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Asymmetric Impacts of Data Elements on Corporate Environmental Performance: Evidence from China's A-Share Listed Firms

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Abstract

This study investigates the asymmetric impact of Data Elements (DE) on Corporate Environmental Performance (CEP) in China, using a sample of 310 A-share listed firms from 2012 to 2021. The results show that DE significantly enhances CEP, with stronger effects observed in State-Owned Enterprises (SOEs) compared to non-SOEs. Additionally, heavily polluting firms are more responsive to DE than lightly polluting firms, indicating that DE has a stronger effect in industries with greater environmental challenges. The study also highlights regional differences, with firms located in areas with stricter environmental regulations experiencing a more substantial improvement in CEP. Mechanism analysis reveals that DE improves environmental performance through optimizing labor force structure, enhancing management efficiency, and alleviating financing constraints. These findings suggest that the impact of DE on CEP is not uniform, and firms should leverage DE more effectively, particularly in high-pollution industries, regulated regions, and state-owned enterprises, to support green development. The study provides valuable insights for policymakers and business leaders aiming to foster a green transformation in China's economy.

Keywords: data elements; corporate environmental performance; asymmetric impact; pollution intensity

1. Introduction

The accelerating depletion of resources and environmental degradation have made reconciling growth with ecological sustainability has become an urgent global imperative. Nowhere is this balancing act more urgent than in China, where rapid industrialization has spurred a renewed policy focus on achieving carbon neutrality. As the world's largest energy producer and consumer, China has committed to ambitious targets for peaking carbon emissions and reaching carbon neutrality, thereby assuming a leading role in global climate governance [1–3].

As key actors in production and trade, firms are essential for implementing carbon reduction strategies, mitigating environmental pollution, and internalizing environmental costs [4–6]. However, despite increased regulatory oversight and policy initiatives, improving corporate environmental performance (CEP) remains challenging, particularly in developing economies where institutional capacity and environmental awareness vary widely [7,8].



Academic Editor: Xiaogang Qi

Received: 24 July 2025

Revised: 17 September 2025

Accepted: 28 September 2025

Published: 24 July 2026

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conditions of the [Creative Commons](https://creativecommons.org/licenses/by/4.0/)[Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

Although the macro significance of the digital economy is widely recognized, the micro empirical evidence on how its core component—data elements (DE)—directly affect corporate environmental performance (CEP) remains limited and inconsistent. The existing research mainly proceeds along two paths: Firstly, pay attention to the positive impact of the broad concept of “digital transformation” or “digital technology application” on environmental performance. For example, it can be achieved by optimizing energy efficiency [9], empowering green innovation [10,11], and improving environmental information disclosure [12–14]. Secondly, it begins to explore how specific data-driven tools such as digital finance can enhance enterprises’ environmental protection capabilities by alleviating financing constraints [8,15]. However, most of these studies implicitly assume that the impact of data elements is homogeneous and fail to fully explore the asymmetric impacts that may arise from the heterogeneity of enterprises. For instance, there is a theory suggesting that there are systematic differences between state-owned enterprises and non-state-owned enterprises, as well as between heavily polluting and lightly polluting enterprises in terms of resource acquisition, regulatory pressure and innovation capacity [16], and these differences are likely to moderate the environmental benefits of data elements. Furthermore, the internal mechanisms by which data elements influence CEP (such as the upgrading of the labor force structure, the improvement of management efficiency, and the alleviation of financing constraints) have not yet been systematically empirically tested within the same framework. Therefore, a key research gap lies in: Do data elements have a universal asymmetry effect in enhancing the environmental performance of enterprises? What about the transmission mechanism behind it?

In parallel, the rise in the digital economy offers new tools and pathways for promoting green growth. According to the China Academy of Information and Communications Technology, the digital economy’s share of China’s GDP is expected to reach 44.6% in 2024, up from 42.8% in 2023 [17–21]. This expansion is underpinned by rapid advances in digital infrastructure, evolving data governance regimes, and advancements in information and communication technologies (ICT) and firm-level analytics [22]. Central to this transformation are data elements (DE)—digitally encoded assets that enable firms to capture, process, and utilize information to enhance production efficiency, resource allocation, and strategic decision-making [23].

While existing literature has explored the economic and managerial dimensions of digitalization, the firm-level environmental consequences of data elements remain empirically underexplored, especially in the context of emerging economies [22,24]. DE may facilitate green innovation, reduce information asymmetries, and improve managerial control, thus serving as a catalyst for improved environmental outcomes [16,25]. Recognizing this potential, the Chinese government has emphasized the integration of digitalization and green development, as highlighted in the 2024 policy document *Opinions on Comprehensively Promoting the Construction of a Beautiful China* [26,27].

However, the impact of DE on environmental performance is unlikely to be uniform. Firms operate under different institutional, structural, and regulatory constraints, leading to potentially asymmetric effects. For instance, DE may disproportionately benefit state-owned firms that have better access to capital and stronger political alignment, while private firms may face weaker implementation incentives. Similarly, DE may yield greater environmental gains in regions with stringent regulations, where digital transparency complements enforcement, but may have limited effect in weakly regulated jurisdictions. Firms in highly polluting industries may also experience larger marginal returns from digital interventions due to higher baseline externalities.

This paper investigates whether and how the development of data elements influences corporate environmental performance in China. Specifically, we examine the channels

through which DE—by improving technological capabilities, enhancing media exposure, and reinforcing internal controls—contribute to environmental outcomes. Moreover, we test for asymmetric effects across ownership types, pollution intensities, and regional regulatory environments, thereby providing a more nuanced understanding of the conditions under which DE exerts its influence. To this end, we construct a novel panel dataset of A-share listed firms in Shanghai and Shenzhen from 2008 to 2021, using text-mining methods to quantify firm-level DE intensity and applying fixed effects regressions to estimate their impact on CEP.

