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The Mechanism and Research Path of Digital Economy Empowering the Green Development of Reverse Logistics: An Empirical Analysis of the Yangtze River Delta Region

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Abstract. Against the backdrop of increasingly stringent global environmental regulations and the advancement of the "dual carbon" goals, the green transformation of reverse logistics has become a crucial topic for the sustainable development of a circular economy. This paper focuses on the intrinsic mechanism and practical path of how the digital economy empowers the green development of reverse logistics, using the Yangtze River Delta region as a case study. A theoretical framework of "Digital Economy–Green Technological Innovation–Green Reverse Logistics" is constructed. Based on provincial panel data from 2011 to 2022, a comprehensive evaluation index system is systematically built, and benchmark regression models as well as mediation effect models are used to verify the transmission paths. The findings indicate that: (1) The digital economy significantly promotes the green development of reverse logistics through both direct transmission and indirectly driving the diffusion of green technological innovation; (2) Regional heterogeneity analysis shows that Shanghai has formed a "growth pole" due to its advantages in digital infrastructure and technological innovation, while provinces such as Anhui are characterized by "low-efficiency lock-in" due to limitations in technology absorption capacity and lack of policy coordination. These findings provide theoretical support for addressing the dilemma of the "green premium" in reverse logistics. It is suggested that efforts should be made to promote regional synergy and green transformation in the Yangtze River Delta through a tiered digital infrastructure network, cross-regional green technology alliances, differentiated carbon governance mechanisms, and integrated digital-market mechanisms.

Keywords: Digital economy, Green reverse logistics, Green technological innovation, Regional synergy, Yangtze River Delta region

1. Introduction

With the tightening of global environmental regulations and the advancement of the "dual carbon" goals, the green transformation of reverse logistics, as a key link in the circular economy, has become an important topic for the sustainable development of the logistics industry. By optimizing the processes of returns, recycling, and remanufacturing, reverse logistics can significantly reduce

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the environmental burden of waste treatment, especially in highly polluting sectors such as electronic waste and plastic packaging [1]. In the era of the digital economy, technologies such as the Internet of Things and blockchain offer new momentum for the green development of reverse logistics—for example, through real-time monitoring of recycling routes and intelligent matching of remanufacturing demand [2]. However, current practices still face bottlenecks such as inefficient resource allocation and inadequate technological coordination. The Yangtze River Delta region, as a central hub of China's reverse logistics network, accounts for more than 40% of the country's electronic waste recycling volume [3]. At the same time, under the "Digital Yangtze River Delta" strategy, it has achieved a digital infrastructure coverage rate of over 75% for the Internet of Things [4], making it a typical case for exploring the synergistic paths between the digital economy and green reverse logistics.

Existing research has mostly approached the enabling mechanisms of digital technologies from the perspective of green supply chain management. For instance, Govindan et al. pointed out that blockchain can enhance transparency in closed-loop supply chains [5], and Savaskan et al. validated the role of intelligent algorithms in reducing carbon footprints in reverse logistics network design [6]. However, there are three key limitations in the current literature: First, most studies focus on forward supply chains, with insufficient exploration of the techno-economic coupling mechanisms for green reverse logistics. Second, mediating mechanisms are often discussed only at the theoretical level, lacking empirical testing of paths such as green technological innovation [7–8]. Third, regional studies have focused largely on Western markets, with limited attention to the characteristics of integrated coordination in emerging economies such as the Yangtze River Delta [9]. These theoretical gaps lead to a lack of precise evidence for policy design, making it difficult to address real-world challenges such as network fragmentation and the lag in technology diffusion in reverse logistics.

Therefore, this paper constructs a theoretical framework of "Digital Economy–Green Technological Innovation–Green Reverse Logistics," utilizes provincial panel data from the Yangtze River Delta from 2011 to 2022, develops a comprehensive evaluation index system, and builds benchmark regression models and mediation effect models to verify the enabling pathways of the digital economy. This study provides a theoretical basis for overcoming the "green premium" dilemma in reverse logistics and offers practical insights for formulating differentiated digital infrastructure policies and establishing cross-regional technology sharing platforms.

