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The Spatial Spillover Effects of Management Informatization in the Context of Big Data and Digital Networks: The Mediating Role of Digital Factor Flows

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Abstract. The advancement of big data networks is reshaping how management information systems, data resources, and digital governance practices diffuse across firms and regions. From an information systems perspective, this study investigates whether generalized management informatization, measured by firms' digital transformation disclosures, generates cross-regional spillover effects on corporate ESG performance through digital factor flows. Using Chinese A-share listed companies from 2012 to 2022, this paper applies spatial Durbin models, spatial effect decomposition, and spatial mediation analysis to examine the information-diffusion mechanism embedded in big data networks. It also investigates the mediating mechanism of digital factor mobility. The results show that management informatization has a statistically significant positive spatial spillover effect on ESG performance. The effect is not merely a firm-level performance outcome, but reflects a cross-regional information transmission process in which digital management experience, ESG-related data, and governance practices diffuse through big data networks and regional data-factor markets. Digital factor mobility plays a partial mediating role between management informatization and ESG performance, while the development level of big data networks significantly enhances both the local impact and spatial spillover intensity of digital transformation. Heterogeneity analysis indicates that the promoting effects are more pronounced in regions with higher digital economy development levels, non-state-owned enterprises, large enterprises, and highly polluting industries. This study uncovers the intrinsic mechanisms by which management informatization drives regional ESG synergistic improvement in the context of big data networks, providing theoretical foundations and empirical references for optimizing digital strategies and building cross-regional ESG collaborative governance systems.

Keywords: Big data networks; Management informatization; Digital factor flows; Spatial spillover; Information governance; ESG performance

1. Introduction

Driven by the dual objectives of the “dual carbon” goals and the Digital China strategy, the relationship between corporate management informatization and sustainable development has become an important issue in information systems and digital governance research. In the big data network environment, management informatization is not limited to the internal deployment of ERP, MIS, or digital decision-support systems; it increasingly functions as an information infrastructure through which data resources, management routines, and ESG governance practices can be transmitted across organizational and regional boundaries. The enhancement of enterprise informatization management is no longer confined to internal efficiency improvements but extends to broader radiative impacts on environmental, social, and governance (ESG) performance through cross-regional data flow and knowledge spillover. The formation of this spatial radiative effect hinges on the fundamental reshaping of information transmission costs and knowledge diffusion efficiency by big data networks. The organizational experience and digital capabilities accumulated through management informatization are continuously diffusing to geographically adjacent regions and clusters of enterprises via data flow networks (Lu et al.,2025). With the penetration of next-generation digital technologies, the traditionally narrow concept of "management informatization" (e.g., ERP and MIS system applications) has gradually evolved into the "digital transformation" paradigm encompassing underlying technological applications and business process reengineering (Wu & Xu, 2023). To avoid conceptual ambiguity and align with the macro-level context of current big data networks, this study adopts a broad definition: "management informatization" is defined as a dynamic process in which enterprises systematically upgrade management processes, organizational structures, and decision-making models through the application of digital technologies such as big data, artificial intelligence, and cloud computing. This concept aligns with the core connotation of "enterprise digital transformation" commonly recognized in academic discourse.

However, existing research primarily focuses on the impact mechanisms of digital transformation on a firm's own ESG performance, with insufficient attention to its spatial spillover effects across regions and enterprises. In fact, the application of digital technologies continuously extends the boundaries of management informatization. Local firms' digital practices can indirectly enhance the ESG performance of neighboring enterprises through supply chain linkages, talent mobility, and technological demonstrations. Meanwhile, as a new type of production factor, data elements heavily rely on cross-organizational flow and sharing, where digital factor mobility may play a pivotal mediating role. The development level of big data networks further amplifies the positive externalities of digital transformation by reducing information transmission costs and promoting platform interconnectivity (Lu & Hu,2024).

Based on the above analysis, this paper focuses on the following three levels of issues: first, whether corporate digital transformation has a significant spatial spillover effect on ESG performance; second, whether the flow of digital factors serves as an intermediary conduit between digital transformation and ESG performance; and third, how the development level of big data networks regulates the intensity of this spatial spillover effect. Addressing these questions holds important theoretical and practical significance for understanding the spatial diffusion patterns of management informatization in the era of big data networks and optimizing regional ESG collaborative governance.

The potential contributions of this paper are threefold. First, from an information systems perspective, this study explains management informatization as a cross-regional information-diffusion process rather than a purely internal digital investment. It clarifies how big data networks reshape the spatial transmission of digital management practices and ESG-related governance information. Second, this paper identifies digital factor flows as a key information channel linking firm-level management informatization with regional ESG improvement, thereby extending the literature on data-factor markets and inter-organizational information sharing. Third, by applying spatial Durbin models and spatial mediation analysis, this study provides empirical evidence on how digital network infrastructure strengthens the externalities of management information systems, offering implications for regional information governance and digitally enabled service ecosystems (Wang & Tong,2026).

Unlike studies that treat digital transformation only as a firm-level strategic investment, this paper focuses on the information-diffusion function of management informatization. Specifically, big data networks reduce information transmission costs, improve the interoperability of inter-firm data interfaces, and enable ESG-related knowledge to be transferred through regional digital platforms, supply-chain data collaboration, and data-factor markets. Therefore, the theoretical focus of this study is not whether digital transformation improves corporate financial value, but how management information systems and digital network infrastructure generate cross-regional information externalities. This positioning links the study to the information science and service-system concerns of JLISS, especially the role of digital networks in supporting inter-organizational coordination and regional collaborative governance.

2. Theoretical Analysis and Research Hypotheses

2.1. The spatial spillover effect of digital transformation on ESG performance

This study analyzes Management Informationization within the broad framework of the big data era. Unlike the narrow informationization focused on building internal information systems in the early days, the management informationization in this research emphasizes the use of digital technologies such as big data, artificial intelligence, and cloud computing by enterprises to systematically reconstruct and upgrade internal management processes, information systems, and decision-making models. This definition is highly integrated with the core concept of 'Digital Transformation' widely discussed in current literature. Therefore, in the empirical measurement and mechanism analysis in the following text, this article will follow the common practice of existing literature and use 'digital transformation' as the operational expression of 'generalized management informatization' to ensure the consistency between the measurement indicators and the research context.

The impact of management informatization on ESG performance can be understood from two levels. From the perspective of local effects, enterprises can significantly improve the accuracy of environmental data monitoring, transparency of social responsibility, and scientific governance decisions by introducing digital technologies such as big data, artificial intelligence, and cloud computing to build management information platforms. Digital means enable enterprises to collect and analyze environmental data such as energy consumption and pollution emissions in real time, reducing the probability of greenwashing behavior; At the same time, digital platforms enhance stakeholders' ability to monitor corporate social performance and promote the optimization of governance structures (Wang et al.,2026).

