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The Impact of Data Elements on Enterprises' Capital Market Performance: Insights from Stock Liquidity in China and Implications for Global Markets

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Abstract: Amidst a backdrop of global economic challenges and shifting market dynamics, this study highlights the transformative role of data elements in enhancing enterprise performance within capital markets, particularly focusing on China's leading position in the digital economy as a model with implications for global markets. This study utilized a panel data set consisting of 10,493 observations from 2687 listed enterprises in Shanghai and Shenzhen A-shares from 2015 to 2023. An econometric analysis was conducted using a two-way fixed effects model to explore the impact of enterprise data elements on capital market performance in the digital economy and its underlying mechanisms. The research reveals that the digitization of enterprise production factors can significantly enhance performance in the capital market. The study further suggests that enterprise innovation and enterprise value play a crucial role in mediating this effect. This paper introduces a new concept called "data elements", which expands the definition and assessment methods of enterprise data capabilities. It goes beyond just digital transformation at the application level and includes data governance at the basic ability level. This approach provides a more accurate and comprehensive understanding of the different elements of data. Moreover, the research expands the research scope of microeconomic entities' economic benefits, thereby extending the value contributed by enterprise data elements to their performance in the capital market. Additionally, this study reveals the relationship between enterprise data elementization and capital market performance through intermediary analysis of enterprise innovation performance and enterprise value, which unveils the "black box" and clarifies the transmission pathway. The findings of this research hold considerable theoretical value and have far-reaching practical implications for government policies concerning data elements and the development of high-quality enterprises, suggesting pathways for global markets to leverage data for enhanced enterprise performance and economic resilience. The results are particularly useful for policymakers, enterprise managers, and scholars in understanding and implementing data-driven strategies in capital markets.

Keywords: data elements; data governance; econometrics; enterprise performance; capital market performance

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1. Introduction

In today's world, the sustainability of the global economy faces unprecedented challenges, including but not limited to trade wars, global pandemics, and climate change. Trade wars lead to disruptions in the global supply chain, increasing the uncertainty of international trade [1], which in turn affects the stability of global economic growth. The global pandemic, especially the COVID-19 pandemic, has had a profound impact on the world economy, causing widespread economic stagnation, job losses, and a reduction in international exchanges and cooperation [2]. Meanwhile, climate change is threatening the ecological balance of the Earth at an unprecedented rate [3], with frequent extreme weather events exacerbating the instability of food and water resources, threatening the sustainable development of the socio-economic system [4]. Influenced by the weak recovery of the global economy, heightened geopolitical tensions, increased scrutiny of investments by major nations, and high interest rates, global cross-border direct investment remained subdued in 2023. Apart from a few exceptions, the scale of investment attracted by both major developed and developing economies experienced a decline. Global foreign direct investment (FDI) actually fell by 18% in 2023 [5]. In developed economies, the net FDI inflows into the United States decreased by 3% year-on-year [6]; the European Union, after excluding investment "transit stations", saw a 23% year-on-year decline in net FDI inflows; and FDI inflows into other developed regions also stagnated, with a decrease of up to 46% compared to the previous year. Meanwhile, FDI inflows into developing countries dropped to USD 841 billion, marking a 9% decrease year-on-year. These challenges not only impact the macroeconomic level of the global economy but also profoundly change the operations of businesses and capital markets. Trade wars and supply chain disruptions caused by the global pandemic force companies to reconsider and adjust their global supply chain management strategies [7], increasing production costs and affecting the final consumer market. In the capital markets, such uncertainties have led to increased market volatility, affecting investor confidence and investment decisions [8]. At the same time, as climate change has increasingly severe impacts on the economy and society, companies face pressure to shift towards more sustainable business models [9], not only to reduce negative environmental impacts but also to adapt to the growing environmental awareness among consumers and legal requirements for environmental protection by governments. Therefore, businesses and capital markets must continuously adapt to these external challenges, seeking new growth points and investment opportunities to ensure sustainable development in the constantly changing global economic environment.

In this context, the physical flow of globalized trade continues to be negatively impacted, while, conversely, the importance of data elements as a crucial component of the global economy's digital flow is increasingly emphasized. Data elements can empower traditional factors of production such as land, labor, and capital, creating larger value spillover effects, and they have become a key variable influencing economic globalization [10]. A McKinsey report highlighted that as early as 2014, the value directly created by data flows was estimated at USD 2.3 trillion, surpassing the value created by international population movements (USD 1.5 trillion) and foreign direct investment (USD 1.3 trillion), and slightly below goods trade (USD 2.7 trillion). Currently, rapid cross-border data flows are changing the shape of the global economy and, in the medium to long term, will affect the competitive relationship between labor markets in developed and developing countries, reshaping the global labor market, thus impacting the global industrial chain layout and value chain division—moving the mid-to-high end of the global value chain to regions and companies with advantages in data elements and smart technologies.

In the development of the digital economy, China, along with other major economies such as the United States, the European Union, and India, has exhibited significant similarities and differences. The United States has adopted an open digital trade strategy, promoting the liberalization and facilitation of global digital trade through its leading digital platforms to maintain its global competitive advantage in the digital industry [11]. In contrast, the European Union focuses on data protection and privacy while opening up, implementing conditional digital trade policies to promote innovation and protect consumer interests [12]. India places greater emphasis on protecting its digital economy and data sovereignty, adopting relatively conservative digital trade restrictions [13]. The strategy for the development of China's digital economy is characterized by a gradual opening up, aimed at promoting the development of the domestic digital economy and international cooperation through a balance between openness and regulation, while ensuring national security and economic interests are well protected [14].

The potential contribution of the Chinese model to the global market is primarily reflected in promoting the development of the global digital economy and facilitating international digital trade cooperation. Through gradual opening up and participation in the formulation of international rules, China is expected to have a greater influence in the field of digital trade, promoting the healthy development of the global digital economy [15]. However, this model also faces challenges, including how to actively integrate into the global digital economy system while protecting the domestic market, and how to ensure data security and consumer rights while advancing the development of the digital economy [16]. China's strategy and practices will have a significant impact on the formation and trends of global digital trade rules and will also serve as an important reference for the digital economy policy choices of other economies. Therefore, this paper selects China as the research subject to explore the mechanisms through which data elements affect company development, aiming to unveil implications for global markets. Through this lens, we aim to contribute to a nuanced understanding of how data-driven innovations can reshape global economic structures, influence competitive advantages, and foster new avenues for international cooperation in the digital era.

This study utilized a panel data set consisting of 10,493 observations from 2687 listed enterprises in Shanghai and Shenzhen A-shares from 2015 to 2023. An econometric analysis was conducted using a two-way fixed effects model to explore the impact of enterprise data elements on capital market performance in the digital economy and its underlying mechanisms. The structure of this paper is organized as follows: Section 2 is the literature review, Section 3 is theoretical analysis and research hypotheses, Section 4 is research design, Section 5 is data analysis and conclusions, and Section 6 is conclusions and implications.

2. Literature Review

Data represent a recording and description of factual information from the objective world, essentially constituting digitized factual information. However, within the vast array of factual data, only a segment contributes to economic and social production activities, while a substantial portion remains unproductive. With the advent of the digital economy era and the large-scale commercial application of new-generation information and communication technologies, data have increasingly been considered a byproduct of economic activities. Nevertheless, only data that actively contribute to economic and social production can qualify as a production factor [17]. Therefore, data elements are distinct from mere data; they are data resources that participate in and contribute economically to social production and business operations [18].

From the key production factors of land and labor in the agricultural era to the predominance of capital in the industrial age, and subsequently to the emergence of technology and management, the forms of production factors have continually evolved through the socio-economic development process. With the development of the digital economy, information resources such as big data have transitioned into production factors, integrating with other elements in the economic value creation process and profoundly influencing productivity development. According to the "Data Assetization Research Report from the Perspective of Data Elements" released by PwC in 2023, the pathway to data value realization primarily relies on transforming data into information and knowledge, which then supports decision making. For raw data to be directly usable, it must undergo data production, which involves collecting and processing data to extract the "information" or incorporate other products and services [19].

In the value realization process, data become effective data elements through collection, integration, and processing, entailing extensive foundational data governance work. This process ultimately leads to the integration of decision-making results with other production factors, weaving into various production stages and prompting transformations in production methods [20]. The value realization path of data elements adheres to the economic "input-output" logic, addressing both the supply and demand sides of data elements [21]. From the data supply perspective, enterprises generate large amounts of data during their production and operational processes. Collecting this structured and unstructured data and organizing it with the help of data analytics technologies, tools, and experts transforms the initially chaotic data into useful data elements. During this process, data governance measures are implemented to define data architecture, establish unified data standards, and execute data quality PDCA closed-loop control processes, thus ensuring a high-quality supply of data elements. From the data demand perspective, data elements, when combined with digital technologies and tools, offer functionalities such as perception, memory, analysis, and decision making. These are applied in enterprise production processes to empower other production factors, enhance enterprise labor productivity, and promote enterprise digital transformation. Thus, from the perspective of the data element value realization pathway, this paper interprets the connotations of data elements through the lenses of enterprise data governance and digital transformation, which form the core capabilities and crucial assessment indicators of enterprise data elements.

Considerable research has been conducted on data elements. Wang Dexiang [22] argues that data, as a virtual production element, can benefit market entities through market transactions. Cai Yuezhou [23] suggests that incorporating data elements can boost the efficiency of enterprise production and operation, thereby facilitating high-quality development. Data can serve as a production element that promotes economic growth, improves production efficiency, and facilitates the creation of new products and services [24]. Other scholars have discussed the relationship between data elements and traditional production elements in theory. The authors Bai Yongxiu et al. have presented a three-layer mechanism model in their research paper [25]. This model incorporates the concepts of "two-element complementarity", "multi-element coordination", and "total-factor coupling" for a more comprehensive approach. According to Deng [26], there is a U-shaped relationship between traditional production elements and data elements in terms of optimizing economic development. Their research suggests that these elements will undergo profound changes and optimization recombination, which could have a significant impact on high-quality economic development. Data elements have two important connotations that can be understood through relevant theoretical research and corporate practices. Firstly, data are considered a production element that has transformed the social reproduction process and expanded the boundaries of the market. It has enabled remote non-contact transactions that were previously impossible, thereby prompting a comprehensive digital transformation of traditional industries. Secondly, the development of data elements is closely linked to high-quality data governance. It is a vital factor for those who want to participate in the data elements industry chain, as it can activate the potential of data elements and infuse inexhaustible digital power into the advancement of modernization with Chinese characteristics.

