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Data Valuation, AI Ecosystem Restructuring and Enterprise Digital Intelligence Transformation

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Abstract

This paper aims to explore how data valorization drives enterprise digital intelligence by reconstructing the AI ecosystem (covering three dimensions: AI talent, technology, and collaboration). Based on technological economics and innovation theory, this study constructs a theoretical analytical framework of "data valorization—AI ecosystem reconstruction—enterprise digital intelligence" and conducts empirical testing using data from China's Shanghai and Shenzhen A-share manufacturing listed companies from 2014 to 2023. In terms of research design, the core dependent variable "enterprise digital intelligence" is measured using text mining methods based on the BERT large language model, effectively overcoming the limitations of traditional lexical methods in semantic understanding and motivation identification. The findings reveal: First, data valorization has a significant positive driving effect on enterprise digital intelligence, and this conclusion remains valid after a series of robustness tests. Second, mechanism analysis indicates that data valorization empowers transformation through three pathways: first, fostering and optimizing AI talent structures to strengthen human capital foundations; second, systematically enhancing AI technological innovation and engineering applications; and third, deepening AI collaboration by promoting cooperation at the levels of resource utilization, assetization, and capitalization. Third, the transformational effects of data valorization exhibit heterogeneity, being more pronounced in enterprises with strong absorptive capacity, optimal talent structures, and rich governance experience.

Keywords

data valorization, ai, enterprise digital intelligence, large language models

1. Introduction

With the rapid advancement of global digital technologies, enterprises are undergoing profound transformations in production models, organizational structures, and competitive landscapes. Both in developed and developing countries, digital and intelligent transformation has become a critical strategy for businesses to maintain competitiveness and achieve sustainable growth. Governments prioritize corporate digitalization upgrades, as outlined in the "Proposal of the Central Committee of the Communist Party of China on Formulating the 15th Five-Year Plan for National Economic and Social Development," which emphasizes "promoting technological upgrades, facilitating digital and intelligent transformation in manufacturing, developing smart manufacturing, green manufacturing, and service-oriented manufacturing, and accelerating industrial model and organizational restructuring," while advocating "enhancing integration between modern services and advanced manufacturing/agriculture to drive service sector digitalization." Policy signals indicate that enterprise digitalization represents not just technological investment but also a vital component of national strategies, industrial upgrading, and economic restructuring. Nevertheless, many enterprises still face significant challenges during digital transformation. Strategically, these challenges manifest as top-level design deficiencies—disconnection between transformation initiatives and core business strategies, ambiguous leadership commitments, and short-termism in evaluation systems, leading to strategic directionlessness and lack of momentum. Technologically, ineffective data governance creates data silos and information bottlenecks, while legacy systems accumulate technical debt, undermining data-driven decision-making foundations (Liu, Yan, Zhang et al., 2021). Organizational and talent-related barriers—including shortages of interdisciplinary digital professionals, skill gaps among existing employees, resistance to change, and rigid structures—constitute major obstacles to transformation. Ultimately, conflicts between legacy and new systems at operational and process levels have created a disconnect between digital capabilities and business workflows. Coupled with the absence of agile iteration culture and mechanisms, the final mile of value creation remains challenging to achieve. These interconnected dimensions mean that weaknesses in any single aspect may systematically constrain transformation outcomes. Against this backdrop, how to break through bottlenecks in digital-intelligent transformation and establish sustainable, systematic pathways has become a shared focus for both academia and industry. In recent years, data elements have increasingly emerged as a critical driver for industrial transformation and upgrading. The "Data Elements × Smart Manufacturing" initiative outlined in the Three-Year Action Plan for Data Elements (2024-2026) has strategically positioned data as the core element in manufacturing digitalization from a national perspective. However, while the concept of data as a key production factor has gained widespread consensus, the more critical process of "data valorization" still lacks adequate attention and breakthroughs, with no systematic or replicable implementation pathways established. This gap remains the primary obstacle hindering the full realization of data elements' potential. Data valorization fundamentally involves transforming static data resources into quantifiable, tradable, and value-added strategic assets across the entire value chain—from resource utilization to assetization and capitalization. Only through achieving this value leap can data truly become the intrinsic driving force and practical engine for enterprise digital-intelligent transformation.

Furthermore, the key mechanism by which data valorization drives enterprise digital intelligence lies in promoting AI ecosystem restructuring. The rationale for focusing on the interaction between data valorization and enterprise digitalization through AI ecosystem reconstruction is twofold: First, the AI ecosystem serves as both the essential vehicle and realization form for data valorization. Data valorization encompasses a complete chain of resource utilization, assetization, and capitalization, which relies on algorithmic drivers from AI technologies, value extraction of AI talent, and expansion of collaborative scenarios. Without AI ecosystem support, data remains static resources incapable of sustained value creation or strategic empowerment. Second, AI ecosystem restructuring represents a critical pathway to overcome current corporate transformation bottlenecks. Challenges such as strategic misalignment, data silos, organizational rigidity, and skill shortages fundamentally stem from incompatibility between traditional production systems and digital productivity. An ecosystem-driven restructuring centered on AI talent, leveraging AI technologies as platforms, and fostering AI collaborations as networks can systematically break down departmental barriers, optimize decision-making processes, and stimulate innovation vitality, thereby bridging the "last mile" from data to value realization. Thus, focusing on AI ecosystem reconstruction reveals the intrinsic economic logic of data valorization driving enterprise digital intelligence. This perspective not only transcends limitations of single technologies or management approaches but also provides actionable theoretical frameworks for enterprises to establish sustainable intelligent evolution pathways. Building on this foundation, this study adopts an economic perspective to construct a theoretical framework that begins with data valorization, exploring how it drives the restructuring of the AI industry ecosystem—specifically through three key mechanisms: AI talent development, AI technology innovation, and AI collaboration. Ultimately, this framework aims to facilitate enterprise digital intelligence transformation. By providing this analytical framework, we seek to offer new insights for companies addressing transformation bottlenecks and achieving intelligent upgrades, while also serving as a theoretical reference for policy formulation.

2. Literature Review

2.1 Driving Factors of Enterprise Digital Transformation

Corporate digital intelligence, as a pivotal transformation direction in the digital economy era, has become a focal point in management science and industrial economics research in recent years. Scholars primarily examine its driving factors through four dimensions: technology, organization, environment, and resources. From a technology-driven perspective, early studies emphasized the role of information technology applications in corporate digitalization, later expanding to explore the integration effects of emerging digital technologies such as cloud computing, big data, and artificial intelligence. Existing research generally agrees that the improvement of digital infrastructure and the embedding of intelligent technologies serve as core drivers for achieving intelligent production, management, and decision-making in corporate digital intelligence (Fu & Cai, 2024). However, some studies indicate that relying solely on technological investment does not guarantee high-quality digital transformation, with the key lying in whether technologies can be embedded into supply chain ecosystem innovation. From an organizational perspective, research at the organizational level highlights the importance of internal learning capabilities and human capital structure. It posits that building dynamic learning capacity depends on management's perception, learning capabilities, and resource restructuring skills. Guerrero et al. (2023) further emphasize that corporate digital intelligence relies on cultivating innovative cultures and supporting multidisciplinary digital talent teams. From an environmental perspective, macro-level factors such as policy frameworks, industrial ecosystems, and market competition act as significant external forces driving corporate digitalization. International studies propose competitive logic for intelligent products and services, underscoring the importance of external ecosystem synergy (Li, Yang, Jin, Li, Yang, Jin et al., 2023). Domestic scholars further pointed out that the digital intelligence transformation of Chinese enterprises is deeply influenced by policy orientation, particularly guided by strategic policies such as "Digital China" and "New Industrialization". Industrial clusters, supply chain networks, and data sharing platforms have become important external carriers for enterprise transformation. From the perspective of resources and capabilities, in recent years, an increasing number of studies have emphasized enterprises' integration capabilities in three types of resources—data, technology, and organization—based on resource-based theory and dynamic capability theory (Malik, Andargoli, Ali, Malik, Andargoli, Ali et al., 2024). It is noted that enterprise digital intelligence transformation is a data-driven process that requires the formation of a dynamic feedback mechanism within the closed loop of "perception, learning, decision-making, and execution." However, the effective operation of this closed loop hinges on the data valorization process—it serves as the converter that transforms raw data resources into strategic insights and execution momentum. Without systematic data valorization practices, data cannot be effectively distilled into knowledge during the "perception-learning" phase, nor can it precisely drive actions and create business value during the "decision-execution" phase. Therefore, data valorization is the core bridge connecting data resources and enterprise dynamic capabilities, influencing the efficiency of digital intelligence transformation. Overall, existing research reveals multidimensional driving factors for enterprise digital intelligence transformation, but three shortcomings remain: first, the lack of a theoretical framework that systematically interprets how "data valorization" drives enterprise digital intelligence transformation through AI talent, technology, and collaboration, with "data valorization" as the core driving variable. Secondly, there is an excessive focus on isolating and testing the effects of individual driving forces such as technology, organization, and environment, lacking systematic deconstruction of their dynamic co-evolutionary relationships, with their inherent "black box" mechanisms remaining inadequately understood. Thirdly, there exists a certain degree of "winner's bias," where overemphasis on successful paradigms leads to relatively insufficient exploration of failure pathways and underlying obstacle mechanisms in transformation processes.

