialization of traditional scientific and technological achievements, this study explores the empowerment mechanisms and value conduction pathways of large model technologies, and proposes policy optimization directions through empirical validation. First, a three-dimensional empowerment framework of "technology-subject-ecosystem" is constructed to elucidate how large models address traditional challenges through four key value conduction pathways. Subsequent empirical analysis using data from 2021–2023 demonstrates a positive correlation between large model adoption levels and technology transfer success rates, with particularly pronounced effects observed in high-tech enterprises, and R&D investment intensity playing a significant moderating role. Finally, based on the analytical framework and case studies, policy recommendations are formulated across four dimensions, providing actionable insights for overcoming technology transfer challenges.

Keywords: Large model; Technology transfer; Value conduction pathway; Policy optimization; Empirical testing

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1. Introduction

In the era of digitalization and intelligentization, large model technologies are reshaping industrial landscapes. The transformation of scientific and technological achievements into practical applications bridges scientific breakthroughs and economic development, playing a pivotal role in industrial advancement. Large models provide novel pathways for this transformation. Research on how these models can drive technology transfer and optimize policies not only theoretically enriches systemic frameworks but also enables governments to implement targeted strategies, ultimately fostering social development [1]. Currently, systematic and policy-coordinated research on large models enabling technology transfer remains insufficient both domestically and internationally. This study employs a comprehensive approach integrating literature review, case studies, and empirical research to explore the empowerment pathways and policy optimization of large models. From a systems theory perspective, it conducts a holistic analysis of the role of large models across the entire value chain; establishes a novel analytical framework to dissect value conduction pathways; and delivers policy recommendations that are more targeted, actionable, systematic, and synergistic.

2. Theoretical foundations and conceptual definitions

Large models, or large-scale pre-trained models, are AI systems built on deep learning frameworks with massive parameter scales. Through unsupervised or self-supervised pre-training, they acquire general patterns and knowledge, demonstrating strong capabilities in language understanding, generation, and multitasking [2]. Key characteristics include reliance on vast multi-type datasets, parameter sizes far exceeding traditional models, excellent generalization abilities, and outstanding performance across diverse domains. Their development has evolved from early neural networks to the breakthrough of the Transformer architecture (2017), and further to the rapid advancement of the GPT series (2018–present), with continuously expanding application fields. Technology commercialization refers to the management of the entire process from experimental validation to the application of new technologies, divided into three stages: project initiation and research, technology transfer, and industrialization application. The theoretical basis for large models empowering technology transfer lies in their capabilities in knowledge graph construction, machine learning algorithm optimization, and natural language processing.

3. Value conduction pathways of large models empowering technology transfer

Traditional technology commercialization faces multiple challenges, including information asymmetry, low conversion rates, subjective value assessment, talent shortages, and imperfect mechanisms. Large models achieve data empowerment by constructing digital and intelligent service scenarios and efficient collaboration platforms, integrating information resources. Their specific value conduction pathways include as follows:

(1) Precision matching of supply and demand: Utilizing big data analytics to deeply mine enterprise demands and achievement characteristics, achieving efficient docking and promoting industry-university-research integration [3];

(2) Scientific value assessment: Constructing digital intelligence models based on national standards to conduct comprehensive, rapid, and objective evaluations of achievements from multiple dimensions, providing references for decision-making;

(3) Full-chain service support: Providing expert advice, market analysis, data monitoring, and optimization recommendations throughout the R&D, intellectual property, transfer, and industrialization stages, reducing risks and costs while enhancing success rates and returns [4].

Large models create value for multiple stakeholders, including university researchers, research management departments, enterprises and industries, and government parks. For example, they help researchers identify cutting-edge topics and enhance the practicality of their findings; assist management departments in achieving intelligent management; support enterprises in technological innovation and strategic decision-making; and help governments optimize resource allocation and precision investment attraction [5].