From the perspective of spatial spillover, the diffusion of management informatization has significant geographical proximity dependence. Geographic proximity plays an irreplaceable role in knowledge spillovers, industry associations, and institutional convergence. The core carrier for the digital transformation practices of local enterprises to be transmitted to neighboring regions is the cross regional flow of digital elements - data, as a new type of production factor, its non-competitiveness and replicability enable efficient sharing of digital management experience, environmental monitoring methods, and governance optimization models among different enterprises in the form of data flow. Specifically, the flow of digital elements spreads the digital transformation dividends of local enterprises to neighboring regions through supply chain data collaboration, knowledge transfer accompanied by digital talents, and interconnectivity of digital platforms between enterprises. The development of big data networks further strengthens the efficiency of the aforementioned overflow channels, enabling the positive externalities of management informatization to cross enterprise boundaries and generate regional radiation (Zhang et al.,2025). Based on this, a hypothesis is proposed:

H1: There is a significant spatial spillover effect of management informatization on ESG performance, and the digital transformation of neighboring enterprises has a positive impact on the ESG performance of local enterprises.

2.2. The intermediary role of digital element flow

The core characteristics that distinguish data elements from traditional production factors are their non competitiveness and replicability, which means that the value of data is released in the flow and tends to decline in stillness. The flow of digital elements refers to the degree of circulation and sharing of data between different organizations and regions, reflecting the activity and smoothness of data resource allocation in a region. A favorable environment for the flow of digital elements can reduce information search costs, alleviate financing constraints, optimize industrial structure, and ultimately enhance corporate ESG performance (Jiang,2025).

Digital transformation has a direct promoting effect on the flow of digital elements. The improvement of management informatization level has increased the standardization of internal data in enterprises, enhanced the openness and interoperability of data interfaces, and created technical conditions for the flow of data to the outside world. At the same time, digital transformation has driven enterprises to participate in market activities such as data trading platforms and open sharing of data, increasing their participation and activity in the data element network. The enhanced flow of digital elements further amplifies the positive impact of digital transformation on ESG performance (Zhou & Guo,2024). The efficient flow of data elements enables enterprises to more conveniently access external green technology information, environmental governance experience, and advanced management models, reducing information asymmetry in ESG practices and promoting sustained improvement in corporate environmental and social performance. Based on this, a hypothesis is proposed:

H2a: Management informatization has a significant positive impact on the flow of digital elements.

H2b: The flow of digital elements has a significant positive impact on ESG performance.

H2c: The flow of digital elements plays a mediating role in the impact of management informatization on ESG performance.

2.3. The Moderating Effect of Big Data Networks

Big data networks are the core infrastructure for knowledge diffusion and information transmission in the digital age. The level of development of big data networks determines the speed of information transmission, the breadth of knowledge diffusion, and the smoothness of data flow, which is a key condition for the effective transmission of spatial spillover effects in digital transformation. In regions with developed big data networks, enterprises can obtain external information and knowledge resources at lower costs, and the experience and achievements of digital transformation are more likely to accelerate diffusion within the region (Du et al.,2024).

The strengthening effect of big data networks on spatial spillover effects can be decomposed into two paths. On the one hand, big data networks have improved the efficiency of digital element flow, enabling data to be transmitted between different enterprises with lower latency and higher fidelity, enhancing the indirect impact of digital transformation through digital element flow channels. On the other hand, big data networks directly amplify the scope and depth of knowledge spillovers, and the improvement of digital infrastructure makes the channels for enterprises to obtain digital practices in neighboring areas more diverse, significantly reducing learning costs (Wang et al.,2024a). Therefore, big data networks not only enhance the local effects of digital transformation, but also increase the strength of spatial radiation effects by strengthening spillover channels. Based on this, a hypothesis is proposed:

H3: The development of big data networks positively regulates the spatial spillover effects of management informatization on ESG performance.

3. Research Design

3.1. Sample selection and data sources

Using Chinese A-share listed companies from 2012 to 2022 as the initial research sample, the sample selection follows the following criteria: excluding ST, *ST, and PT listed companies, excluding financial and insurance industry companies, and excluding observations with missing data on major variables. To eliminate the influence of extreme values, winsorize all continuous variables at the upper and lower 1% quantiles. Ultimately, 2678 listed companies were obtained, with a total of 22056 "company year" observations covering 31 provinces, autonomous regions, and municipalities directly under the central government (Zhang & Zhang,2024).

In terms of data sources, the digital transformation data of enterprises mainly comes from the CSMAR China Digital Economy Research Database and the China Listed Company Digital Transformation Research Database. The ESG rating data adopts the Huazheng ESG Rating Database, the digital element flow data comes from the CSMAR China Data Element Research Database and provincial statistical yearbooks, the big data network development level data comes from the CSMAR Digital Economy Research Database, and the financial and governance data comes from the CSMAR Company Research Series Database (Batuparan et al.,2025).

3.2. Variable definition and measurement methods

Dependent variable (ESG): Using Huazheng ESG rating data, assign nine levels (C to AAA) as 1 to 9 points.

Explanatory variable (DIG): Following the method proposed by Wu Fei, the frequency of keywords such as artificial intelligence, big data, cloud computing, etc. was extracted from the annual reports of listed companies, and the natural logarithm was taken after summation (Wu et al.,2021).

Explanation on measurement indicators: Although the frequency of annual report text words is often used to measure 'digital transformation', within the theoretical framework of this study, it is an effective proxy variable for generalized management informatization. The reason is that, firstly, signal transmission theory indicates that the digital related vocabulary disclosed in corporate annual reports (such as' smart management ',' cloud office ',' data center ') directly reflects the strategic intention and actual investment of management in embedding digital technology into management processes (Xie et al., 2024), and is an explicit signal of management informatization process. Secondly, the core of generalized management informatization lies in the use of digital technology to reshape management activities, and annual report keywords cover the entire chain from underlying technology applications to top-level management changes, which can overcome the shortcomings of using single financial indicators such as' ERP expenditures' that cannot capture intangible management changes. Therefore, although this indicator is derived from literature on digital transformation, it fully fits the broad definition of 'management informatization under the background of big data' in this study (Zhu & Liu ,2024).

Mediating variable (DFLOW): Given that data element flows mainly occur at the regional level, this article uses the entropy method to synthesize the provincial-level digital element flow index from three dimensions: digital infrastructure, data transaction activity, and data cross regional flow. Due to the fact that the index is at the provincial level, all enterprises within the province share the same value. To alleviate the problem of underestimation of enterprise level standard errors that may arise from this, this paper conducts cluster robust standard errors at the provincial level in regression analysis. Meanwhile, considering the hierarchical differences in variables, this article will supplement and verify the mediating effect through provincial panel data in subsequent chapters to ensure the reliability of the conclusions (Niu et al.,2024).

Moderating variable (BDN): from the three dimensions of 5G base station density, Internet penetration rate, and per capita computing resources, the factor analysis method is used to build the provincial big data network development index.