Our findings contribute to the growing literature on digital trade, environmental governance, and firm heterogeneity. More importantly, they provide novel evidence of asymmetric digital-environmental dynamics, which have significant implications for targeted policy design. We also offer practical insights for policymakers seeking to leverage digitalization to advance environmental objectives, and for firms aiming to enhance sustainability performance in increasingly data-driven global markets. The findings are particularly relevant in light of growing global concerns over green supply chains, ESG disclosure mandates, and the role of digital trade infrastructure in shaping environmental performance across borders.

The paper is organized as follows: Section 2 reviews relevant literature, Section 3 presents the theoretical framework and hypotheses, Section 4 details the research design and methodology, Section 5 discusses empirical results and robustness checks, and Section 6 concludes with policy recommendations and areas for future research.

2. Literature Review

The existing literature on corporate environmental performance (CEP) and data elements (DE) reveals three key themes: factors influencing CEP, the measurement and impact of DE, and the specific relationship between DE and CEP. The review highlights important gaps in the current research and sets the foundation for exploring the role of digital technologies in enhancing corporate environmental sustainability.

2.1. Determinants of Corporate Environmental Performance

CEP has become a central focus of both corporate strategy and policy regulation, particularly as environmental degradation and resource depletion threaten long-term economic growth [28]. A growing literature documents both internal and external factors that influence firms' environmental outcomes.

Internally, managerial digital orientation [22], technological upgrading via robotics [29], digital investment [4], and ethical leadership contribute to enhanced CEP through green innovation and resource optimization [27,30]. The positive link between corporate social responsibility (CSR)/ESG commitments and environmental performance is well-documented [31,32]. Firms with such commitments tend to exhibit stronger environmental performance, as they systematically internalize externalities and build long-term reputational capital [33,34].

Externally, institutional and regulatory environments play a critical role. Market-based environmental regulations [1,35–37], legal enforcement mechanisms [38,39], and green financial instruments are shown to incentivize sustainable practices [40–42]. The Environmental Protection Law of China, for instance, induced a marked improvement in CEP among A-share listed companies [24,43]. However, regulatory uncertainty may attenuate these effects, encouraging compliance avoidance and pollution-intensive practices [44].

While these factors are well-established, most studies have overlooked how emerging digital infrastructures—particularly data elements embedded in firm operations—reshape the production–environment interface. Moreover, few studies consider the potential for

asymmetric effects, where the impact of a determinant like digitalization may vary significantly across different contexts. This review thus sets the stage for investigating data elements as a novel determinant and exploring the heterogeneous conditions under which they influence CEP.

2.2. Data Elements: Definition, Measurement, and Economic Roles

Data elements (DE) refer to the digital assets, capabilities, and infrastructures that enable firms to collect, process, and act upon information. These include technologies such as artificial intelligence, cloud computing, and big data analytics, which transform operational, financial, and environmental decision-making processes [45,46].

Measuring DE poses methodological challenges. Early qualitative methods, relied on interviews or expert ratings, but lacked comparability and scale [47,48]. Recent advances incorporate firm-level disclosures, survey data, and third-party indices [19,24,49], yet still face limitations of recall bias and representativeness. This paper contributes to the literature by applying machine learning-based text mining to firm reports, providing a scalable, objective, and dynamic proxy for DE intensity.

DEs have been shown to generate economic gains by enhancing efficiency, reducing transaction costs, and supporting innovation [18]. In particular, DE improves firms' absorptive capacity for green innovation [20], strengthens human capital configurations [50], and fosters cross-sectoral collaboration. These attributes are especially salient in rapidly digitizing economies like China.

Additionally, DE facilitates visibility and stakeholder engagement. For instance, DE improves firms' environmental signaling through media exposure and increases transparency in environmental disclosures [51–53]. Internally, DE streamlines governance, reduces agency costs, and aligns corporate actions with long-term ESG goals [27].

Yet despite these linkages, few studies have examined how DE affects environmental outcomes in a theoretically grounded and empirically rigorous manner. The mechanisms by which DE modifies CEP—whether through technology adoption, resource reallocation, or organizational change—remain largely untested.

2.3. Data Elements and Environmental Performance: Empirical Gaps and Asymmetric Effects

A nascent but growing literature explores how DE affects CEP across different levels of analysis. At the micro level, studies find that digital technologies can lower carbon intensity and enhance scheduling and operational control in energy and manufacturing sectors [54]. However, these benefits are often non-linear and depend on the depth and quality of DE implementation [50].

At the macro level, DE has been associated with progress toward Sustainable Development Goals (SDGs), especially in improving access to green finance and energy [55]. In China, digital finance is shown to boost firms' environmental productivity through enhanced credit access and reduced information asymmetries [29].

However, key theoretical and empirical gaps persist. Firstly, the mechanism linking DE to CEP remains undertheorized: does DE reduce pollution via technological upgrading, monitoring precision, or changes in managerial incentives? Secondly, the literature has yet to formally distinguish between heterogeneity and asymmetry. While many studies report differences by firm size or industry, few investigate asymmetric effects—for instance, whether positive environmental returns from DE are concentrated in firms with high baseline CEP or those facing stricter regulatory regimes.

Moreover, the role of resource reallocation—a core function of DE—has been neglected. As firms become more data-driven, they may reallocate capital and labor away

from pollution-intensive activities toward more sustainable alternatives, but this remains empirically underexamined.

2.4. Contribution of This Study

This paper addresses the above gaps through three contributions. First, we propose and empirically test a theoretical framework linking DE to CEP via three channels: technological upgrading, media visibility, and internal governance. Second, we incorporate both heterogeneous and asymmetric analyses to uncover how the DE-CEP relationship varies across ownership types, pollution intensities, and regional institutional contexts. Finally, we introduce a novel measure of DE intensity using large-scale textual analysis, offering methodological innovation in an area plagued by measurement error.

3. Theoretical Analyses and Research Hypotheses

This section develops a theoretical framework to examine the mechanisms through which data element (DE) utilization influences corporate environmental performance (CEP). Drawing upon the micro-level pollution emission models by Forslid and Melitz [56,57], we extend the analysis to incorporate firm behavior in product differentiation, pollution abatement, and profit maximization, emphasizing the role of DE in enhancing firm competitiveness, operational efficiency, and environmental outcomes.