2.2 Data Valorization and Corporate Value Creation

With data being formally incorporated into the production factors system, data valorization has gradually become a focal point in academic research. Data valorization emphasizes the process by which enterprises transform potential data value into economic value through data collection, integration, analysis, and application· Existing studies primarily focus on three dimensions: enhancing corporate performance, strengthening innovation capabilities, and optimizing organizational efficiency. Firstly, regarding data valorization and corporate performance, existing research generally indicates that data valorization improves resource allocation efficiency and decision-making quality, thereby enhancing operational performance· Chinese scholar He Ying et al. found that data assetization significantly alleviates financing constraints for specialized, refined, distinctive, and innovative enterprises. Secondly, concerning data valorization and corporate innovation capabilities, from an innovation perspective, data valorization promotes new innovation models by facilitating knowledge flow and technological learning. Mishra noted that data-driven learning processes can substantially boost corporate AI innovation capabilities and R&D efficiency. Studies demonstrate that data valorization stimulates product innovation and process innovation through knowledge sharing and algorithmic innovation. However, some research indicates that the innovation effects of data valorization exhibit heterogeneity, depending on enterprises' data governance capabilities and organizational absorptive capacity. Thirdly, data valorization and organizational efficiency as well as structural optimization. On one hand, leveraging data to drive industrial digital transformation, optimize industrial ecosystems, and promote organizational innovation in industries; on the other hand, enterprises establish algorithm-centric decision-making structures during the process of data valorization, facilitating organizational transition from experience-driven approaches to intelligent decision-making frameworks (Awan, Shamim, Khan, Awan, Shamim, Khan et al., 2021).

Overall, enterprise digital intelligence has become the core pathway to seize opportunities in the digital economy era, with its multifaceted and complex driving factors widely discussed in academic circles. From technological empowerment to organizational adaptation, environmental pressures to resource restructuring, existing research has delineated a multidimensional landscape of transformational drivers. Meanwhile, as data is established as a critical production factor, the process of data valorization—enabling data potential and driving value creation—has garnered sustained attention for its microeconomic effects. However, two limitations remain: first, current literature predominantly focuses on the static economic consequences of data valorization while neglecting its role as a dynamic capability cultivation mechanism in enterprise digital intelligence evolution; second, most studies remain confined to macro-level data element policies or micro-level performance outcomes, lacking meso-level mechanism research that bridges these dimensions—specifically studies examining how data valorization facilitates enterprise digital intelligence. Building upon prior research, this paper proposes constructing a multidimensional, systematic theoretical framework based on the logical chain where data valorization promotes AI talent development, AI technology advancement, and AI collaboration to empower enterprise digital intelligence. This framework aims to provide new theoretical support for comprehending the intrinsic logic of data valorization-driven enterprise digital transformation.

3. Theoretical Analysis and Mechanism of Action

The interplay among data monetization, AI ecosystem restructuring, and enterprise digital intelligence transcends simple linear relationships, forming an intricately coupled closed-loop logic system. This interconnectedness stems from the fundamental principles of digital economy development, with data monetization serving as the enduring core driver and value engine throughout the entire process.

Data valorization is a progressively deepening process that typically follows a trajectory from resource utilization and commercialization to ultimate capitalization (Zakaria, Imane, Youssef, Zakaria, Imane, Youssef et al., 2020), providing initial transformation momentum and continuous value measurement for enterprise digital intelligence initiatives. Without explicit manifestation and enhancement of data value, digital transformation efforts would lack sustainable viability due to undefined ROI metrics. AI ecosystem reconstruction serves as the essential vehicle and core mechanism for achieving enterprise digital intelligence. With exponential growth in data volume and complexity, organizations must rely on AI ecosystems integrating AI technologies, talent pools, and collaborative frameworks to conduct deep data mining, intelligent modeling, and automated decision-making. These ecosystems provide indispensable value extraction tools and operational hubs for digital transformation, addressing the fundamental question of "how to transition." Enterprise digital intelligence represents the ultimate goal and external manifestation of the synergistic interaction between these elements. It signifies how AI-powered ecosystems empower data valorization to reshape business processes, business models, and organizational structures, ultimately driving comprehensive digital transformation. Thus, an inherent logical relationship exists among these three components: data valorization serves as the value source and foundation; AI ecosystem reconstruction acts as the enabler providing momentum; and enterprise digital intelligence constitutes the outcome embodying value realization. These elements are interlocked, with their operational mechanisms illustrated in Figure 1.

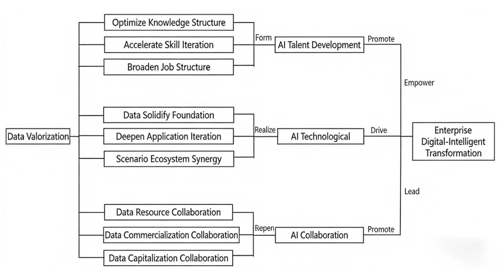

Figure 1. Data Value Creation, AI Ecosystem Restructuring, and Enterprise Digital Intelligence Transformation

3.1 Data Valorization Drives AI Talent Development to Empower Enterprise Digital Intelligence Transformation

From the perspective of human capital and innovation economics, the key to AI talent development through data valorization lies in optimizing knowledge structures, accelerating skill iteration cycles, and diversifying job roles to drive enterprise digital transformation. Firstly, regarding knowledge frameworks, data valorization creates emerging demands for expertise in data governance, valuation modeling, and regulatory compliance frameworks. This compels AI professionals to expand their knowledge systems beyond algorithmic engineering into interdisciplinary domains spanning economics, management, and law. The internalization of such knowledge spillovers enhances AI talents' cognitive breadth and decision-making acumen in addressing digital transformation complexities, thereby improving the scientific rigor and feasibility of corporate digitalization. Secondly, in terms of skill iteration, the high-value feedback loop inherent in data valorization generates strong economic incentives for skill investment (Yao, Zhang, Guo et al., 2024). Human capital theory emphasizes that return on skill investment serves as the primary economic driver for individual capital accumulation. When data value becomes directly measurable and correlates with business outcomes, the marginal contributions and returns of AI skills become clearly visible. This provides clear incentives and strategic guidance for skill development, motivating professionals to proactively pursue continuous skill upgrades. Such efforts cultivate highly adaptable human capital capable of meeting the fast-paced demands of digital transformation, injecting sustained internal momentum into organizational evolution. Finally, innovation economics reveals that technological progress creates new job roles and occupational categories within AI talent frameworks. The monetization of data drives the emergence of new AI talent roles through two key mechanisms: "dematerialization of data requirements" and "specialization of data functions." Specifically, as data becomes a quantifiable and tradable critical production factor, enterprises increasingly prioritize data governance, compliance frameworks, and model management—transitioning from implicit needs to explicit requirements. This has spawned specialized positions like "data architects" and "model compliance officers" dedicated to data accountability and regulatory enforcement. Concurrently, to transform raw data into high-quality AI inputs, previously auxiliary data processing tasks have evolved into standardized functional modules, fostering roles such as "AI trainers" and "data annotation specialists." These emerging AI professionals serve as structural bridges between data assets and AI applications. By establishing data closed loops, optimizing model development pathways, and managing technical risks, they effectively convert data's latent value into sustainable momentum for enterprise digital transformation.

3.2 Data valorization Accelerates AI Technological Innovation, Driving Enterprise Digital Intelligence Transformation

From the perspectives of technical economics and innovation theory, data valorization drives AI technological advancement by systematically enhancing three core elements—data, computing power, and algorithms—thereby providing sustained momentum for enterprise digital transformation. Firstly, at the data level, data valorization transforms raw information into standardized, tradable production factors, establishing a quality foundation for AI development. Through establishing comprehensive mechanisms for rights confirmation, pricing, and circulation (Tang Song et al., 2020), it effectively addresses the large-scale, high-quality data supply challenges required for AI training while significantly reducing transaction costs associated with data acquisition and utilization. High-quality data supply not only directly improves the performance ceiling of AI models but also enables enterprises to build data-driven capabilities spanning entire business processes, serving as an indispensable data foundation for digital transformation. Secondly, at the computing power level, data valorization stimulates demand for scalable and intensive high-performance computing resources, propelling intelligent evolution of computing infrastructure. To process massive datasets and support complex AI training tasks, enterprises are increasing investments in cloud-native architectures and intelligent computing centers. This centralized computing deployment reduces marginal R&D costs while enabling elastic, scalable model iterations and business innovations, providing stable foundational support for end-to-end digital transformation. Finally, at the algorithm level, data valorization creates a closed-loop feedback mechanism of "data-scenario-value," driving continuous optimization and engineering implementation of algorithmic technologies. During data circulation and application processes, algorithm models continuously receive high-frequency feedback from real-world business scenarios, accelerating their transition from laboratory prototypes to industrial deployment. To encapsulate AI capabilities into reusable standardized services, enterprises must systematically enhance their capabilities in algorithm engineering domains such as MLOps and model governance. This fosters a virtuous cycle of "technology iteration—value creation—reinvestment in innovation" (Ma et al., 2020), ultimately driving systemic transformation from localized intelligence to global intelligence.

