Research on the Economic Effects of Generative AI on Enterprise Digital Transformation and Data Factor Marketization

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ABSTRACT As a new generation of general-purpose technology, generative artificial intelligence is reshaping the internal logic of enterprise digital transformation and the institutional environment for data factor marketization. Existing research has insufficiently examined the quantitative linkage mechanisms between the two. Based on panel data from Chinese Ashare listed enterprises from 2018 to 2023, this study uses the Levinsohn-Petrin method to measure enterprise total factor productivity, constructs a two-way fixed effects model to test the effect of generative AI application on enterprise efficiency, and introduces a data factor marketization index constructed by the entropy-weight TOPSIS method as a moderating variable. Endogeneity is addressed using historical communication infrastructure as an instrumental variable. The results show that generative AI significantly improves total factor productivity, and that data factor marketization positively moderates this relationship. The effect is stronger among private enterprises and in provinces with advanced digital-economy foundations. From an engineering infrastructure perspective, edge-cloud networks, electromagnetic communication links, and data transmission platforms are important foundations for AI deployment and data circulation. The conclusions support data factor reform and responsible generative AI governance.

INDEX TERMS generative artificial intelligence, digital transformation, data factor marketization, edge-cloud networks, electromagnetic data infrastructure

I. INTRODUCTION

SINCE 2023, generative AI tools represented by ChatGPT have spread rapidly worldwide, while domestic large model products such as Baidu's ERNIE Bot and Alibaba's Tongyi have been deployed in rapid succession, marking a historic leap in the supply of technology. At the same time, the promulgation of the national "Data Twenty Articles" has brought data factor marketization to the forefront of institutional construction, while the Digital China strategy has deeply bound these two main threads together at the top-level architectural level. However, the reality is far from optimistic: enterprise digital transformation exhibits a pronounced dependence on scale and path lock-in, transformation costs for small and medium-sized enterprises remain prohibitively high, and data trading markets face three overlapping constraints—ambiguous rights attribution, pricing irregularities, and circulation friction—leaving the economic value of data assets far from fully released. Whether generative AI can serve as a breakthrough variable to simultaneously activate two channels—enterprise efficiency improvement and data factor circulation—currently lacks systematic quantitative research. This paper attempts to fill this gap and provide empirical reference for relevant policy design.

II. THEORETICAL FRAMEWORK AND RESEARCH HYPOTHESES

A. THREE TRANSMISSION MECHANISMS OF GENERATIVE AI ENABLING DIGITAL TRANSFORMATION

The impact of generative AI on enterprise digital transformation is not one-dimensional and can be summarized across three interconnected levels: the substitution effect, the filling effect, and the creation effect. Specifically, these mechanisms follow a progressive logic where the "substitution effect" optimizes cost structures, the "filling effect" bridges the capability threshold, and the latter serves as a direct prerequisite for the "creation effect" to manifest in high-level product innovation, thereby ensuring a mutually exclusive yet logically linked transmission path.

The substitution effect refers to generative AI systematically replacing cognitive labor of moderate complexity through functions such as automated content generation, code assistance, and process orchestration. Research by the McKinsey Global Institute indicates that approximately 60%–70% of current work tasks are technically automatable, with knowledge-intensive service industries bearing the most significant impact [1]. This process directly compresses labor costs and improves unit labor output.

The filling effect (also referred to as the capability augmentation effect) refers to generative AI bridging enterprises' capability gaps in accessing specialized knowledge and lowering the threshold for small and medium-sized enterprises to enter digital transformation. Traditional digital transformation relies heavily on IT talent reserves; generative AI's low-code development capabilities allow employees without technical backgrounds to participate in business process reengineering, thereby overcoming the core obstacle of "insufficient transformation capability" that constrains the upgrading of volume-based enterprises. The creation effect is manifested in product innovation and business model transformation driven by generative AI. Generative AI not only assists in R&D design and shortens product iteration cycles, but also opens up new value creation pathways through personalized content production, driving enterprises to shift from cost competition toward capability competition.