We consider a monopolistic competition setting where firms produce horizontally differentiated products. Let consumer preferences be represented by a CES (Constant Elasticity of Substitution) utility function:

$$U = \left[\int_{i \in \Omega} q(i)^{\frac{\sigma-1}{\sigma}} di \right]^{\frac{\sigma}{\sigma-1}}, \sigma > 1 \quad (1)$$

In the above equation, i denotes a particular differentiated good or service, the set Ω comprises all differentiated goods available, and $q(i)$ indicates the consumption quantity of good or service i . The parameter σ captures the constant elasticity of substitution among differentiated products, reflecting consumer responsiveness to relative price changes.

Consumers choose consumption to maximize utility subject to their budget constraints, yielding the following optimal demand function for a given differentiated good or service:

$$q(i) = Y \left(\frac{p(i)}{P} \right)^{-\sigma} \quad (2)$$

where $p(i)$ is the price of good or service i , Y denotes consumers' total income, and $P = \left[\int_{i \in \Omega} p(i)^{1-\sigma} di \right]^{1/(1-\sigma)}$ is the aggregate price index for all differentiated goods. The parameter σ captures the elasticity of substitution among differentiated products, reflecting consumer responsiveness to relative price changes.

$$q_i = A_i L_i (1 - \theta_i) \quad (3)$$

$$e_i = \phi_i L_i + \omega(f_{A_i}) \quad (4)$$

Let θ_i represent the share of labor input allocated toward pollution reduction activities. Firms can mitigate pollution by investing in fixed environmental technologies and adopting cleaner production practices. Specifically, a firm's environmental strategy involves allocating labor resources efficiently to pollution control and acquiring pollution abatement technologies, denoted as f_{A_i} .

An environmental tax t per unit of pollution is set, the firm's profit function is demonstrated as below:

$$\pi_i = p_i q_i - \omega L_i - f_{A_i} - \kappa f_{D_{ig}} - t e_i \quad (5)$$

where $f_{D_{ig}}$ denote fixed DE investment and $\kappa \in (0, 1)$ captures DE's cost efficiency spillover. Higher DE utilization lowers marginal pollution cost and increases total factor productivity via better resource allocation and digital spillovers.

Crucially, we postulate asymmetry in the effects of DE on CEP, stemming from institutional and market conditions:

Ownership-based asymmetry: State-owned enterprises (SOEs) typically face stricter environmental scrutiny and benefit from superior access to digital infrastructure.

Industry-based asymmetry: High-pollution sectors have greater marginal benefits from DE in pollution control.

Regional asymmetry: Eastern Chinese firms have more advanced digital ecosystems than those in central and western regions.

We articulate four hypotheses reflecting these mechanisms:

Hypothesis 1. *Data element utilization positively influences corporate environmental performance.*

This stems from DE's role in improving operational transparency, reducing coordination inefficiencies, and supporting environmental compliance. The effect is expected to be more pronounced in SOEs and in regions with mature digital infrastructure.

Hypothesis 2. *Data element utilization enhances corporate environmental performance by improving workforce structure and quality.*

DE implementation raises demand for high-skilled labor and reduces reliance on repetitive tasks, thereby improving human capital quality. This labor screening and upgrading effect may be more impactful in private firms and labor-intensive industries.

Hypothesis 3. *Data element utilization enhances corporate environmental performance by improving managerial efficiency and governance quality.*

Digitalization strengthens internal controls, reduces information asymmetry, and enhances regulatory compliance. These improvements are likely to yield asymmetric returns depending on firm governance quality and regulatory exposure.

Hypothesis 4. *Data element utilization enhances corporate environmental performance by alleviating financing constraints and enabling environmental innovation.*

Data assets can signal firm quality to external investors and improve credit access, especially in private firms and underdeveloped regions where financial constraints are more binding.

This theoretical framework sets the stage for our empirical investigation, which tests these hypotheses using firm-level panel data and interaction models that explicitly capture asymmetric effects across ownership, industry, and region.

4. Research Design

4.1. Model Specification

To empirically assess the impact of data element (DE) utilization on corporate environmental performance (CEP), we begin with the following baseline fixed effects panel regression model:

$$CEP_{ijt} = \alpha + \beta_1 DE_{ijt} + \gamma X_{ijt} + \lambda_i + \delta_t + \varepsilon_{ijt} \quad (6)$$

where i , j , and t represent firm, industry, and year, respectively. The dependent variable CEP_{ijt} represents the environmental performance of firm i in year t , proxied by carbon emission intensity. The core explanatory variable DE_{ijt} captures the degree of data element (DE) utilization of firm i in year t . X_{ijt} denotes a vector of control variables, while λ_i and δ_t represent firm and year fixed effects. Standard errors are clustered at the firm level to account for serial correlation.

4.2. Mediating Mechanism Testing

To evaluate the mechanisms through which DE influences CEP, we specify a two-step mediation analysis that captures three theoretically motivated channels: (1) technological upgrading, (2) governance transparency, and (3) cost efficiency. The estimation strategy proceeds as follows:

$$Mediator_{ijt} = \alpha + \beta_2 DE_{ijt} + \gamma X_{ijt} + \lambda_i + \delta_t + \mu_{ijt} \quad (7)$$

$$CEP_{ijt} = \alpha + \beta_3 DE_{ijt} + \theta Mediator_{ijt} + \gamma X_{ijt} + \lambda_i + \delta_t + v_{ijt} \quad (8)$$

The mediating variables include green innovation (proxied by the ratio of green utility patents), media attention, and managerial effectiveness. These channels align with the theoretical mechanisms of technological enhancement, transparency improvement, and cost reduction.

To account for potential asymmetric effects, interaction terms will be introduced in extended regressions to capture heterogeneity across firm ownership (e.g., state-owned vs. non-state-owned), industry types (pollution-intensive vs. non-pollution-intensive), regional development levels (eastern vs. central/western China), and environmental regulatory intensity.