3.3 Data Valorization Drives AI Collaboration Deepening and Leads Enterprise Digital Intelligence Transformation

Firstly, data resource collaboration serves as the cornerstone for enterprises to establish data-driven governance internally. Its core lies in breaking down departmental "data silos" through unified data standards and sharing mechanisms, enabling cross-functional data integration and utilization while ensuring data security and compliance. Essentially, this transforms scattered data resources across business units into organization-wide assets that can be leveraged globally. By reducing internal information barriers and collaboration costs, it activates the reuse value of data resources in R&D, production, marketing, and other processes. Such collaborations have spurred the emergence of collaborative models like data middle platforms and business middle platforms, enabling enterprises to conduct intelligent analysis and decision optimization based on comprehensive data. This transition from "department-level intelligence" to "enterprise-level intelligence" systematically strengthens the micro-foundation of digital transformation through enhanced internal collaboration and operational efficiency. Secondly, data assetization collaboration represents a critical pathway for enterprises to participate in data factor market development. When internal data resources are packaged into standardized data products, model services, or intelligent solutions and enter circulation and trading processes, data transforms from a resource form into marketable assets with valuation and trading capabilities. Such collaborations enable enterprises to leverage their data advantages for external empowerment and collaborative innovation. Beyond monetizing data value through market transactions, they foster specialized AI capability specialization and economies of scope across industries, extending corporate digital intelligence from "internal development" to "open ecosystems." Market mechanisms then facilitate effective data asset allocation, significantly expanding the boundaries of digital intelligence capabilities and enhancing external integration depth. Ultimately, data capitalization cooperation represents an advanced form of value co-creation and risk sharing. When data serves as core assets for equity participation or becomes the foundation for asset securitization, it transforms into productive capital, achieving deep integration of "data-capital" synergy (Jiao & Qi, 2024). Collaborating parties form tightly-knit interest communities and risk-sharing entities, jointly investing in forward-looking AI technology R&D and commercialization to sustain AI ecosystem prosperity. This approach not only addresses long-term financing constraints for AI innovation but also strategically directs capital toward cutting-edge digital intelligence frontiers, realizing strategic synergy between financial and data capital. Enterprises thus enter a deep digital transformation phase driven by strategic leadership and ecosystem co-governance. Based on this analysis, this study proposes the following hypothesis:

Hypothesis1: Data valorization exerts significant positive driving effects on corporate digital intelligence development.

Hypothesis2: AI ecosystem restructuring serves as the pivotal pathway for enterprise digital intelligence driven by data valorization. This function is primarily realized through three specific mechanisms:

Hypothesis2a: Data valorization drives enterprise digital intelligence by fostering AI talent development. Specifically, data valorization optimizes talent knowledge structures, accelerates skill iteration, and expands professional roles, systematically promoting AI talent growth and empowering enterprise digital transformation.

Hypothesis2b: Data valorization drives AI technological innovation, thereby promoting enterprise digital intelligence transformation. Specifically, data valorization enhances data element quality, stimulates computational demand, and facilitates algorithm optimization, systematically advancing AI technological innovation and empowering enterprise digital intelligence transformation.

Hypothesis2c: Data valorization deepens AI collaboration to drive enterprise digital intelligence transformation. Specifically, data valorization facilitates systematic internal and external AI cooperation through data resource utilization, assetization, and capitalization, thereby empowering corporate digital intelligence development.

4. Research Design

4.1 Study Sample and Data Sources

This paper selects manufacturing listed companies in the Shanghai and Shenzhen A-share markets from 2014 to 2023 as research samples, and constructs a sample library by combining corporate annual reports, Wind database, CSMAR database, Mark Data Network, China National Intellectual Property Administration, and web-scraped data. Through text mining and keyword recognition technologies, the study identifies corporate AI investments, data valorization levels, and intelligent transformation capabilities. After excluding ST companies and missing values, approximately 3,800 firms' panel data were ultimately obtained.

4.2 Variable Design

Dependent variable: Enterprise Digital Intelligence (DLT)

The dependent variable in this study is corporate digital intelligence, designed to measure the depth and breadth of enterprises 'integration and systematic upgrades through digital and intelligent technologies. Conventional methodologies have long relied on the "dictionary approach" —performing word frequency analysis on textual data such as annual reports of listed companies using pre-built keyword libraries related to digital and intelligent technologies. However, traditional dictionary methods face three fundamental challenges in academic rigor and practical applicability: First, keyword selection in dictionary compilation remains highly subjective, with significant variations across research teams' word libraries, leading to inconsistent measurement results and compromised research robustness. Second, semantic understanding and motivation identification remain inadequate. This approach merely mechanically counts lexical "occurrence" frequencies without comprehending contextual meanings, application depth, or strategic significance. Given that corporate annual reports may contain strategic disclosure motives, the inherent flaws of word-for-word correspondence or semantic disconnection make dictionary methods unable to penetrate textual surface-level information. This prevents accurate quantification of qualitative dimensions in technological integration and transformation, potentially causing signal-noise confusion. To address these limitations, we adopt the cutting-edge methodology from , utilizing large language models for mining annual reports of listed companies.

Specifically: First, we constructed a sentence library for text processing. By collecting annual reports from 3,800 listed manufacturing companies between 2014 and 2023, we extracted two key chapters—"Chapter 1: Table of Contents, Definitions, and Major Risk Disclosure" and "Chapter 3: Management Discussion and Analysis"—and segmented the text into individual sentences to build a decade-spanning sentence database. Second, we conducted manual annotation and model training. Each year, we randomly sampled a subset (Note 1) of sentences from the database (totaling over 20,000 sentences) for precise manual annotation to create a high-quality (Note 2) training dataset. The annotation process involved: To facilitate searching for discussions on digitalization and intelligence in corporate annual reports, we screened sentences containing relevant keywords (Yuan, Xiao, Geng et al., 2021) related to digitalization and intelligent technologies. A 10-member research team then evaluated each sentence according to predefined criteria, with two independent judges scoring individual sentences. Sentences demonstrating applications of six digital technologies including artificial intelligence and blockchain were classified as “digitalization,” while those explicitly referencing intelligent technologies were categorized as “intelligentization.” Enterprises meeting both digitalization and intelligentization criteria were assigned a 1-point score, while those meeting only one criterion or none received a 0 score. Based on these annotations, we performed phased fine-tuning of the BERT model developed by Google. Leveraging its bidirectional Transformer architecture and robust predictive training knowledge base, the model achieves deep contextual understanding of key phrases within sentences, enabling precise identification of whether enterprises genuinely implement digital intelligence technologies. This process ultimately leads to the training of BERT models. The subsequent full-text prediction and metric construction phase utilizes fine-tuned BERT models for automated prediction across the entire sentence corpus, detecting all sentences related to digital intelligence applications. Based on prediction results, we establish the core explanatory variable DLT: If an enterprise’s annual report contains sentences simultaneously reflecting digitalization and intelligent transformation, it indicates active digital intelligence transition, assigning the variable a value of 1; otherwise, it receives a value of 0.

The measurement methodology demonstrates advantages across multiple dimensions: In terms of data foundation, it ensures comprehensive coverage of 3,800 enterprises spanning ten years while maintaining information quality through focused analysis of key chapters; methodologically, it integrates the accuracy of manual annotations with cutting-edge BERT model technology; in measurement precision, the bidirectional attention mechanism of BERT effectively captures contextual understanding, complemented by dual criteria to ensure conceptual accuracy. The approach also exhibits strong replicability, with its streamlined workflow facilitating cross-domain application. To validate results, robustness analysis employs alternative measurement methods for dependent variables: DTT is replaced by the absolute count of BERT-identified effective digital transformation sentences in annual reports (logarithmically transformed after adding 1) and their relative proportion among total sentences, thereby excluding strategic disclosures. The term “strategic” refers to instances where companies may use generic, slogan-like digital transformation terminology in annual reports to align with market trends, policy directions, or investor preferences without substantive technological investments or business applications. This methodology captures the intensity of digital transformation practices, thereby validating the robustness of benchmark regression conclusions.