Most studies concentrate on the measurement of enterprise data elements and their impact on innovation and performance. Ji Xiangxi's [27] research examines how increasing the level of enterprise digitalization promotes value creation and growth. Jiang Shuyu et al. [28] conducted a study to analyze the effect of digital transformation on the innovative development of retail supply chains. The results demonstrate that intelligent supply chains play a pivotal role in promoting innovation within the retail industry. According to [29], the adoption and utilization of digital technology holds the potential to expedite the process of industrial structure and management innovation in enterprises. He [30] find that developing digital economy technology provides momentum and technical support for transforming and upgrading China's physical enterprises. However, according to a study by Qi [31], the favorable outcomes of business model innovation can be impeded by a phenomenon known as the "contraction effect", where digital technology struggles to integrate into enterprise operations, failing to achieve expected results. In terms of the correlation between digitalization and the capital market, numerous decisions relating to corporate production and operations are mirrored in the liquidity of the capital market. This includes the process of digital transformation. According to one study [32], stock liquidity plays a crucial role in the capital market, serving as the lifeblood of its efficient functioning. The study argues that stock liquidity reflects the market's effectiveness in discovering prices and allocating resources, which is intrinsically linked to market recognition. According to He [30], the digital transformation process has the potential to enhance the operational quality of the real economy, leading to a positive feedback loop in the capital market. On the other hand, Xu [33] posit that the benefits of digitalization could be outweighed by the associated costs of management, which may limit the performance-driving effects, particularly when taking into account the long-term and uncertain nature of such a transformation.

These cited studies are valuable references for our paper, but they do have certain limitations that warrant consideration. Firstly, given that data are an essential component in various fields, relying solely on traditional measurements of enterprise data elements through digital transformation may prove insufficient. Secondly, conflicting views exist on the impact of digitalization on enterprises. While some argue it promotes development, others contend that excessive digitalization may impede enterprise capability enhancement. Lastly, there is a lack of literature that effectively links enterprise digitalization with capital market performance at the micro-level; the impact mechanism and transmission path are mainly inferred from the related literature.

This research paper aims to examine the impact of enterprise digital transformation and data governance on capital market performance. It explores the paths and mechanisms of enterprise data elements and their value while highlighting three main contributions. Firstly, it integrates enterprise digital transformation and data governance as core capabilities and critical assessment indicators of enterprise data elements' value, providing a more comprehensive assessment of enterprise data lemmatization. Secondly, it expands the research scope of the economic consequences of enterprise data elements' capabilities, extending the value of enterprise data elements to the capital market and enriching the understanding of the interaction between the market and enterprise data elements. Thirdly, this paper conducts a mediation analysis based on enterprise innovation performance and enterprise value, opening the "black box" between enterprise data lemmatization and capital market performance and clarifying the transmission path. Our findings have the potential to contribute to a better understanding of the importance of data governance and digital transformation for enterprise success in the capital market.

3. Theoretical Analysis and Research Hypotheses

3.1. Direct Impact of Enterprise Data Elements Level on Enterprise Performance

3.1.1. Direct Impact of Enterprise Data Elements Level on Capital Market Performance

In today's era, the digital transformation and governance of enterprise data are essential stages that organizations must undertake to extract the actual value of data elements. It represents a comprehensive integration of all aspects of the business with digital technology to ensure seamless functioning [34]. Many of the decisions made by an enterprise regarding production and operations are directly reflected in the capital market. Therefore, the importance of data elements is inevitably reflected in capital market activities. The circulation of internal and external data significantly enhances an enterprise's information processing and circulation efficiency; the enterprise, in turn, accumulates a greater innovation potential, thus increasing its overall value [35]. When it comes to digital transformation, it can be seen as a way to improve information efficiency and meet the value requirements in the capital market [36]. Without efficient data processing and management, an enterprise's data quality can be low and ineffective, which makes it difficult to make use of inherent data patterns. This is why implementing data governance and digital transformation is necessary to overcome these challenges [37]. Before an enterprise can effectively exploit inherent data patterns, data governance and digital transformation are necessary to overcome inefficiencies and low quality in data processing. The process of digital transformation is deemed effective when it improves the usability of information, enabling external market investors to access more comprehensive information, which in turn reduces information asymmetry and provides a strong foundation for stock trading. According to [38], stock liquidity is crucial for the capital market's functions of information flow and resource allocation, and it is also a reflection of an enterprise's operational quality and vitality.

The value of data is becoming an essential topic for developing productive forces in the new era. Companies often share positive signals externally, such as through annual report disclosures or investments in production technology. This signal attracts higher market expectations and increases the probability of stock trading. This "exposure effect" indirectly establishes a positive correlation between the level of digital transformation and capital market performance [39]. From the discussion above, we find that the integration of data governance and digital transformation is crucial for enhancing information efficiency, improving data quality, and ultimately increasing an enterprise's value and operational vitality in the capital market.

Therefore, this paper proposes the following hypotheses:

Hypothesis 1a. *The increase in an enterprise's digital transformation level will positively impact its capital market performance.*

Hypothesis 1b. *The increase in an enterprise's data governance level will positively impact its capital market performance.*

3.1.2. Direct Impact of Enterprise Data Elements Level on Innovation Performance

Data as a production element involves the integration of digital technology with business and management models, which leads to the reshaping of existing operational modes. The elementization of data has multiple positive effects on enterprise innovation performance. Firstly, higher levels of digitalization enhance innovation capability and willingness, resulting in increased investment in innovation and quantitative improvement in innovation performance [40]. Secondly, higher digitalization levels enable the integration of scattered resource information for innovative enterprises, which demand higher innovation quality [41]. Thirdly, technologies like big data and AI can quickly collect and categorize vast amounts of structured and unstructured data from inside and outside the enterprise, forming various knowledge products and enhancing innovation performance through feedback mechanisms [42]. Finally, enterprises with high digitalization levels are more likely to cooperate with external innovation partners, thus enhancing innovation performance [43]. Therefore, we believe that the integration of digital technology with business models, through data elementization, significantly boosts enterprise innovation by enhancing capabilities, integrating resources, utilizing advanced technologies, and fostering external collaborations.

Based on the aforementioned observations, this paper proposes two hypotheses:

Hypothesis 2a. *The increase in an enterprise's digital transformation level will positively impact its innovation performance.*

Hypothesis 2b. *The increase in an enterprise's data governance level will positively impact its innovation performance.*

3.1.3. The Direct Impact of Enterprise Data Elements Level on Enterprise Value

Enterprise value is a fundamental measure reflecting the total value of a company, considering its capacity to generate future income, its debt levels, and the market's perception of its overall worth. In the modern economic landscape, the interplay between a company's digital transformation level (DTL) and its data governance level (DGL) plays a pivotal role in shaping its enterprise value. These elements contribute to a firm's competitive advantage, operational efficiency, and innovation capacity, thereby influencing its attractiveness to investors and stakeholders.

Digital transformation redefines how enterprises create value, affecting every aspect of their operations and strategic positioning. At its core, DTL enhances a company's agility, enabling it to respond to market changes swiftly and to innovate continuously [44]. A high DTL facilitates the adoption of cutting-edge technologies and processes, leading to improved productivity and the development of new revenue streams. For instance, leveraging advanced analytics and the Internet of things (IoT) can unlock significant value, enhancing the company's performance and, subsequently, its enterprise value [45].

Data governance, on the other hand, provides a structured framework to ensure data accuracy, availability, and security. A sophisticated DGL supports strategic decision making by ensuring the integrity and usability of data. It enables enterprises to harness the full potential of their digital transformation efforts, optimizing operational processes and mitigating risks associated with data breaches and compliance violations [46]. Effective data governance fosters trust among stakeholders, which is crucial for sustaining and enhancing enterprise value in a data-centric world [33].

The synergy between DTL and DGL propels enterprises toward achieving operational excellence and innovation. As companies become more adept at managing and utilizing their data, they can identify and exploit opportunities for growth and efficiency gains more effectively [47]. This, in turn, positively impacts their market valuation by signaling strong future earnings potential and robust management practices to investors.

We believe that the interplay between a company's digital transformation level (DTL) and its data governance level (DGL) is crucial in shaping its enterprise value, enhancing operational efficiency, innovation capacity, and competitive advantage, thereby increasing its capital market performance. We propose the following hypotheses:

Hypothesis 3a. *The increase in an enterprise's digital transformation level will positively impact its enterprise value.*

Hypothesis 3b. *The increase in an enterprise's data governance level will positively impact its enterprise value.*

3.1.4. Mediation Effect of Enterprise Innovation Performance

Companies with stronger innovation capabilities generally demonstrate better fundamental performance, which often garners the attention of stock investors. Specifically, investors tend to be drawn to enterprises with strong technological innovation capabilities. They are more likely to hold stocks of such enterprises, which can result in an increase in stock liquidity [48]. Digital transformation and the incorporation of digital technologies can significantly enhance an enterprise's innovation performance. As previously discussed, innovation performance can be enhanced in four ways: by increasing innovation capability and willingness, integrating dispersed resource information, accumulating internal and external knowledge outcomes, and collaborating with external innovation partners [49]. Improved innovation performance draws investor attention to an enterprise's focus on innovation, and the output of innovation performance makes investors aware of the enterprise's strength in innovation. Fintech can strengthen an enterprise's investment in research and development and its output performance. This effect can send positive signals about the enterprise's future production prospects to the outside world, which can lead potential investors to have high expectations for the enterprise's stocks, thus improving stock liquidity [50].