Control variables: Select company size (SIZE), asset liability ratio (LEV), return on equity (ROE), revenue growth rate (GROWTH), board size (BOARD), independent director ratio (INDEP), institutional investor shareholding ratio (INST), enterprise age (AGE), and regional per capita GDP (PGDP).

To reduce scale-induced coefficient instability and improve comparability across firm-level and provincial-level models, the continuous variables DIG, DFLOW, BDN, and ESG are standardized before the mediation and moderation analyses. The reported coefficients in the mediation models are therefore standardized coefficients, which allows the magnitude of the digital factor flow channel to be interpreted more consistently across different levels of analysis.

3.3. Construction of spatial weight matrix

To characterize the spatial spillover effects of digital transformation on ESG performance, three spatial weight matrices are constructed. The geographic distance weight matrix (W1) is based on the latitude and longitude coordinates of the registered location of the listed company, taking the square of the reciprocal of the geographic distance between cities. The calculation formula is (1):

$$w_{ij}^{(1)} = 1/d_{ij}^2 \tag{1}$$

Where d_{ij} is the spherical distance between cities i and j. The economic distance weight matrix (W_2) is based on the reciprocal of the absolute difference in per capita GDP among provinces, and the calculation formula is (2):

$$w_{ij}^{(2)} = 1/\left|PGDP_i - PGDP_j\right| \tag{2}$$

The economic geographic nested weight matrix (W_3) takes the weighted average of the two matrices mentioned above, and the calculation formula is (3), taking into account the dual spatial dependency structure of geographic proximity and economic similarity.

$$W_3 = 0.5W_1 + 0.5W_2 \tag{3}$$

The spatial panel regression model of this study uses enterprise level data, and the spatial weight matrices (W_1、W_2、W_3) are all calculated based on the geographical coordinates of the city where the enterprise is registered to calculate the distance between cities. The global Moran index test in Table 1 is a descriptive analysis, using annual mean data from each province, and its geographic distance weight matrix is constructed based on the spherical distance between each provincial capital city. The spatial weight matrices at two different scales serve different analytical purposes and are not contradictory.

3.4. Econometric model setting

(1) Global Moran Index

To test whether there is a significant spatial autocorrelation between digital transformation and ESG performance, the global Moran index is first calculated using the formula (4):

$$Moran'sI = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{(\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij})\sum_{i=1}^{n}\sum_{j=1}^{n}(x_i - \bar{x})^2} \tag{4}$$

Among them, n is the number of provinces, x_i is the regional average of ESG performance or digital transformation level of all enterprises in the i-th province, w_{ij} is the spatial weight matrix element, and x is the regional average of each indicator. The range of Moran's index values is [-1,1], with positive values indicating positive spatial correlation and negative values indicating negative spatial correlation.

(2) Spatial Panel Durbin Model (SDM)

Based on the LM test and Hausman test, the spatial Durbin model is chosen to examine the spatial effects of digital transformation on ESG performance. The SDM contains both the spatial lag term of the dependent variable and the spatial lag terms of the explanatory variables, which allows the model to capture both outcome dependence and covariate spillover effects. It should be distinguished from the spatial error model, which focuses on spatial dependence in the disturbance term. Model setting as (5):

$$\begin{aligned} ESG_{it} &= \alpha + \rho W \cdot ESG_{it} + \beta_1 DIG_{it} + \beta_2 W \cdot DIG_{it} + \\ &\gamma X_{it} + \theta W \cdot X_{it} + \mu_i + \lambda_t + \varepsilon_{2,it} \end{aligned} \tag{5}$$

Among them, ρ is the spatial autoregressive coefficient, which measures the influence of neighboring firms' ESG performance on local firms' ESG performance. W·ESGit is the spatial lag term of ESG performance, capturing outcome dependence among spatially connected firms. W·DIGit is the spatial lag term of digital transformation, and its coefficient measures whether the management informatization of neighboring firms has a spillover effect on the ESG performance of local firms, and its coefficient β_2 directly measures the spatial spillover effect of digital transformation; μ_i is an individual fixed effect used to control for heterogeneity characteristics at the firm level that do not change over time; λ_t is a time fixed effect used to control annual macroeconomic shocks; ε_{it} is a random perturbation term (Zhang & Avais,2026).

(3) Spatial effect decomposition method

Based on the estimation results of the SDM model, decompose the total effect of digital transformation on ESG performance into direct and indirect effects. The direct effect reflects the marginal impact of local enterprises' digital transformation on their ESG performance, which includes both the direct contribution of local digital transformation and the spatial feedback effect (i.e. the indirect path through which local changes affect neighboring regions and then return to the local area). The indirect effect is the spatial spillover effect, which reflects the marginal impact of digital transformation of neighboring enterprises on the ESG performance of local enterprises (Wang & Cong,2024). The total effect is the sum of direct and indirect effects.

(4) Spatial mediation effect model

To examine the mediating role of digital element flow in the impact of digital transformation on ESG performance, and to capture both local and spatial spillover pathways, this study adopts a spatial mediation effect model. Construct the following equation system:

The first step is to examine the spatial effects of digital transformation on the flow of digital elements, as shown in formula (6):

$$\begin{aligned} DFLOW_{it} &= \alpha_0 + \alpha_1 DIG_{it} + \alpha_2 W \cdot DIG_{it} + \alpha_3 W \cdot DFLOW_{it} + \\ &\sum \gamma_k Control_{it} + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned} \tag{6}$$

The second step is to examine the spatial effects of digital factor flows on ESG performance (controlling for digital transformation), as shown in formula (7):

$$ESG_{it} = \beta_0 + \beta_1 DIG_{it} + \beta_2 DFLOW_{it} + \beta_3 W \cdot DIG_{it} + \beta_4 W \cdot DFLOW_{it} + \beta_5 W \cdot ESG_{it} + \sum \delta_k Control_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{7}$$

Among them, W is the spatial weight matrix (using the geographic distance weight matrix W1). The mediating effect can be decomposed into:

Local intermediary effect: α1×β2, reflecting that local digital transformation enhances local ESG performance by promoting the flow of local digital elements.

Spatial mediation effect: The sum of paths such as α2×β2 (local digital transformation affects the flow of digital elements in neighboring regions, which then feedback affects local ESG) and α1×β4 (local digital transformation affects the flow of local digital elements, which then spreads to neighboring regions' ESG performance) (Zhao et al.,2023).

The total mediation effect is the sum of local mediation effect and spatial mediation effect. The significance was tested using Bootstrap method (1000 tests) to determine the confidence interval of indirect effects.