Core explanatory variable: Data Valueization (DW)

Current research on measuring data valueization remains relatively limited, primarily due to its inherent measurement challenges. To achieve more objective and comprehensive evaluation of this indicator, this study adopts the research framework and methodology from, utilizing a BERT pre-trained large language model to objectively select keywords, followed by assessing enterprise data valueization levels based on total keyword frequency counts. The measurement process involves three key steps: First, seed vocabulary selection is conducted by defining data valueization's core stages—data resource utilization, data assetization, and data capitalization—through referencing existing literature and theoretical frameworks. Integrating current research findings while considering (Note 3) value creation factors such as data sources, stakeholders, processes, and outcomes, seven keywords were identified as core components: information, network, digitalization, data, value, intelligence, resources, and enterprise data valueization. Second, an initial corpus is constructed by synthesizing relevant policies and literature from documents like the "Three-Year Action Plan (Note 4) for Data Elements." Third, the initial corpus is processed using BERT to generate a keyword database with high semantic alignment. Leveraging BERT's contextual understanding capabilities, deep learning techniques were employed to segment texts and generate 10,372 word vectors. After removing duplicates, 1,309 vectors remained, from which similar terms with high cosine similarity to seed vectors were selected to complete the keyword database construction. Finally, by analyzing the total word frequency of statistical keywords in the Management Discussion and Analysis (MD&A) sections of listed companies 'annual reports, we derive comprehensive indicators reflecting corporate data valorization. Higher total word frequency values indicate greater data valorization levels. Given the right-skewed distribution characteristic of corporate data valorization, this study applies logarithmic transformation to the data. Compared to traditional methods, our keyword dictionary construction approach utilizing BERT word vectors and cosine similarity demonstrates significant advantages: The method employs large-scale corpus-derived word vectors for keyword identification, utilizes cosine similarity for quantitative computation to eliminate subjective researcher bias, ensuring process objectivity and reproducibility; Leveraging BERT's contextual awareness capabilities, it accurately captures semantic associations (e.g., synonyms, hierarchical relationships) within specific policy contexts, guaranteeing the dictionary's alignment with actual conceptual frameworks in official documents; The entire screening process adheres to unified algorithmic threshold criteria, treating all candidate terms equally to avoid inconsistencies and randomness in manual selection, thereby ensuring systematic and objective dictionary construction.

Mechanism Variable 1: AI Talent

When examining the intermediary mechanism of AI talent in driving enterprise digital transformation through data valorization, this study employs corporate online recruitment data to characterize human capital investment and demand in the artificial intelligence sector. The measurement process is structured as follows: First, we obtained nationwide recruitment data from major job platforms spanning 2015-2023, with an initial sample comprising approximately 7 million job postings. To ensure data validity and research relevance, rigorous cleaning and screening procedures were implemented: Keyword Screening: Based on core technologies, tool frameworks, application workflows, and business scenarios in AI, we constructed an AI-related keyword database covering machine learning, deep learning, natural language processing, computer vision, large models, algorithm development, and model deployment (e.g., artificial intelligence, algorithm engineers, machine learning, PyTorch, TensorFlow, computer vision, AIGC). Text matching was performed on job titles and descriptions. Industry Matching: Filtered AI positions were correlated with corporate entities, retaining only recruitment records from listed manufacturing companies to ensure sample alignment with research subjects. Duplicates Removal and Consolidation: Similar positions posted by the same company within the same year were merged to avoid redundancy, ultimately yielding approximately 260,000 valid “company-year-AI position” observation data points. Building on this foundation, we use the number of AI-related positions released by enterprises in the current year as a proxy variable for AI talent, which directly reflects actual human resource investments made by companies in advancing digital and intelligent transformation through AI capabilities during the corresponding fiscal year. To address data gaps caused by some enterprises failing to post AI job listings on selected recruitment platforms, this study implements the following supplementation method: For enterprises with no AI recruitment records in a given year, we substitute them with the industry average number of AI positions across all sampled enterprises in that year to maintain data balance and minimize selection bias. This measurement approach demonstrates strong forward-looking and dynamic characteristics, effectively capturing AI talent investments at different corporate development stages. It provides empirical evidence to validate the mechanism pathway of “data monetization → AI talent acquisition → enterprise digital transformation”.

Mechanism Variable 2: AI Technology

To accurately measure corporate innovation output in artificial intelligence technology, this study adopts the methodology referenced in , utilizing the “Key Digital Technology Patent Classification System (2023)” issued by the National Intellectual Property Administration for measurement purposes. The procedure involves three key steps: First, we obtained complete patent data from 3,802 manufacturing enterprises spanning 2014-2024 through patent databases. Second, based on the International Patent Classification for Artificial Intelligence (IPC/CPC) system—which comprises three primary technical branches (AI hardware platforms, general AI technologies, and key AI technologies), 14 secondary branches, and 27 tertiary branches totaling 44 categories—we identified patents explicitly classified as “AI” technologies. Third, we matched corporate patent data with these classification codes to screen annual AI-related patents. Building on this foundation, the study employs the natural logarithm of the sum of annual AI patent applications as the core explanatory variable, reflecting corporate innovation scale and investment intensity in AI technology. This measurement approach leverages standardized official classification systems, effectively mitigating subjective judgment biases while ensuring authoritative and comparable identification results.

Mechanism Variable 3: AI Collaboration

The AI collaboration variable focuses on the extent of knowledge connectivity and collaboration between enterprises and external parties during their AI technology R&D process. It is measured by taking the natural logarithm of the sum of the total citations received by the enterprise's aforementioned AI patents within five years after application.

controlled variable

Referring to studies [4,38], control variables were systematically selected at three levels—enterprise, province, and industry—to isolate interference from other factors. These control variables inherently correlate with corporate digitalization processes: The enterprise-level debt-to-asset ratio (calculated as total liabilities divided by total assets) directly impacts financial capacity and risk tolerance for digitalization investments. Operating revenue growth rate (calculated as current-period revenue minus prior-period revenue divided by prior-period revenue) reflects corporate growth stages and market expansion needs, with high-growth enterprises often prioritizing digital transformation to support scale expansion. Operating cost ratio (measured as operating costs as a percentage of revenue) indicates operational efficiency, where elevated cost pressures drive adoption of digital solutions for cost reduction and efficiency improvement. Chairman-General Manager overlap status (coded as 1 for dual roles, 0 otherwise) reflects corporate governance characteristics that influence decision-making efficiency and implementation effectiveness for long-term strategies like digitalization. Enterprise age (calculated as current year minus founding year plus 1) represents lifecycle phases, where organizational inertia and path dependence significantly affect digital transformation adoption speed. The largest shareholder's equity concentration ratio demonstrates ownership concentration levels, crucial for assessing decision-making authority and resource support required to advance digitalization strategies. At the provincial level, per capita GDP serves as a proxy variable for regional economic development, determining the quality of local digital infrastructure, technical talent reserves, and innovation policy environments. These external conditions directly constrain or facilitate the implementation conditions and effectiveness of corporate digital intelligence transformation. At the industry level, the Herfindahl Index calculated based on revenue share measures market competition intensity, where intense competition forces enterprises to build competitive advantages through digital intelligence solutions. Meanwhile, the Leiner Index derived from the ratio of operating revenue minus operating costs to total revenue reflects overall industry profitability and market power, influencing corporate resource capabilities and return expectations for digital intelligence investments. By controlling multi-level variables closely related to corporate digital intelligence decisions, this study aims to more accurately identify independent mechanisms through which data valorization and AI ecosystem restructuring impact digital intelligence transformation, thereby enhancing the internal validity and explanatory power of research conclusions.

4.3 Model Specification

$$DLT_{\mathrm{ijt}} = \beta_0 + \beta_1 DL_{\mathrm{ijt\text{-}1}} + \gamma Z + \varphi_{\mathrm{i}} + \lambda_{\mathrm{i}} + \eta_{\mathrm{j}} + \varepsilon_{\mathrm{ijt}} \tag{1}$$

In Equation (1 DL_{ijt-1} DL_{ijt-1}), the core explanatory variable represents the data valuation level of manufacturing enterprise DLT_{ijt} DLT_{ijt} i in city j during period t-1, while the dependent variable indicates the digitalization status of enterprise i in city j at period t through a dummy variable. This variable φ_i takes value φ_i λ_t 0 if the enterprise η_j λ_t has not yet achieved ε_{ijt} η_j digitalization status ε_{ijt} , and value 1 if it has reached digitalization status in the current period or later. Z denotes the set of control variables, including firm fixed effects, time fixed effects, city fixed effects, and random error terms. The Probit regression model is employed for analysis.

5. Empirical Testing

5.1 Benchmark Regression

Table 1 presents the regression results of enterprise data valorization on digital intelligence levels. The core explanatory variable DL represents the lagged first-period variable of data valorization, designed to mitigate potential reverse causality issues in the model and more accurately reveal the long-term dynamic impact of data valorization on enterprise digital intelligence. The estimation results show a DL coefficient of 0.024, which is statistically significant at the 1% level. This indicates that after controlling for other relevant factors, each one-unit increase in the previous-period data valorization level significantly elevates the current enterprise digital intelligence level by 0.024 units. The findings not only demonstrate strong statistical significance but also reflect sustained economic impact, effectively validating Hypothesis H1.