We believe that the integration of digital transformation and technological innovation in enterprises significantly boosts their innovation performance, attracting investor attention and enhancing stock liquidity through increased research and development investments and the signaling of strong future production prospects. We propose the following hypotheses:

Hypothesis 4a. *An enterprise's digital transformation level can enhance the enterprise's innovation performance, which in turn can improve its capital market performance.*

Hypothesis 4b. *A enterprise's data governance level can enhance the enterprise's innovation performance, which in turn can improve its capital market performance.*

3.1.5. Mediation Effect of Enterprise Value

The digital transformation level (DTL) and data governance level (DGL) of an enterprise significantly influence its ability to innovate, operationalize efficiency, and secure a competitive advantage, thereby impacting its intrinsic and market value. These elements, when effectively leveraged, not only enhance the enterprise's internal capabilities but also its external financial attractiveness and stability, evidenced through capital market performance [51].

Digital transformation facilitates the deployment of advanced digital technologies and processes, fostering a culture of innovation and resilience. It enables firms to rapidly adapt to market changes and consumer needs, thus potentially increasing their enterprise value through improved revenue streams and market positioning [45]. This increased value is crucial for bolstering investor confidence and attracting investment, leading to enhanced capital market performance characterized by higher stock prices and lower volatility [52].

Simultaneously, robust data governance ensures the integrity, accessibility, and security of the data, which is paramount in the digital age. Effective data governance strategies enhance decision-making processes, operational efficiency, and compliance with regulatory requirements, thereby improving enterprise value through operational excellence and risk mitigation [53]. This in turn positively influences investors' perceptions and the firm's standing in the capital markets, as reflected by its stock performance and liquidity.

The mediating role of enterprise value in the relationship between DTL, DGL, and capital market performance is predicated on the notion that improvements in digital capabilities and data management directly contribute to the firm's overall worth, both in tangible and intangible assets. This increase in enterprise value is a critical indicator for investors and market analysts, as it reflects the company's future earning potential and stability [54]. Thus, a higher enterprise value, influenced by DTL and DGL, signals to the capital markets a strong, forward-looking, and resilient company, likely leading to better capital market performance through improved investor sentiment and stock valuation [55].

In essence, enterprise value acts as a vital intermediary, translating the benefits of digital transformation and data governance into metrics and indicators that are highly valued in the capital markets. This mediation underscores the interconnectedness of internal capabilities and external market perceptions, emphasizing the importance of strategic investments in digital and data governance capabilities for enhancing capital market performance.

Hypothesis 5a. *An enterprise's digital transformation level can enhance the enterprise's enterprise value, which in turn can improve its capital market performance.*

Hypothesis 5b. *An enterprise's data governance level can enhance the enterprise's enterprise value, which in turn can improve its capital market performance.*

Our research highlights the integral role of digital transformation and data governance in enhancing enterprise value, driving innovation performance, and attracting investor interest, thereby improving stock liquidity and market valuation. We summarize the research model of this paper in Figure 1.

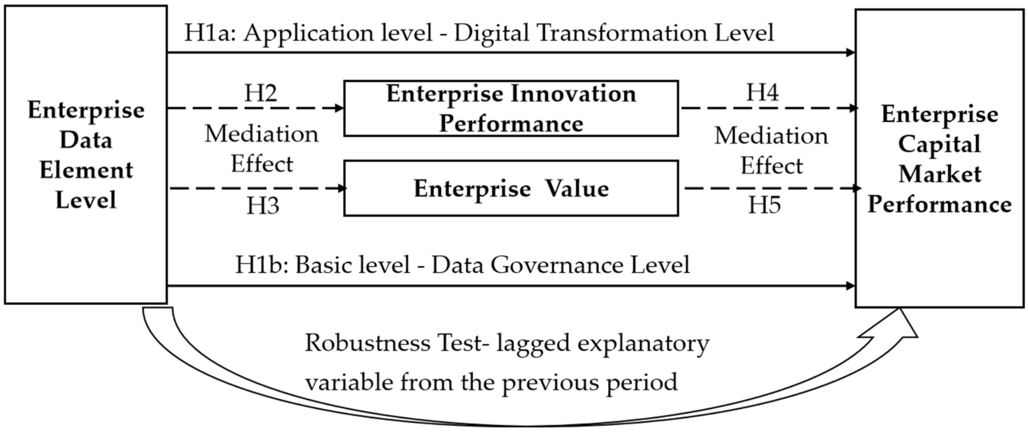

Figure 1. Influence mechanism of enterprise data elements level.

4. Research Design

4.1. Sample Selection and Data Sources

Refer to He's study [30,56], which highlights that China's digital economy was in a nascent stage before 2015. Therefore, this study has selected data from Shanghai and Shenzhen A-share listed enterprises spanning from 2015 to 2023. The data were processed by excluding enterprises with ST status or those that were delisted during the period. Additionally, enterprises that underwent IPOs during the sample period were also excluded. Only samples with no missing data for at least five consecutive years were retained. Moreover, a 1% and 99% winsorization was applied to all micro-level continuous variables to mitigate the impact of outliers. The independent and control variables were lagged by one period to alleviate potential endogeneity issues. Lastly, for the 11 measurement indicators involved in this article, the information is integrated using the company's securities code and company year as the main key information. In order to ensure the validity of the data, the data with all 11 measurement indicators intact are retained, and the data that are missing at least one measurement indicator are discarded. After screening, we selected a total of 2687 sample enterprises, resulting in 10,493 observational data points. The data sources involved in this article and their introduction are as follows (please refer to Table 1 for the detailed access path and caliber of each indicator):

Listed company information, annual report digital indicators, stock liquidity, financial performance, audit information, and other data come from the China Stock Market & Accounting Research Database (CSMAR). CSMAR draws on the professional standards of authoritative databases such as CRSP, COMPUSTAT, TAQ, and THOMSON and combines it with China's actual national conditions to develop an accurate research-based database in the economic and financial fields. The database has covered factor research, human characteristics, green economy, stocks, companies, overseas, and information, funds, bonds, industries, economy, commodity futures, and 19 other major series, including 200+ databases, 4000+ tables, and 60,000+ fields. This article takes data from 2015–2023 on Chinese listed companies.

Enterprise patent data comes from the China Research Data Service Platform (CNRDS). CNRDS is a high-quality, open, and platform-based comprehensive data platform for Chinese economic, financial, and business research. It draws on data platforms created by top foreign business schools such as WRDS to build research data resources with Chinese characteristics. CNRDS has currently established six research series, including listed company operation research, listed company news and public opinion, listed company text information, capital market character characteristics, banking and financial research, and socioeconomic organization research. This article takes data from 2015–2023 on Chinese listed companies.

Table 1. Variable definitions and data sources.

Variable	Name		Data Source	Symbol	Calculation Method
Dependent Variable	Enterprise Capital Market Performance		CSMAR → China Stock Market Return Forecasting Research Database → Monthly Stock Return Table	LnIliqd	Annual average stock liquidity of the enterprise; see description for details.
Independent Variables	Enterprise Data Element Level	Digital Transformation Level	CSMAR → China Listed Firm's Digital Transformation Research Database → Digital Innovation Word Frequency Statistics Table	Digitaltech	Frequency of digitalization terms in annual reports; see description for details.
			CSMAR → China Listed Firm's R&D Innovation Research Database → Intangible Assets Table	DigAssetsPro	Proportion of digital assets to total assets; see description for details.
		Data Governance Level	The official website of the China Electronic Information Industry Federation	DCMM	Data governance capability maturity score; see description for details.
Mediating Variables	Enterprise Innovation Performance		CNRDS → Chinese Innovation Research Database → Listed Company Patent Module	InvPatent	Number of enterprise invention patents
	Enterprise Value		CSMAR → China Stock Market Financial Database—Financial Indices → Relative Value Indicator Table	TobinQ	Market value/total Assets
Control Variables	Enterprise Age		CSMAR → China Listed Firm's Basic Information Database → Basic Information Table	AgeOfCompany	Number of years of operation since inception
	Enterprise Size		CSMAR → China Listed Firm's R&D Innovation Research Database → Main Financial Indicators Table	LnTotalAssets	Log-transformed total assets of the enterprise
	Debt-to-Asset Ratio		CSMAR → China Listed Firm's R&D Innovation Research Database → Main Financial Indicators Table	Lev	Total liabilities/total assets
	Equity Concentration		CSMAR → China Listed Firm's Equity of Nature Research Database → Equity of Nature Table	LargestHolderRate	The shareholding ratio of the largest shareholder
	Audit Opinion		CSMAR → China Stock Market Financial Database–Audit Opinion → Audit Opinion Form	AuditResult	Coded as 0 for standard unqualified opinions issued by accounting firms and 1 for other types of opinions.

The data capability maturity assessment data (DCMM) comes from the assessment data published by the China Electronic Information Industry Federation. The China Electronic Information Industry Federation is entrusted by the government to participate in the organization and formulation of national standards and industry standards in the field of electronic information technology. The federation's official website publishes data based on the review or evaluation results of the DCMM assessment reports of Chinese enterprises by experts. The earliest DCMM assessment data are from 2020, so this article takes the data of Chinese participating companies from 2020 to 2023.

4.2. Variable Measurement and Description

4.2.1. Independent Variables

Digital Transformation Level. Digital transformation in enterprises is about more than just digitizing enterprise data. It involves integrating advanced digital technologies and hardware systems to digitize production materials and processes. However, accurately measuring the level of digital transformation at a micro-level is a challenging task and has gained significant attention from academia, politics, and industry. Existing quantitative research on enterprise digital transformation can be classified into three types. The first type involves constructing a digital evaluation indicator system. For instance, Chanias [57] examined 20 related models and proposed the concept of "digital maturity" to represent the progress of enterprise digital transformation. Wang [58] has improved the digital maturity model. They have identified 5 crucial procedures and 19 primary and 63 secondary indicators. The CSMAR team has collaborated with the Enterprise Management Department of the School of Business Administration at East China Normal University to evaluate the enterprise digital transformation index to construct an evaluation system. There are three types of evaluation systems, among which the second type uses financial statements to quantify the level of enterprise digitalization, which is accomplished by calculating the ratio of digitalization-related items, such as fixed assets and intangible assets, disclosed in annual financial reports to total assets [27,59]. The third type involves text analysis, using word segmentation technology to analyze critical information related to digital transformation in annual reports. The frequency of digital-transformation-related terms in annual reports is used as an indicator [60,61]. These annual reports summarize the enterprise's operations over the past year and plan its future strategic direction.