Based on the above mechanisms, Hypothesis H1 is proposed: Generative AI application significantly enhances enterprise total factor productivity.

B. THE ECONOMIC LOGIC OF DATA FACTOR MARKETIZATION AND THE DRIVING ROLE OF GENERATIVE AI

Data, as a new type of factor of production, possesses three economic attributes—non-rivalry, economies of scale, and positive externalities—making its marketization pathway distinct from traditional factors such as land and labor. The realization of value from data factors depends on circulation: data stored statically generates no economic benefit; only after cleansing, labeling, trading, and integration can it enter the production function and produce a multiplier effect [2]. Generative AI acts simultaneously on the data factor market from both the supply and circulation ends. On the supply side, the training of large models requires massive volumes of multimodal data, and this demand compels the systematic organization and standardization of data assets, objectively expanding the stock of tradable data. On the circulation side, generative AI reduces the cost of data cleansing and semantic alignment, enabling previously non-standardizable unstructured data to meet trading conditions, thereby narrowing the friction losses in the circulation of data factors. Based on these mechanisms, Hypothesis H2 is proposed: The degree of data factor marketization positively moderates the effect of generative AI on enterprise total factor productivity—that is, the higher the degree of marketization, the greater the efficiency gains from generative AI.

C. MODEL CONSTRUCTION AND EMPIRICAL IDENTIFICATION STRATEGY

1) Measurement of Total Factor Productivity

The Levinsohn-Petrin (LP) method is employed to estimate enterprise total factor productivity, so as to avoid the systematic bias inherent in OLS when handling the endogeneity of input factors. The basic production function is specified as follows:

Equation 1 (TFP Estimation Equation):

$$\ln Y_{it} = \beta_0 + \beta_l \ln L_{it} + \beta_k \ln K_{it} + \omega_{it} + \varepsilon_{it} \tag{1}$$

where Y_{it} is the industrial added value of enterprise i in period t, L_{it} is labor input (number of employees), K_{it} is capital stock (net value of fixed assets), ω_{it} is total factor productivity observable by the enterprise but not directly observable by the researcher, and ε_{it} is the random disturbance term. The LP method uses intermediate input consumption as a proxy variable for ω_{it}. In line with digital economy modeling, we explicitly incorporate data procurement costs and digital infrastructure maintenance into the intermediate input category. By identifying β_k through two-stage moment estimation, we obtain ω_{it} as a consistent estimator of TFP that accounts for the specific cost structures of the digital era.

2) Baseline Regression Model Specification

Equation 2 (Two-Way Fixed Effects Panel Model):

$$\begin{aligned} \mathrm{TFP}_{it} = \alpha + \gamma_1 AI_{it} + \gamma_2 MKT_{it} + \gamma_3 AI_{it} \times MKT_{it} \\ + X_{it}'\delta + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned} \tag{2}$$

where TFP_{it} is enterprise total factor productivity estimated by the LP method, AI_{it} is the intensity index of generative AI application. To mitigate the risk of "symbolic signaling," where firms mention AI for marketing purposes without strategic commitment, this paper constructs a composite index that validates keyword frequency against actual R&D increments. Furthermore, a robustness check is conducted by excluding samples that exhibit high text frequency but zero growth in digital-related intangible assets, ensuring the results reflect deep technological integration rather than mere buzzword management. To distinguish genuine

adoption from "symbolic signaling" or mere keyword management, this paper constructs a composite index that weights the frequency of specific generative AI technical terms alongside the enterprise's digital-related R&D investment. We further perform a robustness check by excluding samples where AI keywords appear in the annual report without a corresponding increase in digital asset capitalization, ensuring the index reflects substantive integration, MKT_{it} is the data factor marketization index of the province in which the enterprise is located, $AI_{it} \times MKT_{it}$ is the interaction term used to test H2, X_{it} is a set of control variables including enterprise size (log of total