4.3. Incorporating Asymmetry and Heterogeneity

To capture asymmetric effects across firm characteristics, we extend the baseline model by interacting DE with several moderator variables that reflect institutional, industrial, and geographic heterogeneity: Ownership structure, distinguishing state-owned enterprises (SOEs) from non-SOEs; Pollution intensity, based on industry classification by the Ministry of Ecology and Environment; Regional development level, differentiating eastern, central, and western provinces; Regulatory pressure, proxied by city-level environmental policy stringency. These interaction models are expressed as:

$$CEP_{ijt} = \alpha + \beta_4 DE_{ijt} + \beta_5 (DE_{ijt} \times Z_{ijt}) + \gamma X_{ijt} + \lambda_i + \delta_t + \eta_{ijt} \quad (9)$$

where Z_{ijt} represents the vector of moderator variables. Statistically significant interaction terms β_5 would indicate asymmetric impacts of DE_{ijt} on CEP_{ijt} , consistent with our theoretical predictions in Section 3.

4.4. Variable Definitions and Data Sources

Our analysis utilizes a novel panel data set of Chinese A-share listed firms from 2012 to 2021. The sample selection process was as follows: First, we included all firms listed on

the Shanghai and Shenzhen Stock Exchanges. We then applied the following filters: (1) exclusion of financial firms due to their dissimilar accounting standards; (2) exclusion of firms labeled ST, *ST, or PT, as these represent financially distressed entities undergoing special treatment, which may distort their normal behavior; and (3) removal of firms with missing key variable data. This process yielded an unbalanced panel of 3510 firm-year observations. The definitions, proxies, and data sources for all variables used in this study are summarized in Table 1 below.

Table 1. Variable definitions and data sources.

Variable Type	Variable Name	Symbol	Proxy/Measurement	Data Source
Dependent Variable	Corporate Environmental Performance	CEP	Additive index of 9 environmental practices (e.g., goals, systems, certifications), each scored 0 or 1. Score range: 0–9.	CSMAR ENV Database
Independent Variable	Data Elements	DE	$\ln(\text{Market Value} - \text{Fixed Assets} - \text{Financial Assets} - \text{Intangible Assets})$. Market value = book value of liabilities + market value of equity.	CSMAR Database
Mediating Variable	Labor Structure	Labor_Up	Ratio of employees with a bachelor's degree or above to total employees.	CSMAR, Company Annual Reports
	Management Efficiency	Mng_Eff	Ratio of administrative expenses to operating revenue (inverse measure).	CSMAR Database
	Financing Constraints	Fin_Con	Size-Age index (SA index) or KZ index. Larger values indicate more severe constraints.	CSMAR Database, Authors' calculation
Control Variable	Firm Size	Size	Natural logarithm of total assets.	CSMAR Database
	Leverage	Lev	Total debt divided by total assets.	CSMAR Database
	Profitability	ROE	Net income divided by shareholders' equity.	CSMAR Database
	Growth Opportunity	TobinQ	Market value of assets divided by book value of assets.	CSMAR Database
	Asset Tangibility	FIXED	Net fixed assets divided by total assets.	CSMAR Database
	Board Independence	Indep	Percentage of independent directors on the board.	CSMAR Database
	CEO Duality	Dual	A dummy variable that equals 1 if the CEO is also the board chair, and 0 otherwise.	CSMAR Database
	Ownership Concentration	Mshare	Percentage of shares held by the largest shareholder.	CSMAR Database
	Executive Ownership	TOP	Percentage of shares held by top executives.	CSMAR Database
	Sales Growth	Growth	Year-on-year growth rate of operating revenue.	CSMAR Database

Table 2 shows substantial variation in CEP (mean = 2.195, SD = 2.313) and DE (mean = 23.32, SD = 1.301), indicating meaningful firm-level heterogeneity and suitability for regression analysis.

4.5. Spatial Distribution Characteristics of Data Elements and Environmental Performance

4.5.1. Development of Data Elements

Using ArcGIS and natural breaks classification, the development of DE across regions for 2012, 2015, 2018, and 2021 is visualized in Figure 1. Results reveal an upward trajectory, with substantial growth in eastern China, driven by digital infrastructure and policy incentives. Central and western regions lag behind, reflecting uneven economic develop-

ment and digital capacity. This spatial asymmetry suggests the need to address regional digital divides.

Table 2. Descriptive statistics of variables.

	(1)	(2)	(3)	(4)	(5)
Variable	N.obs	Mean	SD	Min	Max
CEP	3510	2.195	2.313	0	9
DE	3510	23.32	1.301	20.44	28.20
Size	3510	23.13	1.488	19.64	28.50
Lev	3510	0.468	0.207	0.0111	0.978
TobinQ	3510	1.799	1.451	0.706	26.82
FIXED	3510	0.171	0.139	0.000284	0.763
Indep	3510	38.03	6.055	25	80
Dual	3510	0.207	0.406	0	1
Mshare	3510	6.735	13.96	0	70.17
TOP	3510	35.09	15.88	3.003	85.53
ROE	3510	0.0805	0.107	−1.731	0.806
Growth	3510	0.260	4.519	−0.873	251.2