Table 1. Basic Regression and Robustness Analysis

	(1)	(2)	(3)
	DLT	DLT-sentence count	DLT-sentence proportion
DL	0.054***	0.208***	0.464***
	(3.55)	(15.07)	(6.66)
lev	-0.423***	0.431***	2.452***
	(-4.21)	(5.00)	(3.50)
growth	-0.103**	-0.031	-0.795***
	(-2.81)	(-0.99)	(-4.53)
cost_ratio	0.684***	1.374***	3.696***
	(5.15)	(7.36)	(3.72)
dual	-0.153**	0.162**	0.474***

	(-2.63)	(3.14)	(3.45)
age	0.096***	0.012	0.141*
	(21.78)	(0.82)	(2.21)
top1	-0.001	-0.006***	-0.024***
	(-0.89)	(-4.20)	(-4.27)
pgdp_pc	0.038*	0.411**	1.115*
	(2.16)	(3.03)	(2.34)
hhi	-0.760***	-0.427**	4.493***
	(-5.64)	(-3.27)	(5.03)
lerner	1.218***	1.470***	4.115***
	(6.43)	(8.81)	(5.22)
N	24560	24529	24529
r2		0.814	0.428
r2_a		0.787	0.345

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5.2 Robustness Test

5.2.1 Replace Variables

To test the robustness of baseline regression results, this study conducts robustness tests using the following variable substitutions: First, replacing the dependent variable. Drawing on text analysis methodologies applied in economic research, we employ machine learning-based metrics for measuring corporate digital intelligence. Specifically, through manual annotation of training datasets, feature engineering, and model optimization, we establish a high-precision text classification model for automated recognition of annual report texts. The metrics include both the number of predictive sentences containing "digital intelligence" -related statements and their proportion of total annual report sentences, serving as surrogate indicators for corporate digital intelligence. Results from Columns (2) and (3) in Table 1 demonstrate that the coefficients for data valorization of core explanatory variables remain significantly positive at the 1% significance level whether using absolute quantities or relative proportions. This confirms the robustness of core conclusions when the dependent variable is reconstructed through machine learning methods.

5.2.2 Placebo Testing

The placebo test provides rigorous support for the benchmark conclusion from the perspective of counterfactual causal inference. By randomly assigning enterprise data valuation variables and conducting 500 repeated estimations, we constructed the empirical distribution of coefficient estimators under the null hypothesis of no true effect. As shown in Figure 2, the randomized coefficients exhibit a normal distribution closely clustered around zero, consistent with the typical characteristics of placebo distributions in econometrics, indicating no systematic bias in model specification. In contrast, the true estimated coefficients in the benchmark regression appear at the right tail of this distribution, with occurrence probabilities below conventional significance thresholds. These findings suggest: First, the observed significant effects do not originate from unobservable confounding factors or model mispecifications; Second, the causal relationship between data valuation and enterprise digitalization meets the reliability requirements for causal inference in empirical economic research through rigorous counterfactual testing.

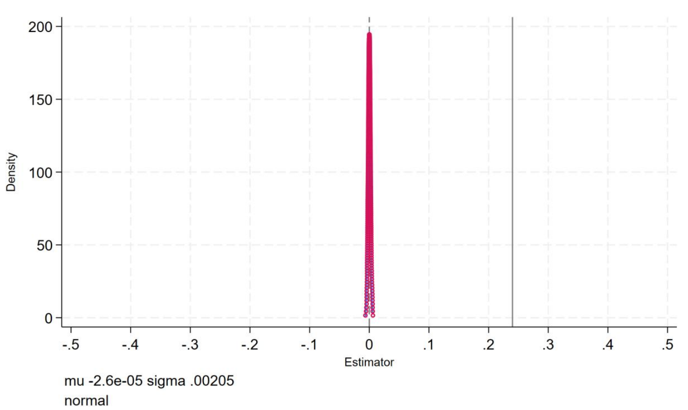

Figure 2. Placebo Test

5.2.3 Endogeneity Analysis

(1) Exclusion of major shocks

The digital and intelligent transformation process of enterprises is closely related to the data factor market environment and macro financial stability conditions in which they operate. For example, under the impact of major adverse events, the market-based allocation efficiency of data factors may significantly decrease, thereby hindering enterprises 'data valorization practices and potentially slowing their digital and intelligent transformation process. Ignoring the exploration of such macro structural factors can easily lead to endogenous interference, thereby weakening the estimation effectiveness of data valorization. In the time series of sample data in this paper, there are two significant systemic risk events at both international and domestic levels: first, the global impact of the COVID-19 pandemic (2020); and second, major changes in the regulatory environment of China's platform economy (2021). Objectively speaking, existing literature struggles to accurately capture and isolate the complex impacts of such exogenous shocks through variable construction methods. Based on this, this paper draws on design concepts from relevant frontier research to perform sample exclusion for the aforementioned shock factors to enhance the robustness of research conclusions: First, excluding the global impact of the COVID-19 pandemic. Considering the persistent shocks caused by the pandemic on global supply chains, offline business operations, and cross-border data flows, this paper removes all enterprise samples from 2020 to 2023 in robustness tests, retaining only pre-pandemic observations for regression analysis. Second, after excluding pandemic shocks, further control for the impact of platform economy regulatory policies is implemented. To more purely examine the role of data valorization under normal market conditions, this paper selects samples from the relatively stable time window of 2014-2019 and conducts regression tests again. This period coincides with the rapid growth phase of China's big data industry while avoiding subsequent major exogenous shocks.

(2) instrumental variable

To address potential endogeneity issues, this study employs instrumental variable estimation with urban-level "optical cable line length (10,000 kilometers)" as the control variable. The rationale lies in two key aspects: First, correlation requirements. As physical infrastructure for data circulation, the completeness of regional optical cable networks directly reduces corporate costs in data acquisition, transmission, and processing. This establishes fundamental conditions for enterprises to identify data value and develop data applications, thereby creating strong theoretical relevance between this variable and corporate data valorization. Second, exogeneity constraints. Urban cable length is primarily determined by macro-level communication planning, geographical conditions, and historical investments, constituting exogenous supply variables for individual enterprises. These factors do not bypass the specific behavioral process of "data valorization" and thus cannot directly impact the effectiveness of "digital transformation." Using urban optical cable length as a control variable for corporate data valorization, the two-stage least squares (2SLS) estimation results shown in Column (2) of Table 2 demonstrate a significant positive correlation between data valorization and digital transformation, with a coefficient of 5.085 statistically significant at the 1% level. The validity test of instrumental variables reveals two key findings: First, the Kleibergen-Paaprk LM statistic (54.011) strongly rejects the null hypothesis of insufficient instrumental variable identification. Second, the Kleibergen-Paaprk Wald F statistic (53.975) significantly exceeds the critical value of 16.38 under the 10% significance level of the Stock-Yogo test, indicating no weak instrumental variable problem. This confirms that after addressing endogeneity bias, data utilization continues to exert a significant positive impact on corporate digital transformation, with robust conclusions from the benchmark regression analysis.

Table 2. Robustness Analysis

	(1) Instrument variable-Urban optical cable length	(2) DLT- instrumental variable	(4) DLT-Exclusion 2020_2023
DL	1.075*	5.085***	0.039***
	(2.57)	(7.39)	(5.51)
controlled variable	yes	yes	yes
firm fixed effect	yes	yes	yes

year fixed effect	yes	yes	yes
urban fixed effect	yes	yes	yes
N	17711	18060	9857
r2	0.943	.	0.710
r2_a	0.934	.	0.629
Kleibergen-Paap rk LM statistic		54.011	
Kleibergen-Paap rk Wald F statistic		55.986	

t statistics in parentheses * p < 0.05, ** p < 0.01, *** p < 0.001.

6. Heterogeneity Analysis

To elucidate how data valorization differently impacts enterprise digital intelligence transformation, this study conducts heterogeneity analysis through three dimensions: absorptive capacity, talent structure, and organizational stickiness. The analytical framework is grounded in three key theoretical considerations: First, absorptive capacity reflects an enterprise's knowledge base for identifying, assimilating, and applying external data value, directly determining the technical feasibility of converting data elements into digital intelligence solutions. Second, talent structure mirrors the core human capital conditions for implementing digital transformation, where the scale and quality of digital professionals constitute critical constraints on transformation execution. Finally, organizational stickiness characterizes the institutional environment enabling enterprises to overcome transition resistance and drive organizational change, with effective internal coordination mechanisms and moderate external competitive pressures providing essential organizational safeguards for data value realization. These three dimensions systematically reveal the underlying mechanisms behind differential outcomes in transforming data value into digital intelligence capabilities across enterprises, examining technical foundations, human capital resources, and institutional environments respectively.

6.1 Absorption Capacity Heterogeneity: Differences in Knowledge Foundation and Conversion Efficiency

Given that corporate R&D activities essentially reflect their capacity to absorb and transform external knowledge resources , drawing on the research of Zhang Xiue et al. (Zakaria, Imane, Youssef, Zakaria, Imane, Youssef et al., 2020) we employed patent application counts as a metric for measuring absorption capacity. The sample was divided into high and low absorption capacity groups based on median values for regression analysis. As shown in Tables 1 and 2, the coefficients of core explanatory variables in the low-absorption capacity group and high-absorption capacity group were 0.054 and 0.040 respectively, both passing significance tests. This indicates that corporate absorption capacity significantly enhances the role of data valorization foundations in driving subsequent digital and intelligent development. Enterprises with stronger absorption capabilities can more effectively tap into the latent value of existing data assets and convert them into substantive drivers for digital-intelligent transformation, thereby demonstrating a dynamic, self-reinforcing virtuous cycle between data valorization and digital-intelligent advancement.