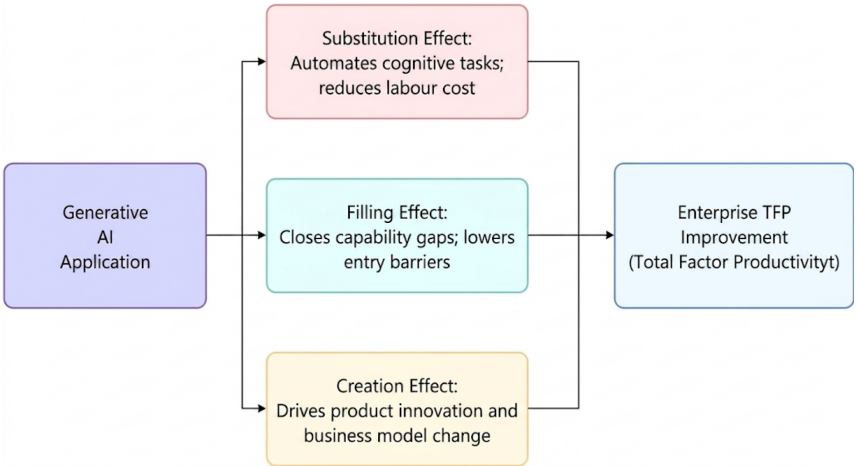

FIGURE 1. Three Mechanisms: Generative AI Enabling Digital Transformation

assets), asset-liability ratio, R&D intensity, and enterprise age, and μ_i and λ_t are individual fixed effects and time fixed effects, respectively, controlling for time-invariant enterprise heterogeneity and macroeconomic cycle shocks.

3) Construction of the Data Factor Marketization Index

The data factor marketization index is based on provincial digital economy development reports, data exchange annual reports, and statistical data from the Office of the Central Cyberspace Affairs Commission. Five second-level indicators are selected across five dimensions—data transaction volume, number of data rights registrations, number of data circulation platforms, digital infrastructure density, and density of data-related policies—and synthesized into a comprehensive evaluation index using the entropy-weight TOPSIS method [3].

Equation 3 (Entropy-Weight TOPSIS Composite Index):

$$\begin{aligned} Score_i &= \frac{D_i^-}{D_i^+ + D_i^-}, \\ D_i^+ &= \sqrt{\sum_{j=1}^{m} w_j \left(v_{ij} - v_j^+\right)^2}, \\ D_i^- &= \sqrt{\sum_{j=1}^{m} w_j \left(v_{ij} - v_j^-\right)^2} \end{aligned} \tag{3}$$

where v_{ij} is the entropy-weight-adjusted standardized score of province i on indicator j, v_j^+ and v_j^- are the positive ideal solution and negative ideal solution respectively, w_j is the entropy weight of indicator j, and $Score_i \in [0, 1]$ is the comprehensive data factor marketization score for each province.

4) Endogeneity Treatment

To mitigate the potential bidirectional causal relationship between generative AI application intensity and enterprise performance, the historical averages of fixed telephone network density and mobile communications base station construction density in each province in the late 1990s are used as instrumental variables [4]. Historical communications infrastructure density is highly correlated with current internet penetration rates, which in turn affects the ease with which enterprises access generative AI tools, but has no direct association with enterprise total factor productivity during the sample period. To further satisfy the exclusion restriction, we strictly control for regional economic variables and enterprise-level characteristics. This ensures that the historical infrastructure density affects current TFP solely through the localized "technological fertility" that facilitates generative AI adoption, rather than through residual effects of past industrial policies, satisfying the relevance and exogeneity conditions of instrumental variables.