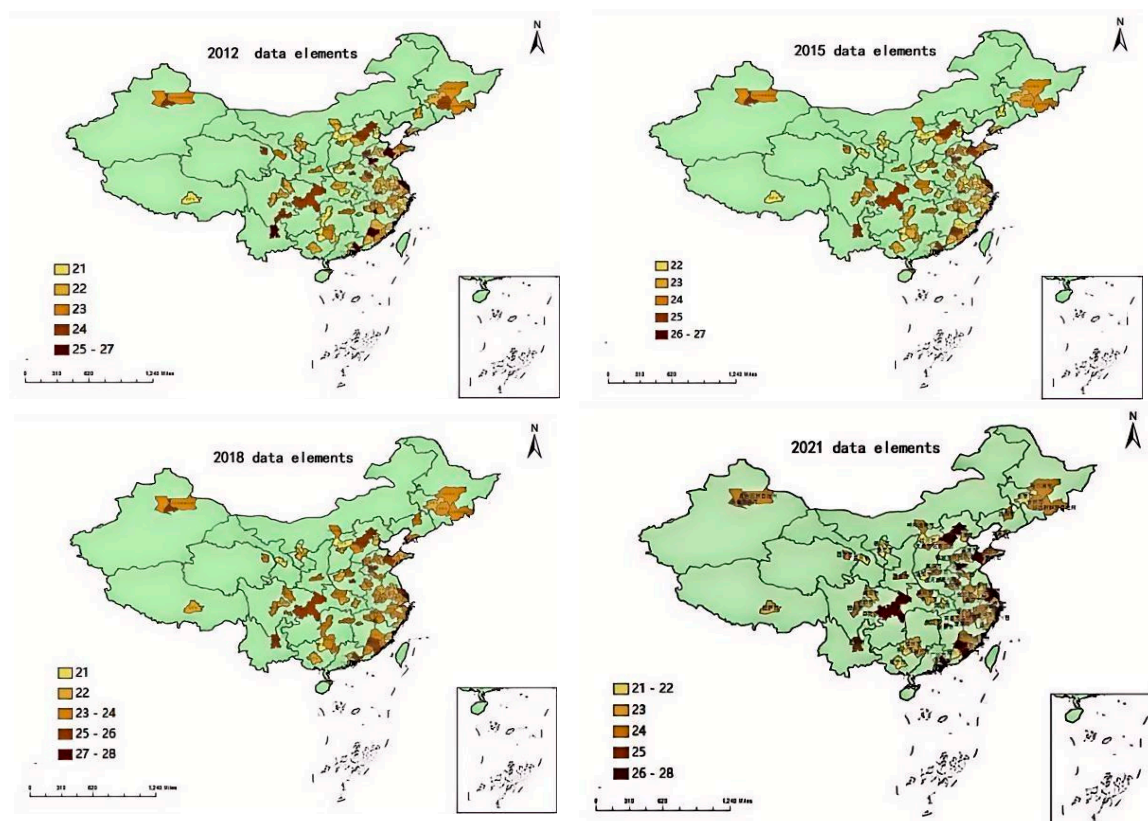


Figure 1. Trend of the development of enterprise data elements in 2012, 2015, 2018, and 2021.

4.5.2. Development of Environmental Performance

Similarly, CEP maps for 2012–2021 show increasing environmental performance, particularly in eastern regions in Figure 2. The observed spatial heterogeneity underscores

how regional regulatory stringency, industrial structure, and firm concentration shape asymmetric environmental outcomes. These patterns motivate further exploration of region-specific policy interactions in the empirical analysis.

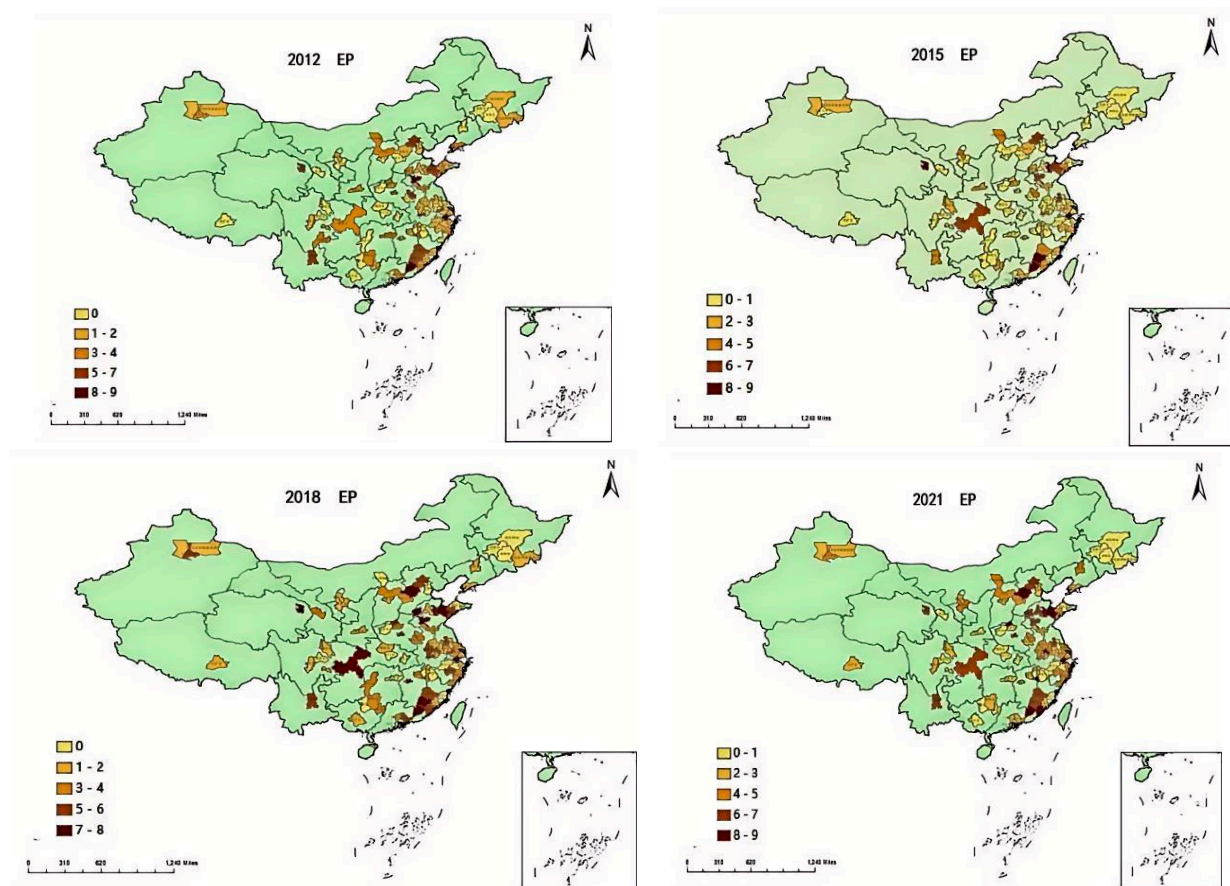


Figure 2. Trend of the Development of Enterprise Environmental Performance in 2012, 2015, 2018, and 2021.