Table 3. Heterogeneity Analysis

	(1) Low absorption capacity	(2) High absorption capacity	(3) Low talent structure	(4) High-quality talent structure	(5) Low tissue viscosity	(6) high tissue viscosity
DL	0.054*	0.040***	0.003	0.093***	0.024	0.035*
	(3.50)	(2.30)	(0.17)	(6.55)	(1.28)	(2.00)
controlled variable	yes	yes	yes	yes	yes	yes
N	9462	9196	10903	12658	11527	13060

t statistics in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

6.2.\ Heterogeneity in Talent Structure: Differences in Professional Competence and Cognitive Breadth

Given that an enterprise's human capital structure directly determines its cognitive breadth in analyzing complex information and executing technological transformations, as well as its implementation effectiveness , this study draws on cutting-edge research to measure talent structure rationality through the proportion of professionals with associate degrees or higher qualifications, examining whether high-caliber talent can enhance data value transformation efficacy. Regression results shown in Table 3(4) indicate significantly stronger coefficients for high-quality talent structures. This demonstrates that optimized talent frameworks substantially amplify data valueization's role in driving subsequent digital-intelligent development. Specifically, this positive moderating effect implies that enterprises must effectively integrate their technology frameworks and data assets accumulated through data valueization with high-caliber talent teams as a "strategic resource" to fully realize transformation potential. A rational talent structure provides enterprises with critical capabilities to convert data insights into business solutions and operationalize technical frameworks, thereby establishing a virtuous cycle where "data empowers talent, and talent drives transformation."

6.3 Organizational Sticky Heterogeneity: Constraints from Governance Structure and Decision-Making Inertia

Given that the average age of corporate management reflects organizational experience accumulation and strategic decision-making characteristics, this study measures organizational cohesion through managerial age distribution and conducts grouped regression analysis by dividing samples into high and low groups based on median values. As shown in Tables 3(5) and 3(6), the low organizational cohesion group failed to pass significance tests, while the high cohesion group demonstrated statistically significant coefficients at the 10% level. This indicates that organizational cohesion plays a differentiated role in the relationship between data valorization and digital intelligence development. Specifically, enterprises with higher organizational cohesion leverage their management teams ‘deep industry expertise and robust resource allocation capabilities to more accurately identify strategic opportunities for data valorization, effectively manage transformation risks, and convert data resources into sustainable digital intelligence competencies. In contrast, organizations with lower cohesion, despite greater inclination toward AI application experimentation and intelligent reforms, have yet to fully demonstrate the driving effect of data valorization. These findings reveal a unique transformation pathway of “experience-enabled innovation,” where senior management teams’ experiential capital not only eliminates transition barriers but significantly enhances the impetus of data valorization for subsequent digital intelligence development.

7. Mechanism effect analysis

7.1 AI Talent Mechanism

$$\text{AI talent}_{\text{ijt}} = \beta_0 + \beta_1 DL_{\text{ijt-1}} + \gamma Z + \varphi_{\text{i}} + \lambda_{\text{i}} + \eta_{\text{j}} + \varepsilon_{\text{ijt}} \tag{5}$$

The regression results in Column (1) of Table 4 indicate that data valorization significantly impacts AI talent development with a coefficient of 0.019 at the 5% significance level. This demonstrates that data valorization can systematically enhance AI talent teams in terms of scale, structure, and capabilities through clear skill ROI metrics, explicit job requirements, and interdisciplinary knowledge demands. When data value is effectively measured and fed back, AI professionals gain clearer learning objectives and stronger investment incentives, enabling proactive knowledge structure optimization, accelerated skill iteration, and driving the evolution of corporate AI positions toward specialization and multidisciplinary integration. Such high-caliber, adaptable talent pools serve as critical operational vehicles for enterprises implementing digital and intelligent transformation. This empirical evidence validates the hypothesis H2a: data valorization promotes AI talent development, thereby accelerating corporate digital and intelligent transformation.

Table 4. Mechanism Analysis

	(1) AI a person of ability	(1) AI technology	(2) AI cooperate
L_DL	0.019**	0.027**	0.052***
	(2.95)	(2.97)	(5.63)
controlled variable	yes	yes	yes

firm fixed effect	yes	yes	yes
year fixed effect	yes	yes	yes
urban fixed effect	yes	yes	yes
N	19602	12447	24557
r2	0.520	0.860	0.671
r2_a	0.433	0.831	0.624

7.2 AI Technology Mechanism

$$\text{AI technology}_{\text{ijt}} = \beta_0 + \beta_1 DL_{\text{ijt-1}} + \gamma Z + \varphi_{\text{i}} + \lambda_{\text{i}} + \eta_{\text{j}} + \varepsilon_{\text{ijt}} \tag{6}$$

To examine the mechanism through which AI technology facilitates enterprise digital intelligence via data valorization, this study employs the natural logarithm of the ratio between a company's AI patent count and its total patents as an AI technology measurement indicator. Regression results in Column (1) reveal a coefficient of 0.027 for data valorization, statistically significant at the 5% level. This indicates that data valorization supports AI technology development by transforming raw data into high-quality strategic assets, while AI technology drives enterprise digital intelligence through three key dimensions: At the job structure level, AI applications foster innovative human-machine collaboration models, reshaping traditional role assignments and workforce configurations; at the knowledge structure level, AI accelerates the digital reconstruction of corporate knowledge systems, facilitating the explicitation and systematization of tacit knowledge; at the skill iteration level, AI expedites employee skill upgrades, synchronizing organizational learning capabilities with technological evolution. The synergistic progression across these dimensions enables enterprises to transition from localized "technology validation" to comprehensive "business empowerment," systematically achieving digital intelligence transformation. This empirical evidence validates the hypothesis H2b: data valorization promotes AI technology development, thereby driving enterprise digital intelligence through enhanced technological capabilities.

7.3 AI Collaboration Mechanism

$$\text{AI collaboration}_{\text{ijt}} = \beta_0 + \beta_1 DL_{\text{ijt-1}} + \gamma Z + \varphi_{\text{i}} + \lambda_{\text{i}} + \eta_{\text{j}} + \varepsilon_{\text{ijt}} \tag{7}$$

To examine the mechanism of AI collaboration in promoting enterprise digital intelligence through data valorization, this study employs the citation count of corporate AI technologies as an indicator of collaboration intensity. This measurement approach demonstrates three key advantages: First, citation frequency objectively reflects external recognition and collaborative depth of AI technologies, with higher citation rates indicating broader industry chain penetration and stronger network connectivity. Second, it avoids measurement biases inherent in subjective surveys by objectively assessing technological acceptance and partnership dynamics. Third, the metric directly captures enterprises 'technological output and synergistic effects in artificial intelligence, aligning with collaborative principles that facilitate bidirectional innovation through technology diffusion. Consequently, the AI collaboration variable derived from patent citation data effectively characterizes enterprises' cooperative positioning and linkage strength within intelligent ecosystems, providing reliable metrics for evaluating data-driven digital transformation mechanisms. Regression analysis in Column (3) reveals a highly significant 1% significance level for data valorization coefficients, demonstrating that this process significantly enhances internal and cross-enterprise AI collaboration through three synergistic dimensions: data resource integration, assetization, and capitalization. Specifically, data resource integration establishes foundations for multi-party data sharing; data assetization facilitates high-value data identification and circulation; while data capitalization enables optimized resource allocation and value realization across broader scopes. These collaborations collectively strengthen AI technology integration and knowledge spillover among enterprises, thereby establishing an open and collaborative AI cooperation network. This network enables companies to overcome limitations in data resources, algorithms, and computing power, driving intelligent upgrades across R&D, production, and marketing processes with lower costs and higher efficiency, ultimately systematically advancing enterprise digital transformation. The empirical findings validate the hypothesis H2c: data valorization drives AI collaboration development, which in turn accelerates corporate digitalization through enhanced value realization.

8. Conclusion and Policy Recommendations

8.1 Research Findings

Based on technical economics and innovation theory, this paper constructs a theoretical analytical framework of "data valorization, AI ecosystem reconstruction, and enterprise digital intelligence transformation," and conducts empirical testing using data from China's listed manufacturing enterprises from 2014 to 2023. The main research conclusions are as follows: First, data valorization has a significant driving effect on enterprise digital intelligence transformation. Benchmark regression analysis shows that for every unit increase in a company's initial data valorization level, the probability of achieving digital intelligence transformation in the current period significantly increases. This conclusion remains valid after a series of robustness tests, including variable substitution, placebo testing, control for high-dimensional fixed effects, and instrumental variable methods, confirming that data, as a new production factor, serves as an indispensable value foundation and economic driver for manufacturing enterprises to achieve digital intelligence transformation. Second, mechanism analysis indicates that data valorization drives digital intelligence transformation by reconstructing the AI ecosystem, specifically through three key pathways: AI talent, AI technology, and AI collaboration. Data valorization not only fosters new composite talents such as "data specialists" and "AI trainers" and optimizes human capital structure, but also systematically promotes AI technology innovation and engineering applications by improving data quality, deploying intensive computing power, and driving algorithmic closed loops. Additionally, it deepens internal and external AI collaboration and builds open innovation technology networks by facilitating the synergy of data at the levels of resource utilization, assetization, and capitalization. These three pathways collectively constitute the mediating channels through which data valorization drives digital intelligence transformation. Third, the transformational effects of data valorization exhibit significant heterogeneity. This phenomenon is particularly pronounced in enterprises with strong data absorption capabilities, optimized talent structures, and extensive governance experience (characterized by relatively older managerial teams). These findings demonstrate that transforming data potential into tangible digital intelligence capabilities depends not only on data elements themselves, but more critically on the knowledge base, human capital, and strategic resolve required for enterprises to internalize data as organizational competencies.