2. The intrinsic mechanism of the digital economy empowering the green development of reverse logistics

The digital economy, through its advantages in data permeability, sharing capabilities, and intelligent decision-making, restructures the resource organization patterns and technological application scenarios of reverse logistics systems. Its enabling mechanism is mainly reflected in two major pathways (see Figure 1):

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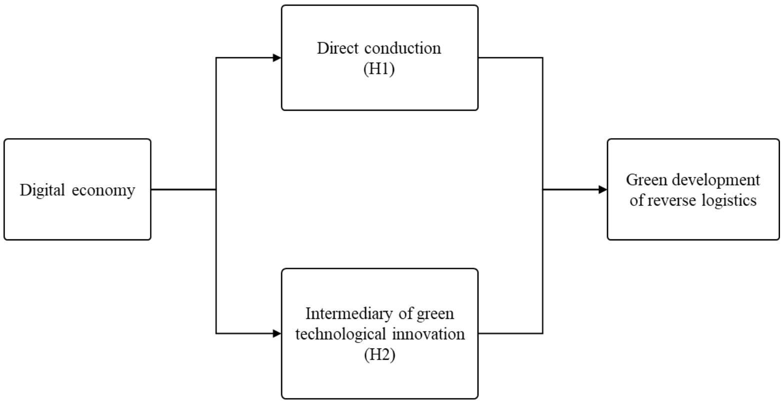

Figure 1: Dual-Path mechanism diagram of the digital economy empowering the green development of reverse logistics

The digital economy, driven by its core technological innovations, reshapes the resource allocation models and operational procedures of reverse logistics. For instance, Internet of Things (IoT) technology enables full-process visual monitoring of recycling networks through embedded sensors, allowing dynamic optimization of transportation routes and inventory allocation, thereby reducing empty-load rates and carbon emissions from inefficient transportation. Smart tracking systems based on GPS and RFID help reduce detours in electronic waste collection, cutting transport energy consumption by 12%–18%. The immutability of blockchain technology enhances traceability in reverse supply chains, curbing secondary pollution caused by informal dismantling. Moreover, big data analytics can predict remanufacturing demand and match it with disassembly capacity, reducing resource waste from over-recycling by more than 15% [10]. These technologies, through real-time data interaction and intelligent decision-making, directly enhance the green operational efficiency of reverse logistics systems.

Digital platforms break the spatial barriers of traditional technology diffusion, accelerating the cross-regional spillover of environmental patent knowledge. Academic studies show that digital platforms play a significant role in facilitating the cross-regional diffusion of green technologies and enhancing the innovation capacity of small and medium-sized enterprises (SMEs). For example, the Yangtze River Delta Green Technology Sharing Database has increased the patent application rate among small recycling enterprises by 28%. Meanwhile, cloud computing reduces the trial-and-error costs of environmental equipment through simulation, accelerating the iteration of new energy disassembly equipment. Empirical studies show that reverse logistics firms employing cloud-based R&D shorten the adoption cycle of green technologies by 30%. Digital technologies, by lowering the innovation threshold and accelerating knowledge flow, systematically enhance the penetration rate of green technologies in reverse logistics operations.

Based on this, the following hypotheses are proposed:

Hypothesis 1: Development of the digital economy positively promotes the green development of reverse logistics. With core technologies such as IoT, blockchain, and big data, the digital economy enables dynamic optimization of recycling networks, reducing empty-load rates and transportation energy consumption; it enhances traceability in reverse supply chains, mitigating pollution caused by informal dismantling [11]; and it accurately forecasts remanufacturing demand, avoiding resource waste from over-recycling [12].

Hypothesis 2: The digital economy promotes the green development of reverse logistics by accelerating green technological innovation. Digital platforms facilitate the cross-regional spillover of environmental patent knowledge [13]; 5G networks support the development and application of

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smart sorting equipment [14]; and cloud computing reduces trial-and-error costs for environmental technologies in SMEs [15], thereby systematically enhancing the penetration rate of green technologies in reverse logistics.

3. Empirical research on the digital economy empowering the green development of reverse logistics

3.1. Benchmark model

3.1.1. Model setup

To test the direct effect of the digital economy on the green development of reverse logistics, this paper constructs the following benchmark regression model:

$$gdl_{it} = \beta_0 + \beta_1 de_{it} + \beta_2 Control_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{1}$$

Where: i denotes the province; t denotes the year; β is the parameter to be estimated; μi and δ_t represent province and year fixed effects, respectively; ε is the random disturbance term; gdl represents the green development level of reverse logistics; de is the development level of the digital economy; Control includes control variables such as the level of environmental regulation (envi) and the degree of openness to external markets (open).