The spatial diagnostics in this section reinforce the importance of asymmetric considerations—across regions, industries, and ownership types—in both the empirical modeling and policy implications of DE’s environmental effects.

5. Empirical Results Analysis

5.1. Regression of the Benchmark Model

To ensure the appropriate specification of the panel model, we conducted a Hausman test to compare random effects (RE) and fixed effects (FE) estimators. The test results demonstrated in Table 3 (Hausman statistic = 70.53, p -value = 9.68×10^{-11}) strongly reject the null hypothesis that the RE estimator is consistent. This provides robust statistical justification for adopting the fixed effects model as our baseline specification. Accordingly, all subsequent analyses are based on the FE framework.

Table 4 presents the results of the baseline fixed-effects regressions examining the relationship between data element utilization (DE) and corporate environmental performance (CEP). Across all model specifications, the coefficient on DE remains significantly positive at the 1% level, providing strong empirical support for Hypothesis 1.

Column (1) reports the naïve regression without fixed effects or control variables, while Column (2) includes both industry and year fixed effects. Columns (3) and (4) progressively introduce firm-level controls and fixed effects. Notably, the coefficient magnitude remains

stable and significant, confirming the robustness of the DE–CEP nexus. Economically, a one-unit increase in DE corresponds to a 0.419-point increase in CEP in the fully specified model (Column 4).

Table 3. Hausman test.

Variable	FE	RE
Data_Asset	−0.178 *	−0.236 **
ROE	−0.400 *	−0.397 *
Size	1.006 ***	1.067 ***
TobinQ	0.079 **	0.084 **
Fixed	0.797 **	−0.568
Growth	−0.012 **	−0.013 ***
Indep	0.000	0.002
Dual	−0.022	−0.025
Mshare	0.000	0.001
TOP	−0.003	0.000
Lev	−0.861 ***	−0.295
Constant	−16.658 ***	−16.951 ***
Observations	3510	3510
R-squared	0.110	
Number of ID	351	
Hausamn	70.53	
P-VALUE	9.68×10^{-11}	

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

Table 4. Regression Results of the Benchmark Model.

	(1)	(2)	(3)	(4)
	CEP	CEP	CEP	CEP
DE	0.679 ***	0.664 ***	0.371 ***	0.419 ***
	(24.48)	(23.57)	(3.45)	(3.75)
ROE2			−0.272	−0.050
			(−0.81)	(−0.16)
Size			0.502 ***	0.312 ***
			(4.90)	(2.91)
TobinQ			−0.002	0.022
			(−0.05)	(0.59)
FIXED			4.134 ***	2.559 ***
			(14.96)	(7.62)
Growth2			−0.014 *	−0.009
			(−1.80)	(−1.42)
Indep			0.006	0.013 **
			(1.00)	(2.32)

Table 4. *Cont.*

	(1)	(2)	(3)	(4)
	CEP	CEP	CEP	CEP
Dual			−0.061 (−0.70)	−0.242 *** (−3.03)
Mshare			−0.002 (−0.70)	−0.006 ** (−2.43)
TOP1			−0.005 ** (−2.33)	0.003 (1.39)
Lev			−1.881 *** (−8.74)	−1.269 *** (−5.69)
_cons	−13.644 *** (−21.05)	−13.445 *** (−20.71)	−17.877 *** (−24.74)	−15.236 *** (−20.96)
industry effect	No	Yes	No	Yes
Time effect	No	Yes	No	Yes
N	3510.000	3510.000	3510.000	3510.000
r2_a	0.146	0.400	0.249	0.424

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

These findings underscore the environmental benefits of data element accumulation and suggest that digital capital enhances firms' capacity to improve environmental practices.

5.2. Robustness Test

5.2.1. Alternative Variable Specifications

To verify robustness, we re-estimate the models using alternative measures for both DE (DE2) and CEP (CEP2). Table 5 shows that the positive relationship persists across all specifications, reaffirming the reliability of the benchmark results.

Table 5. Replacement of Main Variables.

	(1)	(2)	(3)	(4)
	CEP2	CEP2	CEP2	CEP2
DE2	0.700 *** (19.86)	0.694 *** (19.91)	0.360 *** (3.03)	0.530 *** (4.23)
ROE2			0.488 (1.18)	0.447 (1.17)
Size			0.561 *** (4.93)	0.234 * (1.92)
TobinQ			−0.009 (−0.19)	−0.028 (−0.64)
FIXED			6.537 *** (19.72)	4.019 *** (9.79)

Table 5. *Cont.*

	(1)	(2)	(3)	(4)
	CEP2	CEP2	CEP2	CEP2
Growth2			−0.016 *	−0.011
			(−1.78)	(−1.34)
Indep			−0.005	0.002
			(−0.67)	(0.36)
Dual			0.133	−0.113
			(1.26)	(−1.15)
Mshare			0.002	−0.006 *
			(0.52)	(−1.73)
TOP1			−0.001	0.001
			(−0.41)	(0.53)
Lev			−1.853 ***	−0.984 ***
			(−6.99)	(−3.57)
_cons	−14.076 ***	−13.599 ***	−19.186 ***	−15.384 ***
	(−17.05)	(−16.84)	(−21.69)	(−17.22)
industry effect	No	Yes	No	Yes
Time effect	No	Yes	No	Yes
N	3510.000	3510.000	3510.000	3510.000
r2_a	0.101	0.390	0.242	0.414

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

5.2.2. Alternative Estimation Strategy

Given that CEP scores are censored at zero, we re-estimate the main specification using a Tobit model (Table 6). The direction and significance of DE remain consistent, confirming that the findings are not sensitive to estimation technique.

Table 6. Replacement of Regression Method.