(5) Moderating effect model (spatial interaction term)

To examine the moderating effect of the development level of big data networks on the spatial spillover effect of digital transformation, the interaction term and spatial lag term between digital transformation and big data networks are introduced into the SDM model, as shown in formula (8):

$$ESG_{it} = \alpha + \rho W \cdot ESG_{it} + \beta_1 DIG_{it} + \beta_2 BDN_{it} + \beta_3 (DIG_{it} \times BDN_{it}) + \beta_4 W \cdot DIG_{it} + \beta_5 W \cdot (DIG_{it} \times BDN_{it}) + \gamma X_{it} + \theta W \cdot X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{8}$$

Among them, $DIG_{it} \times BDN_{it}$ is the interaction term between digital transformation and big data networks, and its coefficient β_3 measures the moderating effect of big data networks on the local effects of digital transformation; $W \cdot (DIG_{it} \times BDN_{it})$ is the spatial lag term of the interaction term, and its coefficient β_5 reflects the moderating effect of big data networks on the spatial spillover effect of digital transformation (Huang et al.,2024).

(6) Instrumental variable method

To alleviate endogeneity, the average digital transformation of other companies in the same industry is selected as IV. This variable satisfies the following conditions: ① correlation: similar industry technology trends, highly correlated with enterprise digitalization (first stage F-value 58.46); ② Exclusivity: When calculating, the company is excluded, and the model controls for individual, time fixed effects, and spatial spillover terms (W × DIG), excluding channels that directly affect ESG through industry competition or regulatory attention. It is estimated to use IV-2SLS embedded SDM framework: first use IV to predict DIG, and then substitute the fitted value into the spatial Durbin model regression.

4. Empirical Result Analysis

4.1. Spatial autocorrelation test

To verify whether the spatial correlation between digital transformation and ESG performance is statistically significant, as a preliminary descriptive test, the global Moran's I was first calculated at the provincial level based on the annual average values of DIG and ESG. This test reveals whether digital transformation and ESG performance display macro-level spatial clustering across provinces.

Table 1: Results of Spatial Autocorrelation Test (Based on W_1 Geographic Distance Weight Matrix)

Year	Moran's I for ESG ratings	Z value	Moran's I from DIG	Z value
2012	0.246***	7.321	0.298***	8.412
2013	0.258***	7.624	0.304***	8.568
2014	0.264***	7.786	0.312***	8.742
2015	0.272***	7.982	0.318***	8.886
2016	0.281***	8.214	0.326***	9.068
2017	0.288***	8.396	0.334***	9.224
2018	0.294***	8.542	0.342***	9.386
2019	0.306***	8.788	0.356***	9.612
2020	0.318***	8.986	0.368***	9.782
2021	0.324***	9.102	0.374***	9.886
2022	0.332***	9.268	0.382***	9.998

Note: **** $p<0.01$; Calculate based on the geographic distance weight matrix (W_1); The ESG rating and digital transformation level are calculated based on the annual average of each province, and the global Moran index is estimated on an annual basis. The actual cross-sectional sample size involved in the calculation each year is 31 provinces (autonomous regions, municipalities directly under the central government); The entire sample period covers a total of 31 provinces x 11 years=341 province year observations. Z-value corresponds to significance test.*

The test results show that from 2012 to 2022, both ESG scores and the global Moran's index for digital transformation were positive and passed the significance test at the 1% level. The Moran Index for ESG ratings has steadily increased from 0.246 in 2012 to 0.332 in 2022, while the Moran Index for digital transformation has risen from 0.298 to 0.382, with an increase of approximately 28%. The above results indicate that there is a significant spatial positive correlation between the digital transformation and ESG performance of enterprises in various provinces of China, that is, enterprises in geographically adjacent regions have similar distribution characteristics in the above two dimensions, and this spatial agglomeration degree shows a gradually increasing trend during the sample period. The above results provide necessary prerequisites for subsequent spatial econometric analysis.

4.2. Selection inspection of spatial panel model

Before conducting spatial regression analysis, it is necessary to clarify the optimal spatial econometric model applicable to the data structure of this article. This study conducted spatial effect applicability tests and model structure selection tests in sequence, and the test results are summarized in Table 2.

Table 2:Results of spatial econometric model selection test

LM-lag test	126.42	0.000	There is a spatial lag effect
LM-error test	98.36	0.000	There is a spatial error effect
Robust LM-lag test	34.28	0.000	There is a spatial lag effect
Robust LM-error test	16.52	0.001	There is a spatial error effect
Hausman test	186.54	0.000	Choose a fixed effects model
LR test of SDM vs SAR	28.46	0.002	SDM is superior to SAR
LR test of SDM vs SEM	36.12	0.000	SDM is superior to SEM

Note: *The test is based on the geographic distance weight matrix (W_1). SAR is a spatial autoregressive model, while SEM is a spatial error model.*

Both LM test and Robust LM test significantly reject the null hypothesis of "no spatial effect", indicating that both spatial lag term and spatial error term have statistical significance, and spatial dependence exists in both the dependent variable and error term. The Hausman test statistic is 186.54 ($p<0.01$), rejecting the random effects model at the 1% level, and therefore choosing the fixed effects model for estimation. The LR test compared the goodness of fit between SDM and SAR, SDM and SEM, and both comparisons supported SDM being superior to the simplified model. Based on the above test results, the spatial Durbin model that includes both spatial lag and spatial error structural features is selected as the benchmark regression model for this paper (Cheng et al.,2023).

4.3. Regression results of spatial panel Durbin model

Based on three spatial weight matrices, a spatial panel Durbin model was used for benchmark regression, and the regression results are summarized in Table 3.

Table 3:Benchmark Regression Results of Spatial Panel Durbin Model

variable	Geographic distance W_1	Economic distance W_2	Nested matrix W_3
DIG	0.342*** (8.62)	0.318*** (7.48)	0.335*** (8.16)
SIZE	0.172*** (6.48)	0.158*** (5.92)	0.166*** (6.24)
LEV	-0.486*** (-4.96)	-0.452*** (-4.58)	-0.472*** (-4.82)
ROE	1.124*** (7.22)	1.056*** (6.68)	1.092*** (7.02)
GROWTH	0.068* (1.68)	0.062 (1.54)	0.064* (1.72)
BOARD	0.214* (1.92)	0.186* (1.68)	0.198* (1.78)
INDEP	0.872** (2.18)	0.802** (2.02)	0.842** (2.12)
INST	0.006*** (6.62)	0.005*** (6.12)	0.005*** (6.38)
AGE	-0.082* (-1.86)	-0.074* (-1.68)	-0.078* (-1.76)
PGDP	0.224*** (4.48)	0.206*** (4.12)	0.216*** (4.32)
W×DIG	0.168*** (3.86)	0.142*** (3.12)	0.156*** (3.48)
ρ（spatial autoregressive coefficient）	0.284*** (6.48)	0.252*** (5.86)	0.268*** (6.12)
$sigma^2$_e	0.846***	0.872***	0.858***
R^2（within）	0.324	0.308	0.316
Log-likelihood	-3286.4	-3312.8	-3298.6
Individual fixed effects	control	control	control
Fixed time effect	control	control	control
sample size	22056	22056	22056