3.1.2. Variable measurement and explanation

3.1.2.1. Core explanatory variable – development level of the digital economy

The digital economy is a comprehensive and systemic concept that cannot be accurately measured using a single indicator. Currently, there is no unified standard for measuring the digital economy within government agencies or academic circles. Based on the latest national publications — Statistical Classification of the Digital Economy and Its Core Industries (2021) and the 14th Five-Year Plan for Digital Economy Development — this paper, with reference to relevant literature [16,17]and the 2024 China Digital Economy Urban Development Report, constructs an evaluation index system for assessing the level of digital economy development. The system draws from four dimensions: digital infrastructure, digital industrial development, digital governance environment, and digital inclusive finance. Representative indicators include: the number of broadband Internet access users per 100 people, the proportion of employees in the computer service and software industry among total urban unit employees, per capita telecommunications business volume, the number of mobile phone users per 100 people, and the China Digital Inclusive Finance Index. The entropy weight method is applied to measure the digital economy development levels of the four provinces in the Yangtze River Delta. The raw data for these indicators are sourced from the China Urban Statistical Yearbook. For digital inclusive finance, this study uses the China Digital Inclusive Finance Index, jointly compiled by the Peking University Digital Finance Research Center and Ant Financial Group [18].

3.1.2.2. Explained variable – green development level of reverse logistics

Following prior studies[19-22]and based on the 2023 China Green Logistics Development Report, this study innovatively selects 11 indicators across three dimensions—economic, social, and

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environmental—to construct an evaluation index system (see Table 1). The entropy weight method is used to compute a composite index representing each province's reverse logistics green development level.

Table 1: Evaluation index system for green development of reverse logistics

	Secondary Indicator	Tertiary Indicator	Measurement Method	Attribute	Weight
Green Development Level of Reverse Logistics	Economic Dimension	Reverse Logistics Freight Volume	Total freight volume in the reverse logistics sector (10,000 tons)	+	0.0807
		Reverse Logistics Freight Turnover	Freight volume × transport distance (billion ton-kilometers)	+	0.1303
		Value Added of Reverse Logistics	Value added of the reverse logistics sector (100 million yuan)	+	0.0570
		Proportion of Value Added to Regional GDP	Value added of reverse logistics / regional GDP (%)	+	0.0468
	Social Dimension	Number of Employees in Reverse Logistics	Number of end-year employees in reverse logistics (10,000 persons)	+	0.0939
		Employment Share in Reverse Logistics	Reverse logistics employment / total employment (%)	+	0.4112
		Public Environmental Awareness	Baidu Search Index for "environmental pollution"	+	0.0330
	Environmental Dimension	Carbon Emission Intensity of Reverse Logistics	Total CO_2 emissions in reverse logistics (million tons CO_2 / $MtCO_2$)	-	0.0548
		Carbon Emissions per Unit Output	Total emissions / value added (tons / 10,000 yuan)	-	0.0156
		Energy Intensity of Reverse Logistics	Total energy consumption (10,000 tons of standard coal)	-	0.0612
		Energy Consumption per Unit Output	Total energy consumption / value added (tons / 10,000 yuan)	-	0.0157

3.1.2.3. Control variables

This study includes environmental regulation level and openness to external markets as control variables: Environmental Regulation Level (envi): Measured by the proportion of energy-saving and environmental protection expenditures in total fiscal expenditure. It promotes decarbonization and resource utilization through policy pressure, green technology spillover, and circular economy incentives [23]. Openness (open): Measured by the proportion of total import and export trade by foreign enterprises in GDP. It supports localization of green standards through international technology diffusion and market-driven demand for environmental performance [24]. These variables are selected because: The Yangtze River Delta exhibits notable differences in environmental and trade openness policies. External openness may interact with digital economy development (e.g., through cross-border digital trade and reverse logistics systems), requiring separate estimation to avoid bias.