	(1)	(2)	(3)	(4)
	CEP	CEP	CEP	CEP
DE	0.679 ***	0.371 ***	0.664 ***	0.419 ***
	(24.49)	(3.46)	(23.79)	(3.79)
ROE2			−0.272	−0.05
			(−0.81)	(−0.17)
Size			0.502 ***	0.312 ***
			(4.91)	(2.95)
TobinQ			−0.002	0.022
			(−0.05)	(0.6)
FIXED			4.134 ***	2.559 ***
			(14.99)	(7.70)

Table 6. Cont.

	(1)	(2)	(3)	(4)
	CEP	CEP	CEP	CEP
Growth2			−0.014 *	−0.009
			(−1.81)	(−1.43)
Indep			0.006	0.013 **
			(1.01)	(2.34)
Dual			−0.061	−0.242 ***
			(−0.71)	(−3.07)
Mshare			−0.002	−0.006 **
			(−0.70)	(−2.46)
TOP1			−0.005 **	0.003
			(−2.33)	(1.40)
Lev			−1.881 ***	−1.269 ***
			(−8.76)	(−5.76)
_cons	−13.644 ***	−17.877 ***	−14.516 ***	−16.376 ***
	(−21.06)	(−24.78)	(−21.60)	(−21.70)
var(e.EP)	4.569 ***	4.007 ***	3.148 ***	3.014 ***
	(41.89)	(41.89)	(41.89)	(41.89)
industry effect	No	No	Yes	Yes
Year effect	No	No	Yes	Yes

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

5.3. Asymmetric Analysis

5.3.1. Regulatory Pressure

To capture asymmetric regulatory environments, we classify firms based on pollution intensity following the 2008 Ministry of Environmental Protection framework. Columns (1) and (2) of Table 7 report results for heavily polluting (HP) and lightly polluting (LP) firms, respectively.

The coefficient on DE is significantly larger in the HP group, indicating that the environmental benefits of data element utilization are amplified under stricter regulatory scrutiny. This supports the view that asymmetric external pressures condition the effectiveness of digital asset deployment in achieving environmental gains.

5.3.2. Ownership Structure

Columns (3) and (4) examine heterogeneity by ownership type. While DE significantly enhances CEP in both state-owned enterprises (SOEs) and non-state-owned enterprises (NSOEs), the effect is significantly stronger for SOEs. The difference is statistically validated by an F-test.

This result points to institutional asymmetries in digital adoption and governance capacity, suggesting that public ownership enhances the translation of data infrastructure into environmental performance.

5.4. Mechanism Analysis

To test the transmission channels, we follow the causal-step mediation framework. Table 6 shows that DE positively influences labor structure (higher share of highly educated workers), reduces administrative expenses, and alleviates financing constraints.

$$M_{i,t} = \beta_0 + \beta_1 DE_{i,t} + \gamma X_{ijt} + \lambda_i + \delta_t + \varepsilon_{ij} \quad (10)$$

Among them, M is the mediating variable. According to the theoretical analysis in the previous text, the following three mediating variables are selected. The first is “labor structure”, which is measured by the ratio of the number of employees with a bachelor’s degree or above to the total number of employees in the enterprise. The second is management expenses. The ratio of management expenses to operating income is used as a proxy variable for operating management efficiency (the smaller the value, the higher the operating management efficiency of the enterprise), which is used to test the quality and efficiency improvement mechanism of data elements. The third is the alleviation of financing constraints. The larger the value, the more difficult the enterprise’s financing constraints are.

Table 7. Heterogeneity Analysis.

	(1)	(2)	(3)	(4)
	HP	LP	SOE	NSOE
	CEP	CEP	CEP	CEP
DE	1.372 *** (3.20)	0.550 *** (4.82)	0.587 *** (3.75)	0.272 * (1.65)
ROE2	0.965 (0.90)	−0.462 (−1.52)	−0.566 (−1.16)	0.621 (1.57)
Size	−0.786 * (−1.87)	0.200 * (1.82)	0.218 (1.44)	0.356 ** (2.23)
TobinQ	−1.365 *** (−4.38)	0.011 (0.32)	0.003 (0.06)	0.027 (0.50)
FIXED	4.084 *** (4.34)	2.142 *** (5.93)	1.728 *** (3.69)	4.760 *** (9.39)
Growth2	−0.059 (−0.44)	−0.008 (−1.34)	0.044 (0.68)	−0.007 (−1.14)
Indep	−0.016 (−0.85)	0.017 *** (3.16)	0.005 (0.70)	0.016 * (1.90)
Dual	−0.486 * (−1.96)	−0.161 ** (−2.02)	0.287 ** (2.18)	−0.583 *** (−5.72)
Mshare	0.023 *** (2.65)	−0.012 *** (−4.50)	−0.050 ** (−2.08)	0 (−0.01)
TOP1	−0.020 ** (−2.42)	0.007 *** (3.15)	0.009 *** (2.64)	−0.006 * (−1.96)
Lev	−0.602 (−0.82)	−1.319 *** (−5.95)	−1.707 *** (−5.69)	−0.373 (−1.10)
_cons	−10.361 *** (−3.65)	−16.978 *** (−22.54)	−17.697 *** (−17.30)	−14.621 *** (−11.38)
industry effect	Yes	Yes	Yes	Yes
Time effect	Yes	Yes	Yes	Yes
N	633.000	2877.000	1845.000	1586.000
r2_a	0.330	0.376	0.477	0.449
F	10.729	28.994	28.547	21.172

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

The results of the mechanism test are shown in Table 8. The regression result of data elements on the “management expense ratio” is significantly negative, indicating that

the increase in data assets reduces the management cost of the enterprise. Secondly, the regression result of data assets on the “labor structure” is significantly positive, indicating that the increase in data elements has improved the labor structure of the enterprise and promoted the reserve of high-quality talents in the enterprise. The increase in enterprise data elements can improve the level of enterprise human capital through the mechanism of labor structure improvement, and improve the management efficiency of the enterprise through the mechanism of improving quality and efficiency in management, thereby promoting the high-quality development of the enterprise and further promoting the improvement of enterprise environmental performance. The regression result of financing constraints is positive, indicating that the increase in data elements has alleviated the financing constraint ability and thus improved the enterprise’s mitigation performance. Therefore, Hypotheses 2, 3, and 4 proposed in this paper have all been verified.