For this study, we focused on measuring the intensity of enterprise digital transformation by using two indices generated from quantitative description and text analysis. To verify the results, we followed the specific construction methods outlined below: (1) We established a digital transformation feature word library by referring to the academic literature, important policy documents, and research reports. We identified the basic expressions of digital transformation in annual reports, including digital transformation infrastructure and related technologies such as "big data", "smart devices", "mobile apps", "cloud computing", "Internet of Things (IoT)", and "blockchain", as well as application scenarios. We then used Python's Jieba segmentation technology to extract keywords related to digitalization from the annual report texts. By measuring the frequency of these words, we were able to quantify the amount of digital transformation information disclosed. (2) We measured each enterprise's digital transformation level by calculating the proportion of the total amount of digital-related intangible assets to the total intangible assets at the end of the year. Following Wei Ming's approach [62], we screened the annual end-of-year intangible asset details disclosed in listed enterprises' financial reports for 149 keywords related to digital economy technologies, such as "network." We calculated the total amount of digital intangible assets for the same enterprise in the same year and expressed it as a percentage of the total intangible assets for that year, serving as an indicator of the proportion of digital assets.

Data Governance Level. The gradual realization of data's role in driving digital transformation has led to recognition that not all data can provide value to enterprises. As such, the governance of enterprise data has become increasingly important. Standardizing data standards and quality is necessary to ensure that data are valuable and high quality, leading to a virtuous cycle of high-quality data that equips enterprises with robust data capabilities. The data governance level reflects the primary data conditions of an enterprise. It provides a quantitative basis for evaluating its ability to effectively support digital transformation and leverage data elements. The Data Capability Maturity Model (DCMM) is the national standard for assessing data capability maturity. It provides a comprehensive framework for standardizing various stages of enterprise data governance, including 8 significant areas and 28 capability items, offering solid model support for enterprise data governance. A practical and enterprise-specific data governance path can be formed by aligning an enterprise's current data status with the DCMM model [63,64]. The DCMM is now the national standard for data governance in China, assessed by the China Electronics Information Industry Federation. This study utilizes the DCMM assessment results to indicate the data governance level.

4.2.2. Dependent Variable

Enterprise Capital Market Performance. With the data elementization of enterprises, investors can now quickly identify listed enterprises with sound financial health through various channels, which can increase their stock trading volume and enhance the level and efficiency of stock trading. The liquidity of stocks remains a reliable measure of an enterprise's performance in the capital market. However, studies conducted by domestic scholars [38] suggest that the inverse of liquidity indicators is more suitable for measuring the Chinese capital market. Therefore, this paper draws on the research theory by [65] and utilizes the inverse of the stock illiquidity ratio as an indicator, with the following formula:

$$Iliqd_{i,t} = \frac{1}{D_{i,t}} \sum_{K=1}^{D_{i,t}} \sqrt{\frac{|r_{i,t}(k)|}{V_{i,t}(k)}}$$

In this formula, $r_{i,t}(k)$ denotes the daily stock return rate of enterprise i on the k trading day of the year t, considering cash dividend reinvestment. The daily stock trading amount of the stock is denoted as $v_{i,t}(k)$, while $D_{i,t}$ represents the total trading days of the year t. The illiquidity ratio, which is an indicator of stock liquidity, is determined by the price change corresponding to the unit trading volume. The higher the stock liquidity, the smaller the price change. Therefore, a higher $Iliqd_{i,t}$ indicates poorer stock liquidity. In this study, we represent the illiquidity ratio as the natural logarithm of the ratio, which is denoted as $LnIliqd$. This conversion facilitates convenient trend analysis of the illiquidity ratio over time.

4.2.3. Control Variables

This study aims to identify the factors affecting stock liquidity by analyzing the relationships between certain variables. The study controls for several factors, including enterprise age (AgeOfCompany), which is calculated by taking the natural logarithm of the number of years since the enterprise's initial public offering (IPO) plus one; enterprise size (LnTotalAssets) is measured by taking the total asset amount of an enterprise and logarithmically transforming it for analysis; shareholding concentration (LargestHolderRate) is the proportion of shares held by the largest shareholder; the leverage ratio (Lev) is the ratio of total liabilities to total assets; and finally, the audit opinion (AuditResult) is coded as 0 for standard unqualified opinions issued by accounting firms and 1 for other types of opinions.

4.2.4. Mediating Variables

Enterprise Value. Enterprise value is a crucial indicator of an enterprise's operational state over a specific period. Academicians use two primary categories to measure enterprise value. The first category is based on the enterprise's market value, which includes strategic planning, growth, and market share. An example of this measurement is the TobinQ value. The second category employs financial metrics to reflect immediate operational outcomes, such as return on equity (ROE) and return on assets (ROA). However, financial metrics only capture specific aspects of economic performance and do not provide a comprehensive view of an enterprise's overall performance over time. Moreover, they do not reveal the growth potential in the capital market. Therefore, TobinQ is used in this study to assess enterprises' market value and performance, which is in line with the recommendations of domestic scholars [66,67].

Innovation Performance. This research proposes that the adoption of digital technology is a significant contributor to innovation performance. Patents, which serve as a reliable indicator of an enterprise's innovation output, capability, and level, are the chosen metric for measuring enterprise innovation performance. In line with the research of Gao and Ba [68,69], and other scholars, patents are classified into three categories: invention, utility model, and design. Given that utility models and design patents generally have lower technological content, invention patents are deemed to provide a more accurate representation of innovation from the perspective of leveraging data elements. Therefore, this study employs the number of invention patents owned by an enterprise as a measure of enterprise innovation performance.

See Table 1 for the variable definitions and data sources.

4.3. Econometric Model Design

4.3.1. The Impact of Enterprise Data Elements Level on Capital Market Performance and the Mediating Effect of Enterprise Innovation Performance

This study aims to investigate whether enterprise data elements could enhance innovation performance and thereby improve capital market performance. Following the approach by Imai and Kim [70], we employed a two-way fixed effects model controlling for year and industry as the research model for this paper. Three models, Equations (1)–(3), were constructed to test this hypothesis.

$$lniliqd_{i.t} = \alpha + \beta_1 digital_{i,t} + \gamma Control_{i,t} + \theta_{i,t} + \mu_{i,t} + \varepsilon_{i,t} \quad (1)$$

$$InvPatent_{i,t} = \alpha + \beta_1 digital_{i,t} + \gamma Control_{i,t} + \theta_{i,t} + \mu_{i,t} + \varepsilon_{i,t} \quad (2)$$

$$lniliqd_{i.t} = \alpha + \beta_1 digital_{i,t} + \beta_2 InvPatent_{i,t} + \gamma Control_{i,t} + \theta_{i,t} + \mu_{i,t} + \varepsilon_{i,t} \quad (3)$$

The independent variable $LnIliqd_{i.t}$ is used to indicate the enterprise's capital market performance. This variable is calculated by taking the natural logarithm of the enterprise's illiquidity value, where a smaller value indicates better capital market performance and vice versa. The independent variable $digital_{i,t}$ is used to denote the enterprise's data elements level, which includes the proportion of digital assets (DigAssetsPro), the frequency of digital technology words in the annual report (digitaltech), and the enterprise's data governance level (DCMM). The mediating variable $\mathrm{InvPatent_{i,t}}$ represents the enterprise's innovation performance, while the variable $\theta_{i,t}$ is an industry-fixed effect. The variable $\mu_{i,t}$ denotes a time-fixed effect, and the variable $\varepsilon_{i,t}$ represents a random error term. If β_1 in Equation (1) passes the significance test, which suggests that enterprise data elements can enhance enterprise capital market performance, it means that Hypotheses 1a,b are supported. If β_1 in Equation (2) passes the significance test, which suggests that enterprise data elements can enhance enterprise innovation performance, it means that Hypotheses 2a,b are supported. If the variables β_1 in Equation (1), β_1 in Equation (2), and β_2 in Equation (3) pass the test of significance, it suggests that enterprise data elements can enhance enterprise innovation performance, which in turn improves enterprise capital market performance. This result supports the Hypotheses 4a,b.

4.3.2. The Mediating Effect of Enterprise Value

The study aims to determine if incorporating enterprise data elements can enhance enterprise value, thus boosting capital market performance, by analyzing models (1), (4), and (5).

$$TobinQ_{i,t} = \alpha + \beta_1 digital_{i,t} + \gamma Control_{i,t} + \theta_{i,t} + \mu_{i,t} + \varepsilon_{i,t} \quad (4)$$

$$lniliqd_{i.t} = \alpha + \beta_1 digital_{i,t} + TobinQ_{i,t} + \gamma Control_{i,t} + \theta_{i,t} + \mu_{i,t} + \varepsilon_{i,t} \quad (5)$$

The independent variable $lniliqd_{i.t}$ is used to indicate the enterprise's capital market performance. The independent variable $digital_{i,t}$ is used to denote the enterprise's data elements level. The mediating variable $TobinQ_{i,t}$ represents the enterprise value, while the variable $\theta_{i,t}$ is an industry-fixed effect. The variable $\mu_{i,t}$ denotes a time-fixed effect, and the variable $\varepsilon_{i,t}$ represents a random error term. If β_1 in Equation (4) passes the significance test, which suggests that enterprise data elements can enhance enterprise value, it means that Hypotheses 3a,b are supported. If the variables β_1 in Equation (1), β_1 in Equation (4), and β_2 in Equation (5) pass the test of significance, it suggests that enterprise data elements can enhance enterprise value, which in turn improves enterprise capital market performance. This result supports the Hypotheses 5a,b.