Note: ****, **, * respectively indicate significance at the 1%, 5%, and 10% levels; The Z-value is in parentheses, and sigma2-e is the estimated residual variance of the model. Note: The ESG rating of Huazheng Securities is an ordered variable ranging from 1 to 9. Although linear models have limitations, existing literature suggests that OLS estimation is usually robust when the level is ≥ 5, and the core results of this paper have been supported by multiple robustness tests.*

The regression results in Table 3 present the following key findings. The coefficient DIG for local digital transformation is significantly positive at the 1% level across all three spatial weight matrices, with values ranging from 0.318 to 0.342. This result indicates that for every 1 unit increase in the degree of digital transformation of enterprises, the ESG score of local enterprises will directly increase by about 0.33 units, reflecting the robust local promotion effect of digital transformation on ESG performance. The coefficients of W × DIG are significantly positive in all three spatial weight matrices, with values ranging from 0.142 to 0.168. After considering the nested structure of economy and geography, the spatial spillover effect remains robust, indicating that the digital transformation of neighboring enterprises has a significant positive radiation effect on the ESG performance of local enterprises. The spatial autoregressive coefficient ρ is also significantly positive at the 1% level, indicating that the ESG performance of neighboring companies also has a positive impact on the ESG performance of local companies. ESG practices show a clear convergence feature in spatial distribution.

The regression results of the control variables are basically in line with expectations. The significant positive correlation between company size and return on equity indicates that larger and more profitable enterprises invest more resources in ESG practices. The asset liability ratio is significantly negative, and high debt enterprises face greater financial constraints, with relatively limited resource investment in the ESG field. The coefficients of independent director ratio and institutional investor shareholding ratio are significantly positive, indicating that a good corporate governance structure and external supervision have a positive contribution to improving ESG performance.

The coefficient of revenue growth rate (GROWTH) is only significant at the 10% level in some models, indicating that the direction of the impact of corporate growth on ESG performance is relatively unstable, which may be related to its differentiated effects in different economic cycles or industry environments. The within group goodness of fit (R^2 within) of the model is approximately 0.32, which is within the acceptable range of the panel data model, indicating that the selected variables have a certain explanatory power for ESG performance.

4.4. Spatial effect decomposition

On the basis of the SDM model, spatial effect decomposition is required as the parameter estimation results cannot directly reflect the marginal influence of the independent variable on the dependent variable. The decomposition results distinguish the total effect into direct effect and indirect effect (i.e. spatial spillover effect), as shown in Table 4.

Table 4: Decomposition Results of Spatial Effects (Based on Geographic Distance Weight Matrix W_1)

Effect decomposition	coefficient	standard error	Z value	Proportion (%)
direct effect	0.356***	0.042	8.48	67.30
Indirect effects (spatial spillover effects)	0.173***	0.048	3.60	32.70
total effect	0.529***	0.068	7.78	100.00

Note: **** indicates p<0.01; Based on the geographic distance weight matrix (W_1). The direct effects include local direct contributions and spatial feedback effects (i.e. indirect paths through which local changes affect neighboring regions and then return to the local area).*

The effect decomposition results show that the direct effect of digital transformation on ESG performance is 0.356 (accounting for approximately 67.3% of the total effect), and the indirect effect is 0.173 (accounting for approximately 32.7%). The total effect is 0.529, indicating that for every unit increase in digital transformation level, the average ESG performance of enterprises improves by 0.529 units, of which two-thirds come from direct contributions from local enterprises and one-third come from spatial radiation of digital practices of neighboring enterprises. The above decomposition results verify the importance of spatial spillover effects in the transmission mechanism of ESG performance affected by digital transformation, indicating that the positive externalities of digital transformation cannot be ignored in the spatial dimension.

4.5. Intermediary effect test

Based on the unified spatial mediation model presented in Table 5, the total effect of management informatization (DIG) on ESG performance is decomposed within the same equation system. The results show that the direct effect is 0.215, the spatial spillover effect is 0.108, and the total mediated effect is 0.074. The total effect within this unified model is 0.397, yielding a mediation proportion of 18.6%. The Bootstrap 95% confidence intervals for the total mediated effect [0.038, 0.110] and the mediation proportion [12.4%, 24.8%] do not contain zero, confirming the statistical significance of the partial mediation channel. This unified decomposition avoids the inconsistency of comparing coefficients across different model specifications (e.g., benchmark SDM without mediator vs. mediation SDM with mediator).

Table 5: Unified Spatial Mediation Effect Decomposition at the Firm Level (SDM with DFLOW)

Effect Decomposition within the Unified Spatial Mediation Model	Coefficient	Std. Error	Z-value	Bootstrap 95% CI
Direct effect of DIG (Local impact)	0.215***	(0.038)	5.66	[0.142, 0.288]
Spatial spillover effect of DIG (W×DIG)	0.108***	(0.042)	2.57	[0.026, 0.190]
Local mediated effect (DIG → DFLOW → ESG)	0.048***	(0.012)	4.00	[0.024, 0.072]
Spatial mediated effect (DIG → W×DFLOW → ESG)	0.026**	(0.011)	2.36	[0.004, 0.048]
Total mediated effect (Local + Spatial)	0.074***	(0.018)	4.11	[0.038, 0.110]
Total effect (within this unified model)	0.397***	(0.052)	7.63	[0.295, 0.499]
Mediation proportion	18.6%	—	—	[12.4%, 24.8%]

Note: *All continuous variables are standardized. Within this unified spatial mediation model, the total effect (0.397) equals the sum of the direct effect (0.215), spatial spillover effect (0.108), and total mediated effect (0.074). Bootstrap confidence intervals are based on 1,000 replications. *** $p < 0.01$, ** $p < 0.05$.*

Due to the fact that Digital Factor Flow (DFLOW) is a provincial-level variable, the estimation of the mediating effect at the enterprise level mainly captures the average response of enterprise digital behavior to the provincial-level data environment, as well as the macro impact of the provincial-level data environment on micro enterprise ESG (Bao,2019).

4.6. Moderation effect test

To investigate the moderating effect of the development level of big data networks on the spatial spillover effect of digital transformation, the interaction term and spatial lag term between digital transformation and big data networks are introduced into the SDM model. This section still uses the same three spatial weight matrices as the benchmark regression mentioned earlier (geographic distance W_1, economic distance W_2, and economic geographic nested weight matrix W_3), and the estimated results are shown in Table 6. It should be noted that after adding the interaction term, the model simultaneously reports the coefficients of the low order main effect terms (DIG and W × DIG) to fully present the moderating effect. To further clarify the transmission mechanism at the provincial level, this article will then aggregate the samples to the provincial level for further testing (see Section 4.9).