8.2 Policy Recommendations

Building on the empirical findings of this study that data valorization drives enterprise digital transformation through restructuring the AI ecosystem (AI talent, AI technology, and AI collaboration), we propose the following systematic policy recommendations to better unlock the potential of data elements and promote high-quality development in manufacturing:

First, implement a tiered cultivation program for “data-AI” interdisciplinary talents to establish a talent support system for industrial transformation. Policymakers should prioritize the development of versatile AI professionals as a long-term strategy, creating a comprehensive training framework spanning basic education to career advancement. Education authorities should promote interdisciplinary programs in “data intelligence” at key universities, developing curriculum systems that integrate data governance, algorithmic ethics, and economic management. Labor departments must collaborate with industry leaders to establish AI talent certification standards, introduce professional qualifications such as “Data Specialists” and “AI Trainers,” and establish industry-academia training bases within industrial parks. Enterprises actively recruiting and nurturing interdisciplinary AI talent should receive targeted subsidies, along with policy incentives including residency benefits and housing support. This will create a complete talent ecosystem encompassing “training-certification-employment-development,” providing sustainable human capital support for data valorization and AI ecosystem synergy.

Second, innovate the “data-driven AI R&D” incentive mechanism and establish a comprehensive innovation support network. It is recommended that finance and science and technology departments collaborate to design multi-tiered incentive policies, offering 200% additional tax deductions on R&D expenses for enterprises’ investments in foundational areas such as data governance, data annotation, and high-quality AI training dataset construction. A national-level “Data Empowerment for AI Innovation” special fund should be established, adopting a “call-for-bids and leader selection” mechanism to prioritize breakthroughs in key technologies like advanced algorithms, MLOps platforms, and privacy-preserving computing for smart manufacturing. Concurrently, several national industrial data training bases should be developed to provide compliant, low-cost data and computing support services for enterprises, particularly small and medium-sized businesses. By establishing AI technology diffusion centers, we can facilitate the industrial chain adoption of mature AI solutions, systematically reduce technical barriers and R&D costs for corporate AI innovation, and accelerate the conversion efficiency of data value into technological advantages.

Third, establish an industrial data space featuring collaboration among government, industry, academia, and research institutions to foster an open innovation ecosystem. Led by the Ministry of Industry and Information Technology (MIIT), key universities, research institutes, and leading enterprises in industrial chains will jointly develop several national-level industrial data spaces. These spaces should adopt a “data available but not visible” technical architecture, establish unified standards for data asset registration, quality evaluation, and circulation transactions, and implement robust mechanisms for data rights allocation and security supervision. Building on this foundation, priority will be given to developing open-source AI model communities in key industries such as automotive, electronics, and equipment manufacturing. Enterprises across the supply chain will be encouraged to share anonymized industrial data, co-create industry-wide large models, and collaborate on algorithmic innovations. Participating enterprises engaged in data sharing and collaborative R&D will receive preferential support in evaluations for specialized, refined, distinctive, and innovative enterprises (SRDI enterprises) and government procurement processes. Through pilot programs for data capitalization, innovative models like data equity participation and data securitization will be explored, ultimately forming a virtuous cycle of “data sharing – joint technology development – shared risk – mutual benefits” to comprehensively enhance the digital intelligence capabilities of industrial chains.

Appendix 1: Selected keywords from labeled sentences

Digital keywords

Blockchain; Blockchain, block structure, chain data structure, Merkle tree, smart contracts, consensus mechanism, proof of work, proof of stake, proof of authority, practical Byzantine fault tolerance, distributed ledger, distributed network, peer-to-peer network, decentralization, sidechain, multi-chain, state channel, cross-chain, public chain, private chain, consortium chain, permissioned chain, permissionless chain, BaaS (Blockchain as a Service), digital assets, token economy, non-fungible token (NFT), token issuance, STO, oracle, lightning network, hash locking, atomic exchange, on-chain governance, off-chain data, privacy protection, zero-knowledge proof, ring signature, confidential transactions, traceability, evidence storage, double-spending attack, 51% attack, sharding, DAG (Directed Acyclic Graph), Libra, Diem.

Big Data: Big data, data lake, data warehouse, data middle platform, data governance, data lineage, data catalog, data security, data encryption, data backup, data recovery, data archiving, data lifecycle management, master data management, metadata management, data quality, data standards, data architecture, data services, data development, data analysis, data science, data application, data operations, DataOps, data insights, business intelligence (BI), BI dashboard, data visualization dashboard, real-time data, batch data processing, stream computing, in-memory computing, distributed computing, MPP, data mining, text mining, web mining, spatial data mining, multimedia data mining, web mining, privacy-preserving computation, multi-party secure computation, federated learning, differential privacy, homomorphic encryption.

Artificial Intelligence: AI, artificial intelligence, machine learning, deep learning, reinforcement learning, transfer learning, active learning, semi-supervised learning, self-supervised learning, small sample learning, meta-learning, neural networks, convolutional neural networks, recurrent neural networks, generative adversarial networks, Transformers, attention mechanisms, pre-trained models, large-scale models, knowledge graphs, cognitive computing, intelligent computing, swarm intelligence, Swarm Intelligence, intelligent decision-making, intelligent recommendation, intelligent search, intelligent speech processing, intelligent image processing, intelligent video processing, intelligent text processing, NLP, natural language processing, computer vision, CV, pattern recognition, biometrics, speech recognition, image recognition, face recognition, behavior recognition, emotion recognition, gesture recognition, OCR, text recognition, AR, augmented reality, VR, virtual reality, MR, mixed reality, digital twins, intelligent robots, service robots, industrial robots, chatbots, smart customer service, RPA, robotic process automation, autonomous driving, self-driving, driverless vehicles, ADAS, intelligent transportation, smart healthcare, smart education, smart finance, smart manufacturing, smart agriculture, smart home systems, smart cities, intelligent security systems.

Mobile Internet: Mobile internet, mobile communications, 5G,6G, mobile networks, wireless networks, WLAN, WIFI, Bluetooth, NFC, mobile terminals, smartphones, smart devices, wearable technology, smart hardware, mobile apps, mini-programs, quick apps, mobile office solutions, mobile government services, mobile commerce, mobile payments, QR code payments, NFC payments, facial recognition payments, contactless payments, mobile banking, digital yuan, mobile social platforms, WeChat, Weibo, mobile video streaming, short videos, live streaming, mobile gaming, mobile games, mobile advertising, mobile marketing, LBS (Location-Based Services), location-based services, AutoNavi Maps, Baidu Maps, mobile search, mobile e-commerce platforms, Taobao, JD.com, Pinduoduo, Meituan, Didi, sharing economy models, bike-sharing systems, ride-hailing services, online education platforms, remote work solutions, smart healthcare systems, digital government services, one-stop online service portal.

Cloud Computing: Cloud computing, cloud services, cloud-native technologies, cloud architecture, cloud security, cloud management, cloud operations, cloud migration, cloud monitoring, cloud cost management, cloud billing, public cloud, private cloud, hybrid cloud, industry-specific cloud, government cloud, healthcare cloud, education cloud, financial cloud, industrial cloud, gaming cloud, video cloud, IaaS, PaaS, SaaS, DaaS, CaaS, FaaS, BaaS, containers, Docker, Kubernetes, K8s, microservices, Service Mesh, service grid, DevOps, continuous integration, continuous delivery, continuous deployment, infrastructure as code, immutable infrastructure, declarative APIs, serverless architecture, Serverless computing, function computing, service orchestration, configuration management, image repositories, container networking, container storage, service discovery, load balancing, elastic scaling, auto-scaling, resource scheduling, performance monitoring, log analysis, application performance management, trace systems, disaster recovery, backup and disaster recovery, multi-active architecture.

Blockchain: Blockchain, distributed ledger, consortium chain, public chain, private chain, sidechain, cross-chain, state channel, sharding, DAG, directed acyclic graph, smart contracts, consensus mechanisms, PoW, PoS, DPoS, PBFT, RAFT, hash algorithms, asymmetric encryption, digital signatures, Merkle tree, zero-knowledge proofs, ring signatures, homomorphic encryption, privacy protection, identity management, DID, decentralized identity, digital assets, token economy, Token economy, NFT, non-fungible token, STO, security token, DeFi, decentralized finance, DAO, decentralized autonomous organization, oracle, oracle, data on-chain, evidence storage, traceability, supply chain finance, cross-border payments, digital currency, central bank digital currency, CBDC, Libra, Diem, blockchain as a service, BaaS, node management, network monitoring, wallet services, key management, cold wallet, hot wallet, multi-signature, Gas fees, transaction fees, TPS, throughput, scaling solutions, Layer 2, Layer 2 networks, state channel, Plasma, Rollup, ZK-Rollup, Optimistic Rollup

Intelligent keywords:

1.Core Infrastructure: Internet of Things (IoT), Industrial Internet, Perception Layer, Sensors, RFID, Barcode Recognition, Machine Vision, Laser Scanning, BeiDou Positioning, 5G Networks, Edge Computing Nodes, Smart Meters

2.Data Acquisition and Connectivity: Data Collection, Device Interconnection, System Compatibility, Data Interfaces, Information Upload, Real-time Data Transmission, Condition Monitoring, Operational Parameters, Environmental Data, Behavioral Data, Internet of Everything, Human-Machine-Object Interconnection

3.Status Visualization and Transparency: Panoramic Visualization, Transparent Factories, Process Transparency, Full Traceability, Asset Visualization, Supply Chain Visualization, Real-time Dashboards, Digital Mirrors, Clear Overview, Comprehensive Control

4.Macro Strategic Framework: Comprehensive Sensing, End-to-End Data Integration, Full-Chain Data Management, End-to-End Visualization, Cyber-Physical Systems, Digital Twin Foundation, Neural Network Architecture, Information Island Integration

5.Core Technology Engines: Artificial Intelligence (AI), Machine Learning, Deep Learning, Neural Networks, Big Data Analytics, Data Mining, Intelligent Algorithms, Predictive Models, Knowledge Graphs, Natural Language Processing, Computer Vision, Intelligent Inference.