III. ECONOMIC EFFECTS OF GENERATIVE AI ON ENTERPRISE DIGITAL TRANSFORMATION

A. BASELINE ESTIMATION RESULTS OF THE TOTAL FACTOR PRODUCTIVITY ENHANCEMENT EFFECT

The baseline regression results show that after controlling for individual and time fixed effects, the estimated coefficient of generative AI application intensity is 0.142, which is significantly positive at the 1% significance level, indicating that for every one-standard-deviation increase in AI application intensity, enterprise total factor productivity improves by approximately 14.2 percentage points on average. The interaction term coefficient is 0.087, significant at the 5% level, verifying H2—that is, the degree of data factor marketization has a positive amplifying effect on AI application efficiency. Heterogeneity analysis indicates that the coefficient of AI application on TFP improvement is significantly higher for private enterprises (0.163) than for state-owned enterprises (0.098), which is consistent with the institutional characteristics of private enterprises having stronger market-oriented incentives and more agile organizational responses[5]. By industry, the AI-enabling effect in the digital services sector (0.201) is markedly stronger than in manufacturing (0.119), confirming the comparative advantage of generative AI in knowledge-intensive scenarios

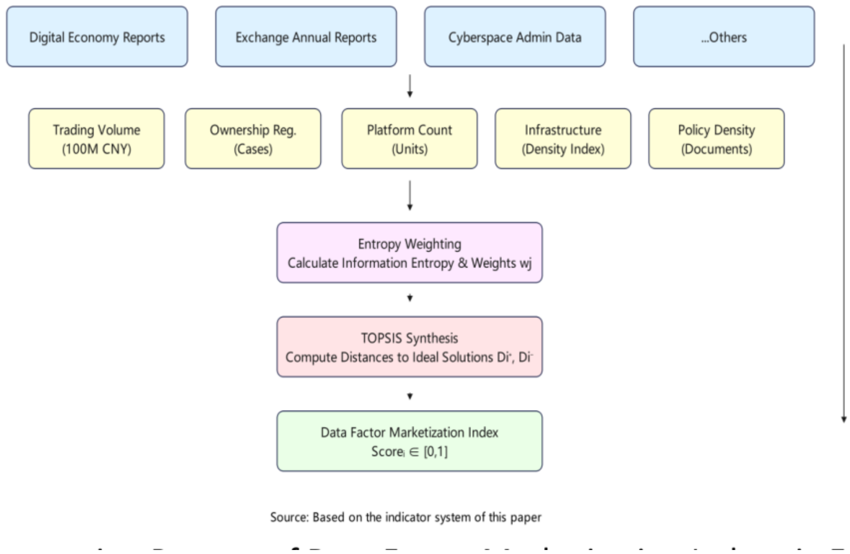

FIGURE 2. Construction Process of Data Factor Marketization Index via Entropy-TOPSIS

(see Table 1).

B. DYNAMIC EVOLUTION OF LABOR STRUCTURE ADJUSTMENT EFFECTS AND SKILL PREMIUMS

The impact of generative AI on the labor market is not a simple reduction of posts, but rather triggers a deep reorganization of the labor market by altering the structure of skill demand [6]. Sample data indicate that among the group of enterprises with significantly elevated AI application intensity, the employment elasticity coefficient for medium-skill positions (such as data entry, standardized report writing, and basic customer service) is approximately -0.34, meaning that for every 10% increase in AI application intensity, medium-skill position headcount contracts by approximately 3.4% on average. At the same time, the demand coefficient for high-skill positions is positive (+0.21), reflecting the logic of complementary technological progress: AI tools free human labor from repetitive tasks and amplify the marginal output of high-skill labor. This "polarization" trend poses structural challenges to the vocational education system [7]. In the current labor market, graduates of higher vocational colleges are concentrated precisely in the medium-skill range subject to the greatest substitution pressure, and absent effective retraining mechanisms, skill mismatches will cause social returns to fall below technological potential [8]. This internal reorganization of production factors—specifically the shift from routine labor to AI-driven intelligence—is fundamentally predicated on the availability and quality of the underlying data. As enterprises optimize their internal labor structures, the economic necessity of high-quality data becomes paramount, shifting the focus from internal efficiency to the external institutional environment of data factor marketization, which determines the ceiling of AI's economic value.