Table 6:Results of moderation effect test

Variable	Geographic distance (W_1)	Economic distance (W_2)	Nested Matrix (W_3)
DIG	0.316*** (7.12)	0.302*** (6.84)	0.308*** (6.96)
W×DIG	0.154*** (3.42)	0.140*** (3.08)	0.148*** (3.26)
BDN	0.156*** (3.18)	0.142*** (2.86)	0.148*** (3.02)
DIG × BDN	0.198*** (4.26)	0.182*** (3.88)	0.194*** (4.12)

Variable	Geographic distance (W_1)	Economic distance (W_2)	Nested Matrix (W_3)
W×DIG × BDN	0.112** (2.48)	0.098** (2.18)	0.106** (2.34)
control variable	control	control	control
Fixed spatial effect	control	control	control
Fixed time effect	control	control	control
R^2（within）	0.342	0.326	0.336
Log-likelihood	-3256.8	-3284.2	-3268.4
sample size	22056	22056	22056

Note: **** and ** indicate significance at the 1% and 5% levels, respectively; values in parentheses are Z-scores; DIG represents the degree of corporate digital transformation, BDN represents the level of big data network development, and W represents the corresponding spatial weight matrix; the main effect terms (DIG and W×DIG) are the coefficients of lower-order terms reported in the model after including the interaction term; control variables are consistent with those in Table 3.*

The moderation effect test results in Table 6 reveal the two-dimensional moderation effects of big data networks. The coefficients of the local interaction term DIG × BDN are significantly positive at the 1% level for all three spatial weight matrices, with values ranging from 0.182 to 0.198. This result indicates that in regions with high levels of big data network development, the positive impact of digital transformation on local ESG performance has been significantly strengthened. The coefficient of the spatial interaction term W × DIG × BDN is significantly positive at the 5% level, with values ranging from 0.098 to 0.112. This result indicates that big data networks not only enhance the local effects of digital transformation, but also indirectly strengthen the spatial spillover effects of digital transformation radiating from neighboring regions to the local area by reducing information transmission costs and promoting smooth channels for knowledge diffusion (Liang et al.,2023).

In regions with developed big data networks, the local and spatial spillover effects of digital transformation exhibit stronger resilience. The policy implications of this discovery are that digital infrastructure construction is not simply hardware investment, but an important institutional prerequisite for digital transformation to unleash spatial radiation efficiency.

4.7. Robustness test

To ensure the reliability of the benchmark regression results, robustness tests were conducted from five different dimensions. The test results are summarized in Table 7.

Table 7:Summary of Robustness Test Results

Robustness testing method	Inspection content	Core Findings	Conclusion
Replace the explained variable	Shangdao Ronglv ESG Rating	DIG coefficient 0.286***	robust
Replace core explanatory variables	Peking University Digital Economy Index matches listed companies	DIG coefficient 0.312***	robust
Replace the spatial weight matrix	Inverse distance squared weight matrix	W × DIG coefficient 0.152***	robust
Instrumental Variables Method	IV-2SLS (IV=average DIG of other companies in the same industry)	The first stage has an F-value of 58.46 and a DIG coefficient of 0.412***	robust
System GMM estimation	Dynamic panel spatial model	DIG coefficient 0.304 * * *, AR(2)>0.05	robust
Exclude special samples	Excluding direct sales markets and data from 2020-2022	DIG coefficient 0.358***	robust

Note: **** indicates $p < 0.01$.*

Specifically:

(1) Replace the dependent variable: regress using the ESG rating data from SynTao Green Finance, with a DIG coefficient of 0.286 ($p<0.01$), consistent with the benchmark results.

(2) Replace the core explanatory variable: Use the Peking University Digital Economy Index to match listed companies, with a DIG coefficient of 0.312 ($p<0.01$), and the conclusion is robust.

(3) Replace the spatial weight matrix: use the inverse distance squared weight matrix, with a W × DIG coefficient of 0.152 ($p<0.01$), and the spatial spillover effect is still significant.

(4) Instrumental variable method: As shown in Table 7, the IV estimation results indicate a DIG coefficient of 0.412 **. The IV coefficient is greater than the baseline regression (0.342), indicating that the baseline OLS may have underestimated the true effect due to reverse causality. The results after IV correction are still significant, confirming the robustness of the conclusion.

(5) System GMM estimation: To alleviate the potential issues of reverse causality and endogeneity in dynamic panels, the system GMM method is used to estimate the dynamic spatial panel model. The results showed that the DIG coefficient was 0.304 ($p<0.01$). The Arellano Bond test results showed that the P-value of AR (1) was 0.021 (<0.05), and the P-value of AR (2) was 0.152 (>0.10), indicating that there was no second-order sequence correlation in the residuals and that the instrumental variable setting was effective. The core conclusion is consistent with the benchmark regression (Wang et al.,2024b).

(6) Excluding special samples: Considering the particularity of Beijing, Shanghai, Tianjin, and Chongqing in terms of administrative level and resource allocation, as well as the possible abnormal impact of the COVID-19 on digital transformation from 2020 to 2022, this paper separately excludes the samples of municipalities directly under the Central Government and the data of this period for regression. After exclusion, the remaining sample size is 16842 'company year' observations, and the core explanatory variable DIG coefficient is 0.358 ***, which is highly close to the benchmark regression result (0.342), indicating that the conclusion is not affected by sample selection bias.

In summary, all robustness tests support the core finding of benchmark regression, which is that digital transformation has a significant positive spatial spillover effect on ESG performance.

4.8. Heterogeneity analysis

To investigate whether there is heterogeneity in the impact of digital transformation on ESG performance, grouping tests were conducted from four dimensions: regional level of digital economic development, corporate property rights, corporate size, and industry attributes. The results of heterogeneity analysis are detailed in Table 8.

Heterogeneity grouping criteria: (1) Regional digital economy: grouped according to the median annual digital economy index of each province; (2) Property rights nature: state-owned enterprises and non-state-owned enterprises; (3) Enterprise size: grouped by median total assets; (4) Pollution level: Referring to the "Guidelines for Environmental Information Disclosure of Listed Companies" issued by the Ministry of Environmental Protection, heavy polluting industries are classified as high pollution groups, while the rest are classified as clean groups (Tang & Lan,2024).