6.Core Analytical Capabilities: Intelligent Analytics, Deep Insights, Trend Forecasting, Demand Prediction, Sales Forecasting, Fault Prediction, Smart Diagnostics, Root Cause Analysis, Pattern Recognition, Correlation Analysis, Data Insights, Business Intelligence

7.Advanced Application Platforms: Digital Twins, Intelligent Simulation, Virtual Debugging, Smart Brain Systems, Decision Support Systems, Cognitive Intelligence, Early Warning Models, Risk

Profiling, User Profiling, Credit Rating Models

8. Process and Value Description: Data-driven analytics, knowledge discovery, decision support, scientific evaluation, precision analysis, intelligent modeling, model optimization, cognitive computing.

9. Intelligent Decision-Making and Planning: Smart decision-making, autonomous decision-making, data-driven decision-making, adaptive optimization, intelligent planning, automated production scheduling, intelligent scheduling, route planning, resource allocation, dynamic pricing, intelligent purchase recommendations, risk self-assessment.

10. Automated Execution and Control: Automatic execution, self-sustaining operation, adaptive control, precision control, robotic process automation, intelligent scheduling, autonomous driving, unmanned operations, automated sorting, automated packaging, automated delivery, agile response.

11. System-Level Autonomy and Closed Loop: Closed-loop management, self-organization, self-optimization, self-adjustment, self-repair, intelligent systems, unmanned operations, dark factories, flexible manufacturing, adaptive systems, smart operations, real-time response.

12. Business Scenario Description: One-click ordering, automated reconciliation, AI-powered customer service, precision marketing, personalized recommendations, intelligent inventory replenishment, process automation, customized production.

Appendix 2: Specific requirements for labeling

To accurately quantify the depth of digitalization and intelligent technology applications in corporate annual reports, this research design employs manual scoring criteria: sentences meeting both technical specificity and application relevance receive a score of 1, while others receive 0. The evaluation standards are categorized as follows: 1) Statements describing concrete technological deployments and implementation actions, including explicit records of substantive initiatives such as system development, technical innovation, data platform construction, or hardware upgrades. 2) Sentences demonstrating verifiable technological outcomes, requiring quantifiable results like performance enhancements, quality improvements, or process transformations. 3) Clear descriptions of technology-enabled business scenarios. Scoring excludes vague strategic statements, abstract conceptual references, future-oriented descriptions, or technical enumerations without substantive content. For example, “The company deployed Yonyou Intelligent Financial System in 2022 to achieve automated voucher generation” receives a score of 1 due to specified system implementation, whereas “Digital transformation is the company’s core strategy” receives 0 due to lack of technical substance. All scoring was independently conducted by 11 team members to ensure measurement reliability.

Appendix 3. Keyword Dictionary for Data Valorization

Data Valueization Dictionary Database

data	network	figure	value	information	resource	intelligence
data security	portals	dynamic data	strategic position	Public Information	resource management	artificial intelligence
technological means	network security	science and technology	bargain price	Government Information	the distribution of resources	core technology
data management	resources integration	calculating center	price level	information safety	public resource	functional localization
Provide data	information network	initial data	index number of price	personal information	resource sharing	smart home
data service	cyber games	numerical information	value system	Business Information	teaching materials	field of science and technology
Public data	internet	Digital Home		information technology	human resources	Technology Upgrade
data handling	internetwork communication	subscriber number		key technology	computing resource	business intelligence
DC	cyberspace	embodied computing power		electronic information	Resource type	automatic recognition
information processing	Internet Protocol	digital certificate		geographic information	Server resources	
service platform	Integrated Information	computing technology		information technology		
information system	service network	computer technology		information content		
business model	network facility	analysis model		basic elements		
data model	network engineering			information industry		

Research Specialist Staff	Communication platform	spatial information
technical equipment	network topology	service center
project	Network Services	information management
data protection	information center	Information Management System
transmission service	weblog	information science
Industrial base	networking protocol	financial information
system integration	Internet Services	basic function
building project	network technology	Service Guide
decision analysis	network platform	Information Age
data analysis system	National network connection	information resources management
data service	Network media	Status Update
data mining	administration of networks	Information and News
data warehouse	network application	
heterogeneous computing		
strategic decision		
infrastructu		

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product
scientific
calculation
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supervision
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Technolog
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monitoring
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data
retrieval
Define data
administrat
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test data
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system
technical

plant
high speed
data
spatial data
reference
model
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up to
specificatio
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products
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Scientific
Standards
statistical
data
data test
Structural
rationality
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ng
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Service
provider

data
structure

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Note

Note 1. See Appendix 1

Note 2. See Appendix 2

Note 3. "Data Elements × Three-Year Action Plan" and "2016- Cybersecurity Law of the People's Republic of China, Anhui Province Big Data Development Regulations, Beijing Municipal Digital Economy Promotion Regulations, Action Plan for Promoting Big Data Development, Industrial and Information Technology Sector Data Security Management Measures (Trial), Ministry of Industry and Information Technology Guidelines on Industrial Big Data Development..., Ministry of Industry and Information Technology Issued <Industrial and Information Technology Sector Data Security Management...>, Guangdong Province Digital Economy Promotion Regulations, Guangxi Zhuang Autonomous Region Big Data Development Regulations, Guizhou Province Big Data Security Assurance Regulations, Guizhou Province Big Data Development Application Promotion Regulations, Guizhou Provincial Government Data Sharing and Openness Regulations, National Development and Reform Commission and Other Departments on Promoting High-Level Data Industry Development..., National Data Administration and Other Departments on Promoting Enterprise Data Resource Development..., National Informatization Development Strategy Outline, General Office of the State Council Issued National Integrated Government Big Data..., General Office of the State Council Issued Market-oriented Allocation of Factors..., General Office of the State Council Issued Government Information Systems..., State Council Guidelines on Strengthening Digital Government Construction..., Hainan Province Big Data Development and Application Regulations, Hebei Province Digital Economy Promotion Regulations, Heilongjiang Province Big Data Development Application Promotion Regulations, Hubei Province Data Regulations, Jilin Province Big Data Development Application Promotion Regulations, Accelerating the Construction of <China> Characteristic Data Basic Institutional System to Promote Full..., Jiangxi Province Data Application Regulations, Shandong Province Big Data Development Promotion Regulations, Shanxi Province Big Data Development Application Promotion Regulations, Shaanxi Province Big Data Regulations, Shanghai Municipal Public Data Openness Interim Measures, Shanghai Municipal Data Regulations, Shenzhen Special Economic Zone Digital Economy Industry Promotion Regulations Measures for Data Outbound Security Assessment, Sichuan Province Data Regulations, Tianjin Regulations on Promoting Big Data Development and Application, Interim Measures for Data Transaction Management in Tianjin (Draft for Comments), Zhejiang Province Public Data Regulations, Zhejiang Province Digital Economy Promotion Regulations, Interim Measures for Government Information Resource Sharing Management, Central Committee of the Communist Party of China and State Council on Building a More Complete

Factor..., Central Committee of the Communist Party of China and State Council on Building a Better Data Foundation System..., Central Committee of the Communist Party of China and State Council on Issuing the Overall Plan for Digital China Construction..., General Office of the Central Committee of the Communist Party of China and General Office of the State Council on Accelerating Public..., Personal Information Protection Law of the People's Republic of China, Data Security Law of the People's Republic of China, Chongqing Data Regulations, 14th Five-Year National Informatization Plan, 14th Five-Year Digital Economy Development Plan, National Data Standard System Construction Guidelines, Jiangsu Province Digital Economy Promotion Regulations, Fujian Province Big Data Development Regulations, Pilot Work Plan for Public Information Resource Opening, Measures for Improving Data Circulation Security Governance to Better Promote Data Utilization..., National Data Infrastructure Construction Guidelines, Trusted Data Space Development Action Plan (2024-2028)..., Liaoning Province Big Data Development Regulations (2022), Interim Provisions on Accounting Treatment of Enterprise Data Resources, National Integrated Big Data Center Collaborative Innovation System Computing Power Hub..., Shenzhen Special Economic Zone Data Regulations (2021), Key Development Directions for Data Technology and Industry, Data Asset Appraisal Guidelines

Note 4. See Appendix 3