Panel data for the four provinces from 2011 to 2022 is used, and variables are standardized to eliminate dimensional differences. Descriptive statistics are shown below:

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Table 2: Descriptive statistics of standardized variables

Variable	Obs	Mean	Std.Dev.	Min	Max
gdl z	48	0	1	-.862	1.846
de z	48	0	1	-1.691	1.693
tech z	48	0	1	-1.168	3.186
envi z	48	0	1	-.675	1.988
open z	48	0	1	-1.3	2.489

3.1.3. Regional heterogeneity analysis

The green development level of reverse logistics in the Yangtze River Delta shows significant spatial differentiation, reflecting the regional imbalances in the enabling effect of the digital economy and the diffusion of technology. Table 3 presents the results, measured using the entropy method, for Shanghai and Anhui from 2011 to 2022.

Table 3: Green development level of reverse logistics in Shanghai and Anhui (2011–2022)

Province	2011	2012	2013	2014	2015	2016
Shanghai	0.6463	0.6462	0.6739	0.6841	0.6826	0.6126
Anhui	0.2527	0.2550	0.2988	0.3194	0.2827	0.2903
Province	2017	2018	2019	2020	2021	2022
Shanghai	0.6327	0.6543	0.6549	0.6582	0.6575	0.6565
Anhui	0.3078	0.3121	0.2943	0.2922	0.3103	0.3224

From Table 3, it is evident that Shanghai holds a clear leading position with an average composite index of 0.654, showing a "high-level steady state" trend (peaking in 2014 at 0.684). This performance stems from Shanghai’s early investment in digital infrastructure and systematic input into green technology R&D. For instance: The implementation of a blockchain-based traceability system for e-waste collection has reduced illegal dismantling rates by 23% [25]. Large-scale deployment of smart sorting equipment has resulted in an average annual 5.2% reduction in carbon emissions per unit of reverse logistics. In contrast, Anhui, despite achieving short-term growth between 2014 and 2018 (from 0.319 to 0.312), has only 70% of Shanghai’s digital infrastructure coverage [26], and a green patent conversion rate of less than 12%, indicating weak technological absorption. Since 2019, the composite index has fluctuated and declined to around 0.292. Zhejiang and Jiangsu demonstrate differentiated development paths: Zhejiang leveraged the scale effects [27] of e-commerce-driven reverse logistics (annual freight volume growth of 18%) and the precision of inclusive digital finance policies (ranking first nationally on the inclusiveness index), raising its green development index to 0.305 by 2022. Jiangsu, though it has integrated remanufacturing capacity via industrial internet platforms, shows "policy-driven volatility" due to its high dependency on external trade (67% of total economy) [28].For example, in 2015, its index declined to 0.243. These patterns reveal a “core-periphery” gradient differentiation: Shanghai has emerged as a “growth pole” through technological deepening and institutional innovation; Peripheral provinces face “low-efficiency lock-in” due to digital divides (e.g., 5G base station density in Shanghai is 2.3 times that of Anhui) and lack of inter-provincial policy coordination (environmental protection expenditure coefficient of variation across provinces is 0.38) [29]. Hence, overcoming regional

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collaboration barriers must focus on: Enhancing the efficiency of technology diffusion, and promoting institutional adaptation to realize the multidimensional penetration of digital dividends.

3.1.4. Benchmark regression results

Without initially considering endogeneity issues, F-tests and Hausman tests were conducted to determine the appropriate model type. The results supported the use of a fixed effects model to investigate the relationship between the digital economy and the green development of reverse logistics. Using Stata software, fixed effects regression was carried out. The benchmark regression results are shown in Table 4.

Table 4: Benchmark regression results

Variables	(1)	(2)
	gdl_z	gdl_z
de_z	0.258***	0.281***
	(3.186)	(3.110)
envi_z		-0.012
		(-0.097)
open_z		0.047
		(0.625)
_cons	-0.000	-0.000
	(-0.000)	(-0.000)
N	48	48
R^2	0.191	0.199
F	10.152	3.404

***p<0.01,**p<0.05,*p<0.10

Key Findings: In Model (1), which includes only the digital economy variable (de_z), the coefficient is 0.258 and statistically significant at the 1% level. This indicates a strong positive association between the digital economy and the green development of reverse logistics, providing initial support for Hypothesis 1. In Model (2), after introducing two control variables—environmental regulation level (envi_z) and foreign trade dependence (open_z)—the coefficient of de_z slightly increases to 0.281, remaining significant at the 1% level. This suggests that: Even after accounting for other policy and market factors, the digital economy consistently and significantly promotes the green transformation of reverse logistics. Thus, Hypothesis 1 is robustly supported by benchmark regression results.