Table 8:Heterogeneity Analysis Results

Grouping dimension	subgroup	Sample size (N)	DIG coefficient	W × DIG coefficient	Inter group difference test
Development level of regional digital economy	High level regions	12,400	0.418*** (8.96)	0.226*** (5.12)	$\chi^2(1)=18.46$***
	Low level areas	9,656	0.286*** (6.24)	0.124** (2.48)	
Nature of Enterprise Property Rights	state-owned enterprise	10,000	0.264*** (5.68)	0.142** (2.86)	$\chi^2(1)=12.38$***
	non-state-owned enterprises	12,056	0.396*** (8.42)	0.196*** (4.38)	
Company size	large enterprise	11,000	0.372*** (7.96)	0.184*** (4.02)	$\chi^2(1)=15.22$***

Grouping dimension	subgroup	Sample size (N)	DIG coefficient	W × DIG coefficient	Inter group difference test
	small and medium-sized enterprises	11,056	0.298*** (6.38)	0.146** (2.94)	
Industry attribute	Highly polluting industries	8,000	0.348*** (7.48)	0.188*** (3.88)	$\chi^2(1)=14.56$***
	clean industries	14,056	0.338*** (7.26)	0.158*** (3.28)	

Note: **** and ** indicate significance at the 1% and 5% levels, respectively. The sample size (N) of each group is the observation value of "company year", and the sum of the sub group sample sizes in each dimension is equal to the total sample size of 22056. The inter group difference test uses the seemingly unrelated model (Suest) to jointly test the coefficients of the two groups, reporting the chi square value (χ^2) and significance. The control variables, individual fixed effects, and time fixed effects have all been included in the regression models of each group.*

Heterogeneity analysis presents the following four types of differential characteristics:

From the perspective of regional differences, regions with higher levels of digital economy development have a DIG coefficient of 0.418 and a W × DIG coefficient of 0.226. In areas with lower levels of digital economy development, the DIG coefficient is 0.286 and the W × DIG coefficient is 0.124. The chi square value of the inter group difference test was 18.46 ($p<0.01$), indicating that the significant differences in regional digital infrastructure endowments moderated the intensity of digital transformation effects. In areas with developed digital infrastructure, big data networks provide smoother channels for cross regional information flow, and the elasticity of local and spatial spillover effects is higher than that of underdeveloped areas. The differences in regional digital infrastructure endowments have a significant moderating effect on the strength of digital transformation effects.

From the perspective of differences in the nature of enterprise property rights, the DIG coefficient in the non-state-owned enterprise sub sample is 0.396, and the W × DIG coefficient is 0.196. The DIG coefficient in the sub sample of state-owned enterprises is 0.264, and the W × DIG coefficient is 0.142. The inter group difference test showed that the above differences were statistically significant (chisq=12.38, $p<0.01$). Non state-owned enterprises have advantages in decision-making flexibility and market response speed in digital transformation investment, and the enthusiasm of digital management information systems radiating to neighboring enterprises is higher.

From the perspective of differences in enterprise size, the DIG coefficient in the sub sample of large enterprises is 0.372, and the W × DIG coefficient is 0.184. The DIG coefficient in the sub sample of small and medium-sized enterprises is 0.298, and the W × DIG coefficient is 0.146. The chi square value of the intergroup difference was 15.22 ($p<0.01$). Large enterprises have more abundant digital investment budgets and more complete information management systems, and have better basic conditions for implementing ESG management.

From the perspective of industry attribute differences, the DIG coefficient in the high pollution industry sub sample is 0.348, and the W × DIG coefficient is 0.188. The DIG coefficient in the sub sample of the clean industries is 0.338, and the W × DIG coefficient is 0.158. Highly polluting industries are facing stricter environmental regulatory pressures and environmental information disclosure requirements. The demand for monitoring and reducing environmental pollution emissions through digital transformation is becoming more urgent. Therefore, they are more proactive in using digital means to improve ESG performance (Dai & Jin,2024).

4.9. Re examination of the intermediary effect at the provincial level

Given that the mediating variable (DFLOW) mentioned earlier is a provincial-level indicator, in order to ensure the establishment of the transmission chain of "digital transformation → digital factor flow → ESG performance" at the regional level, this section aggregates micro enterprise data to the provincial level, constructs balanced panel data for 31 provinces (autonomous regions and municipalities) from 2012 to 2022, and re verifies the mediating effect.

(1) Variable handling

The provincial level of digital transformation (DIG_prov) is measured by the annual average of the digital transformation index of listed companies within each province; Provincial ESG performance (ESGprov) is measured by the annual average ESG rating of listed companies in each province, including Huazheng Securities; The mediating variable DFLOW and the moderating variable BDN are measured as described in Section 3.2.

(2) Model setting

This study adopted the classic stepwise regression method for mediating effects and combined it with a provincial-level spatial Durbin model for testing (Wu et al., 2023).

(3) Result analysis

Table 9 reports the provincial-level mediation test using a correct nested model sequence. Model (1) estimates the effect of provincial management informatization on digital factor flows. Model (2) estimates the total effect of provincial management informatization on ESG performance without including the mediator. Model (3) adds DFLOW to the ESG equation and estimates the direct effect of DIG_prov after controlling for the mediator. The results show that DIG_prov significantly promotes DFLOW in Model (1). In Model (2), DIG_prov has a significant positive total effect on provincial ESG performance. After DFLOW is introduced in Model (3), the coefficient of DIG_prov decreases compared with Model (2), while DFLOW remains significantly positive. This nested pattern supports the existence of a partial mediation effect at the provincial level. The Z-value of the Sobel test at the provincial level is 3.86 ($p<0.01$), confirming that the flow of digital elements does indeed play a mediating role at the provincial level. This result is directionally consistent with the firm-level findings, but the magnitude of the mediation effect is larger at the provincial level. This difference is theoretically reasonable because DFLOW is measured as a provincial-level indicator and mainly captures the activity of regional data-factor markets, digital infrastructure, and cross-regional data circulation. Therefore, the provincial model is more capable of identifying the macro transmission channel from regional management informatization aggregation to ESG improvement, whereas the firm-level model captures the average response of individual firms to the provincial data-flow environment.

Table 9:Results of Intermediate Effect Test at Provincial Level

Variable	(1) DFLOW	(2) ESG(Total Effect Model)	(3) ESG(Direct Effect Model)
DIG_prov	0.312***	0.727***	0.458***
	(4.52)	(6.18)	(6.24)
DFLOW	—	—	0.862***
	—	—	(3.96)
Controls	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	341	341	341
R^2	0.486	0.508	0.524

Note: *All variables are standardized. Model (2) is the newly added total-effect model (without mediator), which is necessary for the mediation proportion calculation. The Sobel Z-value and Bootstrap 95% CI for the indirect effect are reported in the text (Section 4.5). *** p<0.01, ** p<0.05.*

5. Conclusion and Policy Implications

5.1. Main conclusions

This article is based on panel data of Chinese A-share listed companies in Shanghai and Shenzhen from 2012 to 2022, and comprehensively uses spatial Durbin model, mediation effect model, and spatial decomposition method to examine the spatial radiation effect of enterprise digital transformation on ESG performance and the mediating effect of digital factor flow under the empowerment of big data networks. The main conclusions are as follows.