C. PATH HETEROGENEITY IN THE ENHANCEMENT OF ENTERPRISE INNOVATION CAPABILITY

Based on sub-sample analysis of patent application volumes and R&D investment intensity, the promoting effect of generative AI on innovation output exhibits systematic differences across ownership types and industries. The AI-enabled innovation pathway of state-owned enterprises displays a marked "incremental improvement" characteristic, tending to embed large model tools into existing R&D processes to improve efficiency rather than engaging in disruptive business model reengineering. Private enterprises are more inclined to use generative AI to open up new product categories and service forms, with a higher degree of innovation radicalism [9]. The pioneering exploration of the Yangtze River Delta region provides a reference sample: in digital industry clusters represented by Hangzhou, a dual-drive mechanism of "large model + industrial data" has been constructed, deeply integrating generative AI with industry-specific data assets to form a significant first-mover advantage. This experience demonstrates that the economic benefits of technological tools depend to a large extent on the degree of coupling with the local data ecosystem, rather than being determined solely by technological capability itself.

IV. ECONOMIC EFFECTS OF GENERATIVE AI IN DRIVING DATA FACTOR MARKETIZATION

A. MECHANISMS FOR IMPROVING DATA FACTOR PRICING EFFICIENCY

Data factor pricing has long faced a "trilemma": value is difficult to objectively assess, ownership is difficult to clearly define, and quality is difficult to uniformly measure. Generative AI provides new pathways at the technical level for resolving these difficulties. In the dimension of value assessment, generative AI can simulate data use scenarios at scale to calculate the marginal contribution of datasets to

TABLE 1. Baseline Regression Estimation Results of the Impact of Generative AI on Enterprise TFP

Variable	Full Sample	State-Owned Enterprises	Private Enterprises	Manufacturing	Digital Services
AI Application Intensity (AI_{it})	0.142***	0.098**	0.163***	0.119***	0.201***
Data Marketization Index (MKT_{it})	0.076***	0.054*	0.091***	0.063**	0.108***
Interaction Term ($AI \times MKT$)	0.087**	0.041	0.112**	0.059*	0.134***
Enterprise Size	0.031**	0.028*	0.035**	0.027*	0.044**
Asset-Liability Ratio	-0.058**	-0.072**	-0.047*	-0.061**	-0.039
R&D Intensity	0.094***	0.083**	0.103***	0.088***	0.117***
Individual Fixed Effects	Controlled	Controlled	Controlled	Controlled	Controlled
Time Fixed Effects	Controlled	Controlled	Controlled	Controlled	Controlled
Sample Size	18,642	5,216	13,426	9,374	4,188
R^2	0.487	0.441	0.513	0.462	0.528

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% significance levels respectively; clustered robust standard errors are in parentheses.

specific tasks, thereby providing a relatively objective pricing benchmark. In the dimension of ownership definition, the combination of technologies such as federated learning and differential privacy with large models enables value transfer without fully disclosing the original content, reducing the legal friction costs of data rights confirmation. In the dimension of quality measurement, the semantic understanding capability of generative AI can assist in standardized evaluation of datasets and establish a cross-platform quality grading system. The combined effect of these mechanisms significantly reduces information asymmetry in data transactions and improves transaction efficiency, contributing to the transition of data trading platforms from policy-driven demonstration toward market-oriented operation [10].