5. Data Analysis and Conclusions

5.1. Descriptive Statistics

The study employs the technique of winsorization on the variables, specifically at the 1% levels, and subsequently conducts the descriptive statistics (Table 2).

Table 2. Descriptive statistics of variables.

	Count	Mean	SD	Min	p50	Max
LnIliqd	10,493	1.771	1.952	−1.338	1.399	9.010
InvPatent	10,493	1.456	1.273	0.000	1.386	5.283
TobinQ	10,493	2.125	1.295	0.860	1.736	8.457
DigAssetsPro	10,493	2.813	5.657	0.005	0.999	37.391
DigitalTech	10,493	6.637	14.881	0.000	1.000	92.000
DCMM	256	2.766	0.777	1.000	3.000	5.000
LnTotalAssets	10,493	22.185	1.246	20.064	22.011	26.142
Lev	10,493	0.389	0.191	0.058	0.378	0.852
AuditResult	10,493	0.980	0.139	0.000	1.000	1.000
LargestHolderRate	10,493	33.459	14.391	8.480	31.170	72.110
AgeOfCompany	10,493	19.279	5.460	8.000	19.000	34.000

5.2. Correlation Analysis

Table 3 exhibits the correlation matrix, showing that capital market performance has a negative correlation with enterprise innovation performance, Tobin's Q, enterprise's data elements level, total assets, debt-to-asset ratio, and enterprise age. It means that the more innovative an enterprise is, the higher its Tobin's Q, which is a measure of its market value. Additionally, enterprises with a higher data elements level tend to have more excellent total assets, higher gearing ratios, and older age. The better the enterprise's capital market performance, the more significant the change in the same direction. Furthermore, the relationship between capital market performance, audit opinion, and equity concentration correlation coefficient is significantly negative and belongs to the reverse trend change. Additionally, the level of enterprise data elements is positively correlated with enterprise innovation performance ability and enterprise value at a 1% confidence level, suggesting that higher data element levels in an enterprise correspond to better innovation and operational capabilities trends. The correlation coefficients among control variables are mostly within 0.3, indicating no severe multicollinearity interference.

Table 3. Variable correlation matrix.

	LnIliqd	InvPatent	TobinQ	DigAssetsPro	DigitalTech	DCMM	LnTotalAssets	Lev	AuditResult	LargestHolderRate	AgeOfCompany
LnIliqd	1.000										
InvPatent	−0.222 ***	1.000									
TobinQ	0.091 ***	−0.074 ***	1.000								
DigAssetsPro	−0.024 **	0.058 ***	0.117 ***	1.000							
DigitalTech	−0.045 ***	0.059 ***	0.083 ***	0.372 ***	1.000						
DCMM	−0.275 ***	0.193 ***	0.169 ***	0.353 ***	0.245 ***	1.000					
LnTotalAssets	−0.557 ***	0.419 ***	−0.347 ***	−0.060 ***	−0.043 ***	0.317 ***	1.000				
Lev	−0.305 ***	0.187 ***	−0.299 ***	−0.056 ***	−0.067 ***	0.173 ***	0.544 ***	1.000			
AuditResult	0.056 ***	0.018 *	0.002	−0.012	−0.007	−0.033	0.004	−0.106 ***	1.000		
LargestHolderRate	0.081 ***	0.067 ***	−0.075 ***	−0.087 ***	−0.142 ***	0.039	0.139 ***	0.042 ***	0.064 ***	1.000	
AgeOfCompany	−0.250 ***	0.022 **	−0.085 ***	−0.043 ***	−0.035 ***	−0.275 ***	0.196 ***	0.152 ***	−0.041 ***	−0.037 ***	1.000

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.3. Regression Analysis

In light of the panel data nature of our study, we employed a two-way fixed effects model [70] to analyze the data, which effectively controlled for industry and year effects, and employed the method proposed by Wen [71] to conduct the mediation effect analysis.

5.3.1. The Impact of Enterprise Data Elements Level on Capital Market Performance

The results presented in Table 4 indicate that the regression coefficients of DigAssetsPro and DigitalTech in regressions 1 and 2 are both negative and significant at a 1% confidence level. This result means that an increase in the level of enterprise data elements significantly reduces the illiquidity of enterprise stocks and enhances the performance in the capital market to a considerable extent. Therefore, the findings support Hypotheses 1a,b.

Table 4. The impact of enterprise data elements level on capital market performance.

	(1)	**(2)**	**(3)**
	LnIliqd	***LnIliqd***	***LnIliqd***
DigAssetsPro	−0.017 ***		
	(−6.931)		
DigitalTech		−0.007 ***	
		(−7.007)	
DCMM			−0.487 ***
			(−3.017)
LnTotalAssets	−0.882 ***	−0.878 ***	−0.776 ***
	(−58.332)	(−58.047)	(−10.679)
Lev	0.007	−0.005	0.693
	(0.075)	(−0.052)	(1.158)
AuditResult	0.547 ***	0.553 ***	−0.162
	(7.325)	(7.404)	(−0.759)
LargestHolderRate	0.019 ***	0.019 ***	0.026 ***
	(17.548)	(17.184)	(4.137)
AgeOfCompany	−0.042 ***	−0.042 ***	−0.069 ***
	(−14.199)	(−14.221)	(−2.994)
_cons	21.029 ***	20.951 ***	20.744 ***
	(64.279)	(64.130)	(13.264)
N	10,493	10,493	256
R^2	0.380	0.380	0.537
Homescedasticity test	5702.58 (0.000)	6751.38 (0.000)	6395.16 (0.000)

t-statistics in parentheses, *** $p < 0.01$.

The regression outcomes underscore that the augmentation in the magnitude of corporate data elements exerts a significantly positive influence on the enterprises' capital market performance. This influence can be dissected through the prism of production factor theory and the efficient market hypothesis (EMH).

Viewed through the lens of production factor theory, data elements emerge as pivotal inputs in the realm of corporate research and development, catalyzing the generation of knowledge and amplifying the efficiency of innovation and R&D endeavors within enterprises. Data, harvested from consumer interactions during the consumption process and assimilated by entities engaged in the production of intermediate or final goods, elevate the caliber of ideas and knowledge. This elevation, coupled with the proliferation and qualitative enhancement of knowledge as well as its spillover effects, fortifies the innovation capability and efficiency of enterprises. Such dynamics lead to an enriched diversity of new products, bolstering the innovation and value of enterprises, which subsequently enhances their performance in capital markets. Additionally, data elements serve either as standalone elements or as complementary or substitutable components in conjunction with traditional production factors. As assets, these data elements evolve into data capital, directly impacting production processes. Beyond this direct impact, data elements facilitate the optimal reconfiguration of production inputs, fostering the enhancement and upgrading of other production elements, which in turn promotes advancements in total factor productivity and an expansion in output scale. This cascade of effects culminates in the elevation of corporate performance, thereby augmenting the enterprise's presence and performance in capital markets.

From the vantage point of the EMH, in an efficiently functioning stock market, the pricing of stocks instantaneously and accurately reflects all pertinent information, encapsulating both the anticipated returns and the underlying fundamental and risk factors of the securities. The adept utilization of data elements enriches the informational content embodied in prices, diminishing the repercussions of informational friction in transactions, and by extension, amplifying investment efficiency. Furthermore, the broad application of data elements imposes constraints on managerial investment behaviors. Technological advancements enable tech enterprises to amass real-time, precise metrics of fundamentals, which are then disseminated to professional investors. By reducing the barriers to information acquisition, this influx of data enhances the informational richness of prices, curtailing managerial tendencies towards speculative trading. Concurrently, data revelations concerning potential downturns in business operations or the unveiling of future growth avenues improve the efficiency of managerial investment decisions. Data elements play a crucial role in mitigating information asymmetry and friction, thus augmenting the efficiency of information alignment within capital markets and fostering a more effective operational framework. Within this mechanism, the utility derived from data elements adheres to the principle of diminishing marginal returns, underscoring the nuanced and multifaceted impact of data elements on capital market dynamics.

5.3.2. The Impact of Enterprise Data Elements Level on Innovation Performance

The results presented in Table 5 indicate that the coefficients for enterprise data elements are positive and significant at a 10% confidence level in all three regressions. This result suggests that an increase in the level of enterprise data elements significantly improves the enterprise's patent output and research and development innovation capabilities during the same period. Therefore, Hypotheses 2a,b are supported.

Table 5. The impact of enterprise data elements level on innovation performance.

	(1)	**(2)**	**(3)**
	InvPatent	***InvPatent***	***InvPatent***
DigAssetsPro	0.027 *** (12.120)		
DigitalTech		0.013 *** (14.759)	
DCMM			0.181 * (2.292)
LnTotalAssets	0.526 *** (44.899)	0.519 *** (44.367)	0.619 *** (23.394)
Lev	−0.130 * (−1.880)	−0.110 (−1.597)	−2.112 * (−2.462)
AuditResult	0.086 (1.170)	0.077 (1.039)	−1.180 * (−2.170)
LargestHolderRate	−0.002 ** (−2.553)	−0.001 * (−1.781)	−0.012 ** (−2.908)
AgeOfCompany	−0.008 *** (−3.885)	−0.008 *** (−3.840)	0.031 (1.546)
_cons	−10.100 *** (−40.456)	−9.980 *** (−39.880)	−10.927 *** (−18.147)

Table 5. *Cont.*

	(1)	(2)	(3)
	InvPatent	***InvPatent***	***InvPatent***
N	10,493	10,493	256
R^2	0.283	0.287	0.293
Homescedasticity test	154.10 (0.000)	147.76 (0.000)	35.45 (0.000)

t-statistics in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.3.3. The Impact of Enterprise Data Elements Level on Enterprise Value

Based on the results in Table 6, the coefficients for enterprise data elements are positively and significantly correlated with a 1% confidence level in all three regressions. This result implies that an increase in the level of enterprise data elements greatly enhances the Tobin's Q value of the enterprise during the same period, ultimately resulting in better enterprise value. Hypotheses 3a,b are supported.