Firstly, generalized management informatization (i.e. digital transformation) has a significant positive spatial radiation effect on ESG performance. The empirical results based on the spatial Durbin model show that the improvement of local enterprise management informatization level not only improves their own ESG performance, but also generates significant cross regional radiation effects through the connection of big data networks. The spatial effect decomposition results show that local direct effects account for about 67.3% of the total effects, while spatial spillover effects from management informatization practices in neighboring regions account for about 32.7%. This discovery confirms that in the context of big data, the value of management informatization has broken through organizational boundaries and become an important force in promoting regional ESG collaboration.

Secondly, the flow of digital elements plays a partial mediating role in the process of improving ESG performance through management informatization. Mechanism testing shows that the improvement of enterprise management informatization level does not occur in isolation. It indirectly empowers the improvement of ESG performance by accelerating the flow and sharing of data resources within the region (i.e. promoting the flow of digital elements). The mediation analysis shows that digital factor flows serve as a statistically significant transmission channel between management informatization and ESG performance. At the firm level, the mediated effect accounts for a relatively limited but non-negligible share of the total effect. At the provincial level, the mediation proportion is larger, indicating that digital factor flows mainly operate as a regional information and data-market mechanism. These results suggest that the data-flow channel should be interpreted as a cross-level mechanism rather than a purely firm-level behavioral channel. This indicates that management informatization is not only a technological change within the enterprise, but also a key driving force for activating the regional data element market and optimizing resource allocation (Zhu et al.,2023).

Thirdly, the development level of big data networks has significantly strengthened the dual effect of management informatization on ESG performance. The moderation effect test confirms that the improvement of big data network infrastructure not only amplifies the direct promotion effect of local management informatization on ESG, but also significantly expands the radiation radius of its spatial spillover. This indicates that big data networks are the key institutional environment and physical carrier for the release of externalities in management informationization.

Fourthly, heterogeneity analysis shows that in regions with higher levels of digital economy development, non-state-owned enterprises, large enterprises, and high polluting industries, the promotion effect and spatial spillover effect of management informatization (digital transformation) on ESG performance are more prominent.

Fifthly, the impact of enterprise characteristic variables on ESG performance shows structural differences. Enterprises with larger scale, stronger profitability, and more complete governance structure (higher proportion of independent directors and more institutional investors holding shares) have better ESG performance, while high debt enterprises lag behind in ESG investment due to financial constraints. This finding indicates that the improvement of ESG performance is not only dependent on digital transformation, but also constrained by the financial health and governance capabilities of the enterprise itself (Niu & Yang,2024).

5.2. Policy Implications

Strengthen the construction of digital infrastructure and provide carrier support for the spatial radiation of digital transformation. The big data network is the fundamental condition for the smooth transmission of spatial radiation effects in digital transformation. We should moderately advance the construction of digital infrastructure such as 5G base stations and data centers to enhance the breadth of network coverage and the density of computing resources. The central and western regions as well as underdeveloped digital infrastructure areas should accelerate the layout of digital infrastructure, narrow the "digital divide" between regions, and create conditions for underdeveloped areas to undertake spatial spillover of digital technology and ESG practices.

Build a unified national data-factor market and improve inter-regional information service infrastructure. The empirical results show that digital factor flows are an important channel through which management informatization affects ESG performance. Therefore, policy makers should not only promote data transactions, but also improve data standards, interface compatibility, data-rights confirmation, privacy protection, and cross-regional data service platforms. These measures can reduce information search costs and improve the efficiency of ESG-related information sharing among firms, regions, and supply-chain partners. The flow of digital elements accounts for nearly one-fifth of the intermediary transmission share between digital transformation and ESG performance, and has significant spatial spillover characteristics. We should eliminate barriers to local protection and market segmentation, establish unified rules for data ownership, pricing, and trading, and cultivate regional data trading markets. It is particularly important to leverage the driving effect of digital agglomeration in developed regions on the flow of data elements in surrounding areas, and to promote regional synergy in ESG practices through efficient cross regional flow of data elements.

Implement a differentiated digital transformation strategy, focusing on the exemplary and leading role of non-state-owned enterprises and large enterprises. Empirical analysis shows that the digital transformation of non-state-owned enterprises and large enterprises has a more significant impact on ESG performance. Therefore, these enterprises should be encouraged and supported to take the lead in upgrading their management information technology and exploring ESG practices, and to leverage the diffusion effect of "leading first and driving later" to accelerate the digital transformation process of small and medium-sized enterprises and state-owned enterprises (Zhang,2024).

Build a cross regional ESG collaborative governance mechanism to achieve regional linkage improvement in ESG performance. The spatial spillover effect indicates that ESG practices have regional convergence characteristics, and developed regions should be encouraged to export digital management experience and ESG evaluation standards to underdeveloped regions. With the help of spatial radiation effects, a regional development pattern of ESG synergistic enhancement should be formed to promote the achievement of regional green and sustainable development goals.

Pay attention to digital financing support for high debt enterprises and alleviate financial constraints on ESG investment. This study found a significant negative correlation between asset liability ratio and ESG performance, indicating that high debt enterprises face greater financial pressure when promoting digital transformation and ESG practices. Policy makers should combine digitalization with green finance tools, such as establishing a "digitalization+ESG" special refinancing program to provide low interest loans to high debt but strong digital transformation willingness enterprises; Encourage financial institutions to incorporate the level of digital transformation of enterprises into their ESG rating system as a reference indicator for green bond issuance; Provide tax exemptions or subsidies to high debt enterprises that significantly improve their environmental performance through digital means. By reducing financial constraints, more enterprises can cross the initial threshold of digital investment, thereby amplifying the spatial radiation effect of digital transformation.

5.3. Limitations and Future Research Directions

This study has the following limitations that need to be further improved in future research.

Firstly, the sample scope is limited to listed companies, and caution should be exercised when extrapolating research conclusions to non listed companies. There are significant differences between non listed companies and listed companies in terms of digital investment capabilities, information disclosure levels, and management standards. Future research can include non listed companies in the analysis framework.

Secondly, ESG rating data mainly comes from one institution, Huazheng Securities, and there are differences in standards among different rating agencies. Future research can comprehensively utilize data from multiple rating agencies to test the sensitivity of research conclusions to different rating systems.

Third, although this paper uses both firm-level and provincial-level analyses, the hierarchical matching between micro-level firm behavior and macro-level digital factor flows remains a limitation. DFLOW is measured at the provincial level and therefore cannot fully capture firm-level data transactions, supply-chain data sharing, or platform-based information collaboration. Future research can collect micro-level data on data exchanges, digital platform participation, logistics information sharing, and inter-firm information service networks to further identify the specific channels through which management informatization generates spatial spillovers. Due to the limited availability of data, the mediating variable (flow of digital elements) in this article mainly adopts provincial-level macro indicators, which to some extent limits our accurate characterization of specific transmission channels between micro enterprises, such as supply chain data collaboration and talent flow. Although this article verifies the establishment of macro mechanisms through re examination at the provincial level, obtaining micro level data on data transactions or data sharing at the enterprise level in the future will further enhance the explanatory power of micro transmission mechanisms.

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