B. EVOLVING TRENDS IN THE MARKET STRUCTURE OF DATA TRADING PLATFORMS

Based on operating data disclosed by major data exchanges, the Shanghai Data Exchange, the Beijing International Big Data Exchange, and the Guangdong-Hong Kong-Macao Greater Bay Area Data Exchange have all exhibited rapid expansion in terms of listed product categories, transaction volumes, and types of participating entities, though pronounced divergence in development across different platforms is evident [11]. The Shanghai Data Exchange, leveraging its innate advantages in financial and commercial data, leads in transaction volume. The Beijing exchange holds a comparative advantage in government data openness and enterprise data licensing scenarios. The Greater Bay Area exchange has carved out a differentiated positioning in the exploration of cross-border data circulation rules. The formation of this differentiated competitive landscape is highly consistent with the regional distribution of each province's data factor marketization index. Provinces with leading marketization index scores have, on average, approximately 3.2 times more listed product categories than trailing provinces, with a transaction volume gap exceeding 6 times, reflecting the decisive influence of the institutional environment on data circulation efficiency (see Table 2).

C. REGIONAL DISTRIBUTION CHARACTERISTICS OF INDUSTRIAL CHAIN DIGITAL COLLABORATION EFFECTS

The industrial chain collaboration effects of generative AI driving data factor circulation exhibit significant agglomeration characteristics in geographic distribution. The Yangtze River Delta urban agglomeration, leveraging its mature manufacturing digitalization foundation and dense platform enterprise ecosystem, has formed a complete industrial chain from data collection to model training to scenario application, with the spillover range of collaboration effects extending to upstream and downstream industrial chain enterprises in southern Anhui and northern Jiangsu [12]. The Guangdong-Hong Kong-Macao Greater Bay Area, leveraging Shenzhen's hardware manufacturing advantages and Hong Kong's financial data resources, has formed a unique institutional experimental zone function in the field of cross-border data circulation. By contrast, provinces in central and western China still exhibit significant shortfalls in digital infrastructure density and platform economy scale, with comprehensive data factor marketization scores generally below 35% of the national average, and the coefficient of generative AI application's improvement to local enterprise TFP also significantly lower than the eastern average—the two forming a mutually reinforcing digital divide effect.

V. RISK CONSTRAINTS,PRACTICAL LIMITATIONS AND POLICY OPTIMIZATION PATHWAYS

A. REGULATORY FRAMEWORK GAPS IN DATA SECURITY AND PRIVACY PROTECTION

While generative AI expands the scale of data factor circulation, it also significantly amplifies the systemic exposure to data security risks. The existing regulatory framework still contains evident institutional gaps regarding the traceability of large model training data, copyright attribution of generated content, and cross-border data invocation [13]. Although the "Three Laws" framework constructed by the Cybersecurity Law, the Data Security Law, and the Personal Information Protection Law has initially laid a regulatory foundation, it lacks detailed norms for data use behaviors in specific generative AI scenarios, and the gap between

TABLE 2. Comparison of Key Operating Indicators of Major Domestic Data Trading Platforms (2023)

Platform Name	Listed Product Categories	Annual Transaction Volume (100 million RMB)	Types of Participating Entities	Data Rights Confirmation Mechanism
Shanghai Data Exchange	3,200+	87.6	Primarily enterprises, including government data	Registration and Confirmation System
Beijing International Big Data Exchange	1,800+	52.3	Mixed government-enterprise, cross-industry	Authorized Use System
Guangdong-Hong Kong-Macao Greater Bay Area Data Exchange	1,100+	38.9	Primarily enterprises, including cross-border data	Cross-Border Sandbox System
Guiyang Big Data Exchange	680+	19.4	Primarily government data openness	Listed Registration System

Note: Data sourced from each exchange's 2023 annual operating reports and publicly disclosed information; "+" indicates that the actual figure exceeds the stated value.