Table 6. The impact of enterprise data elements level on enterprise value.

	(1)	(2)	(3)
	TobinQ	***TobinQ***	***TobinQ***
DigAssetsPro	0.016 ***		
	(7.027)		
DigitalTech		0.004 ***	
		(4.589)	
DCMM			0.388 ***
			(3.269)
LnTotalAssets	−0.248 ***	−0.251 ***	−0.174 ***
	(−19.537)	(−19.697)	(−2.757)
Lev	−0.958 ***	−0.950 ***	−0.885 **
	(−11.953)	(−11.827)	(−2.074)
AuditResult	−0.174 *	−0.178 *	0.953 ***
	(−1.836)	(−1.869)	(4.550)
LargestHolderRate	−0.001	−0.001	−0.017 ***
	(−1.366)	(−1.269)	(−4.147)
AgeOfCompany	0.009 ***	0.009 ***	−0.006
	(3.914)	(3.840)	(−0.386)
_cons	8.001 ***	8.075 ***	4.979 ***
	(28.659)	(28.885)	(4.924)
N	10,493	10,493	256
R^2	0.264	0.261	0.289
Homescedasticity test	187.75 (0.000)	209.75 (0.000)	205.17 (0.000)

t-statistics in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.4. Mediation Effect Analysis

5.4.1. Mediation Effect of Enterprise Innovation Performance

Based on the results presented in Table 7, it can be inferred that the use of enterprise data elements level has a positive impact on innovation capabilities, and it significantly reduces the issue of stock illiquidity. This result leads to a marked improvement in the overall performance of the capital market. Therefore, the effect of enterprise data elements on capital market performance is mainly due to their ability to enhance enterprise innovation capabilities. Hypotheses 4a,b are supported by the data.

Table 7. Mediation effect of enterprise innovation performance.

	(1)	(2)	(3)	(4)	(5)	(6)
	InvPatent	*LnIliqd*	*InvPatent*	*LnIliqd*	*InvPatent*	*LnIliqd*
DigAssetsPro	0.027 ***	−0.017 ***				
	(12.120)	(−6.624)				
DigitalTech			0.013 ***	−0.006 ***		
			(14.759)	(−6.516)		
DCMM					0.181 *	−0.484 ***
					(2.292)	(−3.161)
InvPatent		−0.023 *		−0.043 ***		−0.322 ***
		(−1.814)		(−3.665)		(−4.357)
LnTotalAssets	0.526 ***	−0.870 ***	0.519 ***	−0.852 ***	0.619 ***	−0.482 ***
	(44.899)	(−50.862)	(44.367)	(−53.622)	(23.394)	(−5.350)
Lev	−0.130 *	0.004	−0.110	0.141	−2.112 *	0.200
	(−1.880)	(0.043)	(−1.597)	(1.572)	(−2.462)	(0.339)
AuditResult	0.086	0.549 ***	0.077	0.581 ***	−1.180 *	−0.619 **
	(1.170)	(7.372)	(1.039)	(7.892)	(−2.170)	(−1.988)
LargestHolderRate	−0.002 **	0.019 ***	−0.001 *	0.019 ***	−0.012 **	0.023 ***
	(−2.553)	(17.507)	(−1.781)	(17.474)	(−2.908)	(3.690)
AgeOfCompany	−0.008 ***	−0.042 ***	−0.008 ***	−0.042 ***	0.031	−0.061 ***
	(−3.885)	(−14.247)	(−3.840)	(−14.068)	(1.546)	(−2.762)
_cons	−10.100 ***	20.794 ***	−9.980 ***	20.329 ***	−10.927 ***	15.211 ***
	(−40.456)	(57.590)	(−39.880)	(61.379)	(−18.147)	(8.609)
N	10,493	10,493	10,493	10,493	256	256
R^2	0.283	0.380	0.287	0.375	0.293	0.569

t-statistics in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The elevation of enterprise data elements level can enhance an enterprise's innovation performance, which in turn promotes its performance in the capital markets. The data elementization of enterprises yields positive effects on corporate innovation, and an increase in digitalization level facilitates the integration of dispersed resource information within innovative enterprises. This enables a comprehensive assessment of the enterprise's innovation capabilities and directions, heightening the standards for innovation quality and thereby enhancing innovation performance at the quality level. Technologies such as big data and artificial intelligence within the enterprise can swiftly collect, categorize, and organize vast amounts of structured and unstructured data both internally and externally, leading to the creation of various knowledge outcomes and enhancing the enterprise's innovation performance. In the capital market, investors pay particular attention to an enterprise's technological innovation capabilities and are more inclined to hold stocks of such enterprises. An improvement in enterprise innovation performance signifies the enterprise's commitment to innovation and conveys to investors information about stronger innovation capabilities. This, in turn, leads to an increase in the liquidity of the enterprise's stocks, enhancing the enterprise's capital market performance.

5.4.2. Mediation Effect of Enterprise Value

The result presented in Table 8, obtained through a three-step process [71] shows that the level of digital transformation in an enterprise can improve enterprise value, which in turn has a partial positive effect on capital market performance. However, the level of enterprise data governance (DCMM) has no significant mediation effect on the impact of enterprise value on capital market performance. Therefore, Hypothesis 5a is supported, while Hypothesis 5b is not.

Table 8. Mediation effect of enterprise value.

	(1)	(2)	(3)	(4)	(5)	(6)
	TobinQ	***LnIliqd***	***TobinQ***	***LnIliqd***	***TobinQ***	***LnIliqd***
DigAssetsPro	0.016 ***	−0.014 ***				
	(7.027)	(−5.558)				
DigitalTech			0.004 ***	−0.006 ***		
			(4.589)	(−6.313)		
DCMM					0.388 ***	−0.482 ***
					(3.269)	(−3.013)
TobinQ		−0.222 ***		−0.223 ***		−0.135
		(−16.575)		(−16.725)		(−1.262)
LnTotalAssets	−0.248 ***	−0.938 ***	−0.251 ***	−0.935 ***	−0.174 ***	−0.780 ***
	(−19.537)	(−58.613)	(−19.697)	(−58.410)	(−2.757)	(−10.304)
Lev	−0.958 ***	−0.205 **	−0.950 ***	−0.217 **	−0.885 **	0.579
	(−11.953)	(−2.200)	(−11.827)	(−2.323)	(−2.074)	(0.951)
AuditResult	−0.174 *	0.509 ***	−0.178 *	0.513 ***	0.953 ***	−0.110
	(−1.836)	(7.044)	(−1.869)	(7.126)	(4.550)	(−0.495)
LargestHolderRate	−0.001	0.019 ***	−0.001	0.019 ***	−0.017 ***	0.024 ***
	(−1.366)	(17.546)	(−1.269)	(17.195)	(−4.147)	(3.837)
AgeOfCompany	0.009 ***	−0.040 ***	0.009 ***	−0.040 ***	−0.006	−0.073 ***
	(3.914)	(−13.696)	(3.840)	(−13.730)	(−0.386)	(−3.122)
_cons	8.001 ***	22.802 ***	8.075 ***	22.755 ***	4.979 ***	21.208 ***
	(28.659)	(63.173)	(28.885)	(63.106)	(4.924)	(12.351)
N	10,493	10,493	10,493	10,493	256	256
R^2	0.264	0.396	0.261	0.397	0.289	0.541

t-statistics in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The enhancement of an enterprise's data elements level can improve its enterprise value, which in turn promotes its capital markets performance. For enterprises, the deep integration of digital technologies with business and management models, reshaping existing internal operational modes, especially in an environment characterized by sharply increased global economic trade uncertainties, heightened economic downturn pressures, and accelerated economic structural transformations, can effectively boost the economic efficiency of enterprises. As enterprises continually unearth the value of data elements, they effectively break down "data silos", allowing various internal production segments to share dynamic information in real time. This enables upstream and downstream industry chains to share and communicate, significantly reducing transaction and search costs for enterprises. Moreover, a data-driven decision-making management model enhances the efficiency of decisions, better guiding the overall production and operation of enterprises, thereby ensuring steady development and enhancing enterprise performance. In the capital market, research indicates that an enterprise's value plays a crucial role in influencing its capital market performance. Some scholars have employed financial performance and domestic capital market data to empirically derive a series of valuable conclusions and shown that enterprise value indicators, such as profitability, have a significant impact on the liquidity of enterprise stocks.

The Data Capability Maturity Model (DCMM) was only launched in 2018, resulting in insufficient data for inclusion in the regression analysis of this paper. Furthermore, due to the relatively recent deployment of the model, the mediating role of enterprise value in the impact of enterprise data governance maturity (DCMM) on enterprise capital market performance has not yet been fully identified. Therefore, the current regression outcomes are not significant.

5.5. Robustness Test

Most of the time, the development of an enterprise's data elements and its innovation, operating, and capital market abilities may show a mutual causation effect due to endogeneity interference. This paper uses a lagged explanatory variable from the previous period rather than the current period to address the issue. By doing so, the lagged variable can eliminate the endogeneity problem associated with the error term and improve the estimation of the results of the stability. The results indicate that the earlier conclusions drawn in this paper are robust. As seen through the collation, it is still possible to draw the conclusions of this paper's Hypotheses 1–4 and 5a, which indicates that the conclusions drawn earlier are robust and have specific reference significance (Tables 9–13).

Table 9. Robustness analysis of the impact of enterprise data elements level on capital market performance.

	(1)	(2)	(3)
	F.LnIliqd	*F.LnIliqd*	*F.LnIliqd*
DigAssetsPro	−0.006 ***		
	(−3.735)		
DigitalTech		−0.005 ***	
		(−8.713)	
DCMM			−0.217 **
			(−1.982)
LnTotalAssets	−0.658 ***	−0.656 ***	−0.616 ***
	(−76.012)	(−75.931)	(−10.904)
Lev	0.362 ***	0.358 ***	0.753 **
	(6.155)	(6.112)	(2.224)
AuditResult	0.268 ***	0.264 ***	−0.152
	(3.263)	(3.249)	(−0.894)
LargestHolderRate	0.014 ***	0.014 ***	0.022 ***
	(24.452)	(23.872)	(6.190)
AgeOfCompany	−0.008 ***	−0.008 ***	−0.029 **
	(−5.064)	(−5.139)	(−2.165)
_cons	15.112 ***	15.098 ***	15.133 ***
	(77.421)	(77.672)	(16.483)
N	7459	7459	197
R^2	0.561	0.564	0.700

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

Table 10. Robustness analysis of the impact of enterprise data elements level on innovation performance.