4. Policy optimization for technology transfer empowered by large models

China has introduced a series of policies supporting large model technology and technology transfer, but challenges remain, including insufficient policy coordination, weak targeting, and poor implementation effectiveness. The goal of policy optimization is to promote the deep integration of large models with technological achievements, enhance transfer efficiency, stimulate innovation vitality, and build an innovation ecosystem. This requires adhering to principles of innovation-driven development, collaborative development, market orientation, and open cooperation [6]. Specific optimization recommendations include as follows:

(1) Enhancing R&D Support: Establish special funds to attract social capital, support research on fundamental theories and core algorithms, and provide financial subsidies and tax incentives for industry-university-research cooperation projects;

(2) Improving Talent Policies: Attract top domestic and international talent, establish incentive mechanisms, encourage universities to strengthen relevant disciplines and industry-education integration, and improve talent evaluation systems oriented towards innovation value;

(3) Optimizing the Market Environment: Strengthen intellectual property protection, improve evaluation and trading mechanisms, cultivate specialized technology trading markets, and provide one-stop services and policy incentives;

(4) Strengthening Platform Development: Support the construction of technology transfer platforms, improve service functions, encourage collaboration between platforms and universities/research institutes, and promote the integration of platforms with large model technologies to enhance service capabilities [7].

5. Empirical testing

5.1. Study design

Based on theoretical analysis, the following hypotheses are proposed: H1: The application level of large models is positively correlated with technology transfer rates; H2: Policy support has a positive moderating effect on large model-empowered technology transfer. The technology transfer rate (TR) is selected as the dependent variable, large model adoption level (MA) as the independent variable, policy support intensity (PS) as the moderating variable, and enterprise size (ES), R&D investment intensity (ERI), and industry competition intensity (IC) as control variables. Data from 240 enterprises for the period 2021-2023 were collected through multiple channels, including questionnaires, government documents, and authoritative reports. A baseline regression model (testing H1) and a moderating effect model (testing H2) were constructed for econometric analysis.

5.2. Empirical results and analysis

Descriptive statistics show that the sample enterprises have a mean TR of 0.35, indicating room for improvement in overall transfer performance, with significant inter-enterprise variability. The mean MA is 3.2, reflecting uneven application levels. The mean PS is 3.8, indicating regional differences in support intensity. Correlation analysis shows that MA and TR are significantly positively correlated at the 1% level (correlation coefficient 0.52), preliminarily validating H1. PS is also positively correlated with TR (0.38). The correlations of control variables with TR are as expected. Regression analysis results show that in Model 2, the MA coefficient is 0.25 ($p < 0.01$), further validating H1. In Model 3, the coefficient of the interaction term MA×PS is 0.18 ($p < 0.05$), validating H2 and indicating that policy support indeed enhances the promoting effect of large models on technology transfer.

5.3. Robustness testing

Robustness checks were conducted using variable substitution (replacing the original MA indicator with a comprehensive score of application depth and breadth, and replacing the original TR indicator with the ratio of new product sales revenue to R&D investment) and sample segmentation (dividing the sample into eastern and central-western enterprises). The results show that the coefficient signs and significance levels of key variables remain consistent with the original model, confirming the reliability and stability of the research findings.

6. Case analysis

Two typical cases were selected: the collaboration between Hangzhou Technology Transfer Center and Beihang University Hangzhou Research Institute, and the partnership between Keyi Network and Xiamen Medical University. Case analysis shows that large models played a key role in supply-demand matching, value assessment, and full-chain services, validating the practical application of the value conduction pathways. Case insights include emphasizing the application of large models and the construction of intelligent service platforms; strengthening industry-university-research collaboration; and improving service systems to create a favorable environment for technology transfer.

7. Conclusion

This study concludes that by constructing digital service scenarios and collaborative ecosystems, large models achieve precision supply-demand matching, scientific value assessment, and full-chain service support, creating value for multiple stakeholders. Current policies suffer from insufficient coordination, targeting, and implementation, requiring optimization in areas such as increasing R&D support, improving talent policies, optimizing the market environment, and strengthening platform development. Empirical analysis confirms the positive correlation between large model application levels and technology transfer rates, as well as the positive moderating effect of policy support. The study has limitations in sample and data scope; future research can expand the scope of investigation and deepen the exploration of application models, technological ethics, and security considerations.

Disclosure statement

The author declares no conflict of interest.

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