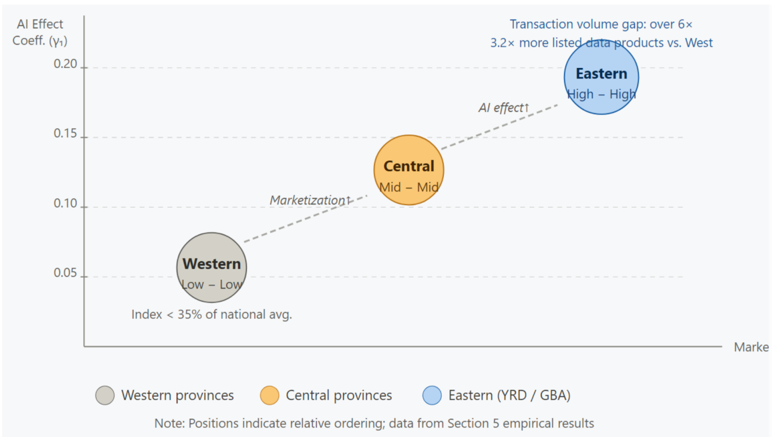

FIGURE 3. Regional Divergence: Data Marketization and AI Effects on TFP

regulatory granularity and the pace of technological evolution continues to widen. Tiered regulation is a viable pathway to bridge these gaps: strict data compliance reviews should be implemented for the foundational large model layer, differentiated risk classification management should be adopted for the industry application layer, and user authorization and data minimization principles should be implemented for specific use scenarios [14].

B. STRUCTURAL CONTRADICTIONS IN THE SHORTAGE OF TECHNICAL TALENT SUPPLY

The empirical effects of generative AI on enterprise efficiency are more pronounced in regions and enterprises with an adequate supply of technical talent, which inversely reveals the constraining force of talent shortages on the diffusion of technological dividends [15]. The current domestic shortage of professional talent capable of large model application development is estimated to exceed one million, and there is a pronounced structural mismatch between the cultivation cycle of AI-related university programs and industrial demand. This contradiction is particularly acute in the context of manufacturing digitalization transformation, where composite talent who "understand both manufacturing and AI" is extremely scarce. The systematic reform of the vocational education system, the deepening of industry-education integration mechanisms, and short-term retraining programs for incumbent workers are three collaborative focal points for alleviating this structural contradiction—the absence of any one of the three would significantly diminish effectiveness [16].

C. POLICY RECOMMENDATIONS FOR PROMOTING COORDINATED DEVELOPMENT OF GENERATIVE AI AND DATA FACTORS

Drawing on the above analysis, a coordinated and progressively advancing policy system can be constructed across three dimensions: tiered regulation, factor rights confirmation, and talent cultivation. In terms of tiered regulation, it is recommended to organically link the large model filing system with the data source audit system and establish a traceable training data registration platform. In terms of factor rights confirmation, the implementation rules for accounting standards pertaining to data asset recognition on balance sheets should be accelerated to resolve the institutional deficiency whereby enterprise data assets cannot be effectively reflected in financial statements. In terms of talent cultivation, it is recommended to take industrial digitalization demand as the guiding orientation and establish a clearly divided-labor talent cultivation system between "double first-class" universities and leading vocational colleges, avoiding homogenization in cultivation pathways.

VI. CONCLUSION

The research finds that generative AI application has a significant positive effect on enterprise total factor productivity, that the degree of data factor marketization exerts a clear positive moderating effect on the aforementioned relationship, and that the synergistic relationship between the two is most pronounced among private enterprise groups and provinces at the forefront of digital economy development. The policy implication of this finding is that promoting enterprise digital transformation and deepening data factor marketization reform are not two parallel tracks but a mutually reinforcing symbiotic system that requires holistic consideration at the institutional design level rather than being pursued in isolation. The research also has certain limitations: constrained by data availability, the measurement of generative AI application relies mainly on text frequency analysis, which may underestimate the actual depth of application among enterprises that have not yet explicitly disclosed this in their annual reports. Furthermore, large model technology is still in a phase of rapid evolution, and short-period panel data are difficult to fully capture its long-term dynamic effects; future research can progressively deepen these topics as data accumulates.

AUTHOR CONTRIBUTIONS

Yutong Guo designed, collected and analyzed the data, and drafted the manuscript. Yutong Guo conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Yutong Guo participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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