	(1)	(2)	(3)
	F.InvPatent	*F.InvPatent*	*F.InvPatent*
DigAssetsPro	0.029 ***		
	(10.443)		
DigitalTech		0.014 ***	
		(13.942)	
DCMM			0.167 *
			(2.424)
LnTotalAssets	0.542 ***	0.536 ***	0.640 ***
	(38.588)	(38.315)	(18.956)
Lev	−0.098	−0.090	−2.435 **
	(−1.149)	(−1.061)	(−2.796)
AuditResult	0.138	0.146	−0.754 ***
	(1.404)	(1.490)	(−5.250)
LargestHolderRate	−0.001	0.000	−0.013 **
	(−0.765)	(0.067)	(−3.361)
AgeOfCompany	−0.008 ***	−0.008 ***	0.024
	(−3.332)	(−3.424)	(1.111)
_cons	−10.498 ***	−10.415 ***	−11.338 ***
	(−34.464)	(−34.258)	(−14.409)

Table 10. *Cont.*

	(1)	(2)	(3)
	F.InvPatent	*F.InvPatent*	*F.InvPatent*
N	7459	7459	197
R^2	0.288	0.294	0.284

t-statistics in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 11. Robustness test of the impact of enterprise data elements level on enterprise value.

	(1)	(2)	(3)
	F.TobinQ	*F.TobinQ*	*F.TobinQ*
DigAssetsPro	0.011 ***		
	(4.610)		
DigitalTech		0.002 ***	
		(2.658)	
DCMM			0.290 **
			(2.269)
LnTotalAssets	−0.202 ***	−0.203 ***	−0.137 **
	(−14.707)	(−14.753)	(−2.021)
Lev	−1.112 ***	−1.112 ***	−0.846 *
	(−12.455)	(−12.426)	(−1.946)
AuditResult	−0.222	−0.222	0.991 ***
	(−1.465)	(−1.465)	(3.250)
LargestHolderRate	0.001	0.001	−0.016 ***
	(1.205)	(1.286)	(−3.664)
AgeOfCompany	0.002	0.002	−0.027
	(0.779)	(0.683)	(−1.310)
_cons	7.045 ***	7.084 ***	4.657 ***
	(21.941)	(22.026)	(4.018)
N	7459	7459	197
R^2	0.211	0.209	0.240

t-statistics in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 12. Robustness analysis of the mediation effect of enterprise innovation performance.

	(1)	(2)	(3)	(4)	(5)	(6)
	F.InvPatent	*F.LnIliqd*	*F.InvPatent*	*F.LnIliqd*	*F.InvPatent*	*F.LnIliqd*
DigAssetsPro	0.029 ***	−0.006 ***				
	(10.443)	(−3.340)				
DigitalTech			0.014 ***	−0.005 ***		
			(13.942)	(−8.332)		
DCMM					0.167 *	−0.207 **
					(2.424)	(−2.099)
InvPatent		−0.021 ***		−0.016 **		−0.204 ***
		(−2.717)		(−2.053)		(−4.354)
LnTotalAssets	0.542 ***	−0.647 ***	0.536 ***	−0.648 ***	0.640 ***	−0.428 ***
	(38.588)	(−66.701)	(38.315)	(−67.156)	(18.956)	(−6.324)
Lev	−0.098	0.362 ***	−0.090	0.358 ***	−2.435 **	0.382
	(−1.149)	(6.164)	(−1.061)	(6.120)	(−2.796)	(1.121)
AuditResult	0.138	0.271 ***	0.146	0.266 ***	−0.754 ***	−0.480 *
	(1.404)	(3.296)	(1.490)	(3.273)	(−5.250)	(−1.759)
LargestHolderRate	−0.001	0.014 ***	0.000	0.014 ***	−0.013 **	0.020 ***
	(−0.765)	(24.425)	(0.067)	(23.865)	(−3.361)	(5.700)
AgeOfCompany	−0.008 ***	−0.009 ***	−0.008 ***	−0.009 ***	0.024	−0.021
	(−3.332)	(−5.154)	(−3.424)	(−5.207)	(1.111)	(−1.651)
_cons	−10.498 ***	14.904 ***	−10.415 ***	14.944 ***	−11.338 ***	11.571 ***
	(−34.464)	(70.352)	(−34.258)	(70.944)	(−14.409)	(9.778)

Table 12. *Cont.*

	(1)	(2)	(3)	(4)	(5)	(6)
	F.InvPatent	***F.LnIliqd***	***F.InvPatent***	***F.LnIliqd***	***F.InvPatent***	***F.LnIliqd***
N	7459	7459	7459	7459	197	197
R^2	0.288	0.562	0.294	0.565	0.284	0.732

t-statistics in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 13. Robustness analysis of the mediation effect of enterprise value.

	(1)	(2)	(3)	(4)	(5)	(6)
	F.TobinQ	***F.LnIliqd***	***F.TobinQ***	***F.LnIliqd***	***F.TobinQ***	***F.LnIliqd***
DigAssetsPro	0.011 ***	−0.004 ***				
	(4.610)	(−2.722)				
DigitalTech			0.002 ***	−0.005 ***		
			(2.658)	(−8.097)		
DCMM					0.290 **	−0.193 ***
					(2.269)	(−16.925)
TobinQ		−0.115 ***		−0.114 ***		−0.026
		(−11.824)		(−11.792)		(−0.487)
LnTotalAssets	−0.202 ***	−0.689 ***	−0.203 ***	−0.686 ***	−0.137 **	−0.620 ***
	(−14.707)	(−75.106)	(−14.753)	(−74.946)	(−2.021)	(−36.867)
Lev	−1.112 ***	0.256 ***	−1.112 ***	0.254 ***	−0.846 *	0.891 **
	(−12.455)	(4.375)	(−12.426)	(4.353)	(−1.946)	(3.885)
AuditResult	−0.222	0.250 ***	−0.222	0.246 ***	0.991 ***	−0.060
	(−1.465)	(3.109)	(−1.465)	(3.097)	(3.250)	(−0.468)
LargestHolderRate	0.001	0.014 ***	0.001	0.014 ***	−0.016 ***	0.022 ***
	(1.205)	(24.556)	(1.286)	(24.001)	(−3.664)	(14.053)
AgeOfCompany	0.002	−0.007 ***	0.002	−0.007 ***	−0.027	−0.026 ***
	(0.779)	(−4.456)	(0.683)	(−4.557)	(−1.310)	(−10.101)
_cons	7.045 ***	16.076 ***	7.084 ***	16.056 ***	4.657 ***	14.993 ***
	(21.941)	(73.987)	(22.026)	(74.152)	(4.018)	(33.615)
N	7459	7459	7459	7459	197	197
R^2	0.211	0.573	0.209	0.576	0.240	0.668

t-statistics in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.6. Endogeneity Test

The instrumental variables in this study are calculated by using the average value of the data elements level of other enterprises in the same industry in the same year, excluding the enterprise itself. This approach is selected based on several reasons. Firstly, there is a correlation between the average data elements level value of other enterprises in the same industry and the explanatory variables. Similar market environments and competitive pressures faced by enterprises in the same industry affect their data elements extent, which may impact the explanatory variables. Secondly, the average data elements extent of other enterprises in the same industry is not associated with the error term. Therefore, this instrumental variable does not directly impact the error term of the explanatory variable, thereby avoiding the endogeneity problem. Thirdly, the mean values of the data element extent of other enterprises in the same industry are typically easier to obtain, making this method highly operational in practice. At the same time, excluding data outside the enterprise itself reduces the risk of the model being affected by outliers or extreme values, improving the robustness of the estimation results.

After analyzing the data, it was found that Hypotheses 1–4 and 5a are supported. The consistent conclusions obtained after overcoming endogeneity have a certain reference value (Tables 14–18).

Table 14. Endogeneity analysis of the impact of enterprise data elements level on capital market performance.

	(1)	(2)	(3)
	LnIliqd	***LnIliqd***	***LnIliqd***
DigAssetsPro	−0.074 ***		
	(−5.813)		
DigitalTech		−0.031 ***	
		(−6.023)	
DCMM			−0.356 ***
			(−3.349)
LnTotalAssets	−0.887 ***	−0.873 ***	−0.796 ***
	(−58.078)	(−57.055)	(−11.030)
Lev	0.123	0.037	0.985 *
	(1.312)	(0.383)	(1.737)
AuditResult	0.598 ***	0.614 ***	0.253
	(7.407)	(7.474)	(1.420)
LargestHolderRate	0.018 ***	0.016 ***	0.022 ***
	(15.070)	(11.607)	(4.323)
AgeOfCompany	−0.051 ***	−0.051 ***	−0.071 ***
	(−16.655)	(−16.605)	(−3.697)
_cons	21.407 ***	21.187 ***	20.471 ***
	(62.311)	(63.236)	(13.729)
N	10,488	10,488	256
R^2	0.331	0.325	0.495

t-statistics in parentheses, * $p < 0.1$, *** $p < 0.01$.

Table 15. Endogeneity analysis of the impact of enterprise data elements level on innovation performance.