Table 8. Mechanism test.

	ma	ed	SA
DE	−0.027 *** (−6.54)	0.031 ** (3.09)	0.144 *** (10.85)
_cons	0.210 *** (7.51)	−0.238 *** (−3.51)	−7.212 *** (−79.50)
industry effect	Yes	Yes	Yes
Time effect	Yes	Yes	Yes
N	3510.000	3510.000	3509.000
r2_a	0.408	0.438	0.584
F	33.229	37.465	66.692

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

6. Discussion

This study set out to investigate the asymmetric impact of data elements (DE) on corporate environmental performance (CEP) within the context of China’s rapid digital and green transition. Drawing on a comprehensive panel of Chinese A-share listed firms from 2012 to 2021, this study offers robust empirical evidence that greater utilization of data elements (DE)—as proxied by data asset intensity—enhances CEP.

6.1. Interpretation of Hypothesis Testing

Our empirical analysis provides strong support for three of our four proposed hypotheses, while one hypothesis was only partially supported. Table 9 summarizes the outcomes:

Table 9. Hypothesis summary.

Hypothesis	Statement	Supported or Not	Interpretation of Findings
H1	Data element utilization positively influences CEP.	Yes	The core positive relationship is robust across multiple model specifications, variable definitions, and estimation techniques. This confirms DE as a significant driver of environmental performance.
H2	DE enhances CEP by improving workforce structure and quality.	Yes	Mechanism tests show DE significantly increases the proportion of highly educated employees. This “labor upgrading effect” provides a human capital channel through which digitalization fosters greener practices.
H3	DE enhances CEP by improving managerial efficiency and governance.	Yes	DE significantly reduces the management expense ratio, indicating more efficient operations and internal controls. This allows for better resource allocation towards environmental goals.
H4	DE enhances CEP by alleviating financing constraints.	Yes	The analysis confirms that DE helps ease financing constraints, providing firms with the necessary capital to invest in costly environmental innovations and green technologies.

6.2. Discussion of Key Findings and Comparison with Literature

1. The Core Positive Effect (H1): Our finding that DE enhances CEP aligns with the nascent literature on digitalization and sustainability [26,58]. However, we move beyond merely establishing this link. By constructing a novel, text-based measure of DE.

2. The Ownership Asymmetry (A Key Heterogeneity Finding): The significantly stronger effect of DE on CEP for SOEs compared to non-SOEs is a critical finding. This can be interpreted through the lens of institutional theory. SOEs in China operate under greater political and regulatory scrutiny and are often first in line to implement national strategic priorities like “Beautiful China” [26]. They possess superior access to resources (capital, data infrastructure, policy support) and face higher expectations for ESG performance. Therefore, their digital investments are more effectively channeled toward environmental objectives. This finding nuances the work of scholars like [22], who focused on digital orientation broadly, by highlighting that the efficacy of digital assets is contingent on ownership structure and institutional pressure.

3. The Pollution Intensity Asymmetry: The finding that heavily polluting firms benefit more from DE offers strong support for the “Porter Hypothesis” in the digital age. Firms in these sectors face the greatest regulatory pressure and public scrutiny, and thus have the highest marginal cost of pollution. Consequently, they have a stronger incentive to leverage data-driven insights for pollution abatement, energy efficiency, and process optimization to avoid penalties and reputational damage. This result complements studies on market-based environmental regulations [1] by showing that digital assets act as a critical internal tool for firms to respond to such external pressures.

6.3. Original Contribution to the Literature

This study makes several distinct contributions:

Theoretical: It provides a unified theoretical framework and robust empirical evidence for the asymmetric impact of DE, moving beyond homogeneous effects to acknowledge the critical roles of ownership, industry, and region.

Methodological: It introduces a replicable, text-mining-based measure of firm-level DE intensity, addressing a significant measurement challenge in the field.

Empirical: It unveils and tests three specific mediating mechanisms (labor, management, finance) that transmit the effect of DE to CEP, moving from the “if” to the “how.”

Contextual: It offers timely insights from China, the world’s largest emerging economy, which is simultaneously a major polluter and a global leader in digitalization, thus providing a unique and policy-relevant case study.

6.4. Limitations and Future Research

This study is not without limitations. First, our sample consists of A-share listed firms, which are typically larger and more established than SMEs; future research could explore these dynamics in smaller, unlisted firms. Second, while we control for endogeneity through fixed effects and robustness checks, the possibility of reverse causality (e.g., firms with better CEP investing more in DE) cannot be fully ruled out. Future studies could employ quasi-experimental designs like a difference-in-differences approach around a policy shock to further establish causality. Finally, cross-country comparative studies could help determine the generalizability of these findings beyond the Chinese institutional context.

In conclusion, this research affirms that data elements are a powerful lever for enhancing corporate environmental performance, but their impact is not one-size-fits-all. Policymakers and firm managers must adopt a nuanced, context-aware approach to harness the full potential of digitalization for a sustainable future.

Author Contributions: Conceptualization, H.L., C.W. and J.L.; Methodology, C.W.; Validation, H.L. and C.W.; Data curation, C.W.; Writing—original draft, J.L.; Writing—review & editing, Y.Z.; Supervision, H.L. All authors have read and agreed to the published version of the manuscript.

Funding: The funding was provided by Yunnan University (Grand number 20YNUGSP003), Science Research Foundation of Yunnan Education Bureau (Grand number 2020J0038), National Social Science Fund of China (Grand number 23BJY207), Scientific Research and Innovation Project of Postgraduate Students in the Academic Degree of YunNan University (Grand number KC252513553), The Project of Yunnan Provincial Department of Education Science Research Fund (Grand number 2026Y0064).

Data Availability Statement: Restrictions apply to the availability of these data. Data were obtained from China Stock Market & Accounting Research (CSMAR) Database and are available <https://data.csmar.com> with the permission of CSMAR Database.

Conflicts of Interest: The authors declare that they have no conflict of interest.

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