	(1)	(2)	(3)
	InvPatent	***InvPatent***	***InvPatent***
DigAssetsPro	0.028 ***		
	(4.537)		
DigitalTech		0.011 ***	
		(3.846)	
DCMM			0.192 *
			(1.661)
LnTotalAssets	0.679 ***	0.670 ***	0.602 ***
	(9.369)	(8.961)	(7.607)
Lev	−2.014 ***	−1.747 ***	−1.973 ***
	(−3.884)	(−3.354)	(−3.695)
AuditResult	−1.227 ***	−1.261 ***	−0.975 **
	(−2.621)	(−2.773)	(−2.047)
LargestHolderRate	−0.007	−0.008	−0.011 **
	(−1.270)	(−1.597)	(−2.223)
AgeOfCompany	−0.003	−0.007	0.016
	(−0.159)	(−0.365)	(0.854)
_cons	−11.516 ***	−11.206 ***	−10.568 ***
	(−6.879)	(−6.552)	(−6.100)
N	256	256	256
R^2	0.308	0.293	0.270

t-statistics in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 16. Endogeneity analysis of the impact of enterprise data elements level on enterprise value.

	(1)	(2)	(3)
	TobinQ	*TobinQ*	*TobinQ*
DigAssetsPro	0.044 *** (4.479)		
DigitalTech		0.028 *** (5.282)	
DCMM			0.337 *** (2.800)
LnTotalAssets	−0.260 *** (-20.469)	−0.270 *** (−20.729)	−0.187 *** (−2.782)
Lev	−1.031 *** (−12.448)	−0.929 *** (−10.451)	−0.674 (−1.413)
AuditResult	−0.090 (−0.875)	−0.093 (−0.865)	1.101 *** (6.818)
LargestHolderRate	−0.002 * (−1.778)	0.001 (1.031)	−0.016 *** (−3.766)
AgeOfCompany	−0.001 (−0.648)	−0.001 (−0.215)	−0.024 * (−1.709)
_cons	8.333 *** (28.814)	8.359 *** (28.740)	5.507 *** (5.089)
N	10,488	10,488	256
R^2	0.138	0.074	0.211

t-statistics in parentheses, * $p < 0.1$, *** $p < 0.01$.

Table 17. Endogeneity analysis of the mediation effect of enterprise innovation performance.

	(1)	(2)	(3)	(4)	(5)	(6)
	InvPatent	*LnIliqd*	*InvPatent*	*LnIliqd*	*InvPatent*	*LnIliqd*
DigAssetsPro	0.028 *** (4.537)	−0.012 (−1.425)				
DigitalTech			0.011 *** (3.846)	−0.007 ** (−2.009)		
DCMM					0.192 * (1.661)	−0.314 *** (−3.058)
InvPatent		−0.238 *** (−4.147)		−0.239 *** (−4.408)		−0.248 *** (−4.835)
LnTotalAssets	0.679 *** (9.369)	−0.726 *** (−9.475)	0.670 *** (8.961)	−0.727 *** (−9.759)	0.602 *** (7.607)	−0.646 *** (−9.159)
Lev	−2.014 *** (−3.884)	0.468 (0.803)	−1.747 *** (−3.354)	0.324 (0.565)	−1.973 *** (−3.695)	0.497 (0.865)
AuditResult	−1.227 *** (−2.621)	0.199 (0.720)	−1.261 *** (−2.773)	0.252 (0.884)	−0.975 ** (−2.047)	0.009 (0.036)
LargestHolderRate	−0.007 (−1.270)	0.018 *** (3.133)	−0.008 (−1.597)	0.018 *** (3.250)	−0.011 ** (−2.223)	0.020 *** (3.782)
AgeOfCompany	−0.003 (−0.159)	−0.045 *** (−2.658)	−0.007 (−0.365)	−0.041 ** (−2.420)	0.016 (0.854)	−0.068 *** (−3.648)
_cons	−11.516 *** (−6.879)	18.323 *** (11.664)	−11.206 *** (−6.552)	18.299 *** (11.986)	−10.568 *** (−6.100)	17.852 *** (12.524)
N	256	256	256	256	256	256
R^2	0.308	0.518	0.293	0.516	0.270	0.527

t-statistics in parentheses, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 18. Endogeneity analysis of the mediation effect of enterprise value.

	(1)	(2)	(3)	(4)	(5)	(6)
	TobinQ	*LnIliqd*	*TobinQ*	*LnIliqd*	*TobinQ*	*LnIliqd*
DigAssetsPro	0.044 ***	−0.067 ***				
	(4.479)	(−5.300)				
DigitalTech			0.028 ***	−0.027 ***		
			(5.282)	(−5.282)		
DCMM					0.337 ***	−0.651 *
					(2.800)	(−1.892)
TobinQ		−0.142 ***		−0.153 ***		0.036
		(−10.877)		(−12.367)		(0.330)
LnTotalAssets	−0.260 ***	−0.924 ***	−0.270 ***	−0.914 ***	−0.187 ***	−0.739 ***
	(−20.469)	(−58.857)	(−20.729)	(−57.796)	(−2.782)	(−7.908)
Lev	−1.031 ***	−0.023	−0.929 ***	−0.104	−0.674	1.087 *
	(−12.448)	(−0.251)	(−10.451)	(−1.084)	(−1.413)	(1.779)
AuditResult	−0.090	0.585 ***	−0.093	0.600 ***	1.101 ***	0.123
	(−0.875)	(7.403)	(−0.865)	(7.579)	(6.818)	(0.506)
LargestHolderRate	−0.002 *	0.018 ***	0.001	0.016 ***	−0.016 ***	0.023 ***
	(−1.778)	(15.079)	(1.031)	(11.926)	(−3.766)	(4.135)
AgeOfCompany	−0.001	−0.051 ***	−0.001	−0.051 ***	−0.024 *	−0.088 ***
	(−0.648)	(−16.877)	(−0.215)	(−16.854)	(−1.709)	(−3.398)
_cons	8.333 ***	22.591 ***	8.359 ***	22.464 ***	5.507 ***	20.308 ***
	(28.814)	(63.627)	(28.740)	(63.875)	(5.089)	(12.450)
N	10,488	10,488	10,488	10,488	256	256
R^2	0.138	0.344	0.074	0.344	0.211	0.481

t-statistics in parentheses, * $p < 0.1$, *** $p < 0.01$.

6. Conclusions and Implications

In today's business environment, the role of data has become critically important, particularly in driving sustainable development within enterprises. Data can assist businesses in finding a balance between economic benefits, social responsibility, and environmental protection. Through the collection and analysis of data, businesses are able to better understand the impact of their operations on the environment and society, thereby making more responsible decisions [72]. For instance, data analysis can reveal the environmental footprint in the procurement of raw materials and throughout the product lifecycle, aiding enterprises in identifying and implementing more environmentally friendly practices. Simultaneously, data can help businesses measure the effectiveness of their social responsibility programs, ensuring that these initiatives promote economic growth while also delivering social value and environmental benefits [73].

Faced with global challenges such as trade wars, global pandemics, and climate change, the role of data becomes even more pronounced. Data analysis can aid businesses in optimizing supply chain management: by monitoring and analyzing each link in the supply chain in real time, enterprises can promptly identify and address potential issues, reducing the risk of disruptions caused by trade restrictions or pandemic lockdowns [74]. Furthermore, data-driven market trend forecasts can help businesses more accurately predict changes in demand, adjust production plans accordingly, and thus reduce inventory costs and waste [75]. In combating climate change, data analysis can assist businesses in identifying inefficiencies in energy use, implementing energy-saving measures, and reducing greenhouse gas emissions, while also using historical and real-time meteorological data analysis to predict the impact of extreme weather events and take appropriate measures to mitigate losses [76].

This research conducts an in-depth analysis of the influence of enterprise data elements on the capital market performance of enterprises in the digital economy era. The study reveals that there is a positive correlation between the enhancement of the level of enterprise data elements and their capital market performance. The innovation performance and enterprise value of enterprises act as effective mediators in this relationship.

The paper makes significant contributions in several areas. Firstly, it reconstructs the core concepts and assessment indicators of enterprise data elements value from the perspectives of enterprise digital transformation and data governance. This new methodology assesses the enterprise's data elementization more comprehensively by encompassing the foundational capabilities of data governance instead of limiting the definition of data elements and assessment indicators to digital transformation at the application level. Secondly, the paper extends the research horizons of the economic impact of microeconomic subjects after the construction of enterprise data elements capabilities. It also extends the value brought by enterprise data elements to the capital market, which provides us with a new perspective to understand the interaction mode between the market and enterprise data elements more deeply. Finally, the paper reveals potential transmission paths between enterprise data elementization and enterprise capital market performance through mediation analysis based on enterprise innovation performance and enterprise value. This result broadens the understanding of this crucial area and provides a more explicit reference for future research and practice.

The experiences of Chinese enterprises in utilizing data elements offer significant insights for global enterprises: data elements, as an important resource, provide new avenues for innovation and enhancing market competitiveness. By effectively using data, global enterprises can not only gain deep insights into market demand and consumer preferences but also optimize their products and services through data-driven decision making. Furthermore, an enhancement in data analytics capabilities helps businesses forecast market trends, thereby more flexibly responding to market changes and enhancing economic resilience. Facing global challenges such as trade wars, pandemics, and climate change, enterprises can discover potential risks and opportunities through data analysis, taking effective measures to maintain their competitive edge.

From the perspective of governments and international organizations, establishing a global framework that supports data governance and promotes the enhancement of corporate data capabilities is crucial. China's exploration and practices in establishing a data governance system and promoting cross-border data flows offer valuable experiences. To support the healthy development of the data economy, global policymakers should commit to formulating unified data sharing standards and strengthening international cooperation in data governance, privacy protection, and data utilization. This will not only help address challenges posed by transnational data flows but also create a clearer, more stable operating environment for global businesses, thereby fostering sustainable development and the prosperity of the global economy. Through collective efforts, the global community can better harness the power of data to tackle challenges including trade wars, pandemics, and climate change, contributing to the sustainable development of the global economy.

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List of Abbreviations

DTL	Digital Transformation Level
DGL	Data Governance Level
IoT	Internet of Things
PDCA	Plan-Do-Check-Act
PwC	PricewaterhouseCoopers
CNRDS	China Research Data Service Platform
CSMAR	China Stock Market & Accounting Research Database
DCMM	Data Capability Maturity Model
FDI	Foreign Direct Investment
EMH	Efficient Market Hypothesis
ROE	Return on Equity
ROA	Return on Assets

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