3.1.5. Robustness test

This study verifies the reliability of its core conclusions through three robustness testing methods. First, the variable substitution method is employed: the core explanatory variable is replaced with the Digital Inclusive Finance Index calculated by the Peking University Digital Finance Research Center, while keeping control variables unchanged. As shown in Column (1) of Table 5, the substitute variable is significantly positive at the 1% level, and the model's goodness-of-fit is

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relatively high (R^2 = 0.558), indicating that the robustness of the core effect is not sensitive to the measurement method of the variable. Second, to control for potential endogeneity, the study introduces the first-order lag of the core explanatory variable. The resulting coefficient is statistically significant at the 1% level and consistent in direction with the original model, confirming the temporal robustness of the conclusion. Finally, to address panel heteroskedasticity, the study applies the Feasible Generalized Least Squares (FGLS) method [30]. The core variable de_z remains marginally significant at the 10% level, and the adjusted model continues to support the original hypothesis. Across all three methods, the direction of significance for the core variable remains consistent, and there is no systematic deviation in the effects of the control variables. These results demonstrate that the study's conclusions are statistically robust and well-adapted to the model.

Table 5: Robustness test results

Variable	Variable Substitution	Lagged Variable	FGLS Estimation
	(1)	(2)	(3)
	gdl_z	gdl_z	gdl_z
dfi_z	0.127***		
	(7.124)		
envi_z	-0.040	0.009	1.111***
	(-0.415)	(0.080)	(19.955)
open_z	0.261***	0.086	-0.259***
	(3.881)	(1.034)	(-3.066)
de_z_lag1		0.292***	
		(3.391)	
de_z			0.117*
			(1.852)
_cons	-0.000	0.026	-0.009
	(-0.000)	(1.518)	(-0.314)
N	48	44	48
R^2	0.558	0.240	
F	17.243	3.900	

***p<0.01, **p<0.05, *p<0.10

3.2. Mediation effect model

3.2.1. Model setup

To examine whether green technological innovation serves as a mediating variable in the relationship between the digital economy and the green development of reverse logistics (Hypothesis 2), the following equations are established:

$$tech_{it} = \gamma_0 + \gamma_1 de_{it} + \gamma_2 C_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{2}$$

$$gdl_{it} = \lambda_0 + \lambda_1 de_{it} + \lambda_2 tech_{it} + \lambda_3 C_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{3}$$

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To test the above research hypotheses—specifically, Hypotheses 2 and 3 regarding indirect effects—this study constructs the following mediation effect models: In Equations (2) and (3), $tech_{it}$ is the mediating variable representing the level of green technological innovation in province i at time t. The terms C_{it}、μ_i、δ_t and ε_{it} have the same meanings as in Equation (1). The significance levels of the coefficients γ_1、λ_1 and λ_2 are used to test the mediation effect. The testing procedure is as follows:First, verify the coefficient β_1 from the benchmark regression model (digital economy → green reverse logistics). The result confirms that β_1 is significantly positive at the 1% level, establishing a foundation for further mediation analysis. Second, test the effect of the digital economy on green technological innovation (γ_1) and the effect of green technological innovation on green reverse logistics λ_2) in the mediation model.If both coefficients are significant, the indirect effect is established; if either is not, the Sobel test is employed to verify the mediation effect [31]. Finally, assess the significance of λ_1 to determine whether a direct effect remains, and compare the signs and magnitudes of λ_1 and $\gamma_1\lambda_2$ to evaluate the type and proportion of mediation.

3.2.2. Relevant variables

In accordance with the research hypotheses, the mediating variable—green technological innovation (tech)—is measured by the number of green patent applications in each province [32]. Compared to patent authorizations, patent applications more accurately reflect the current-year innovation capacity of local firms and are less affected by institutional delays or external biases. Furthermore, green patent applications more precisely capture the region's level of environmentally sustainable development, aligning closely with the theme of this study.

3.2.3. Mediation regression results

Following the above testing procedure, a step-by-step regression analysis was conducted on the mediation model. The results are shown in Table 6.

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Table 6: Mediation effect test results

Variables	(1)	(2)
	tech_z	gdl_z
de_z	1.529***	0.175*
	(3.594)	(1.761)
envi_z	0.463	-0.045
	(0.762)	(-0.360)
open_z	-1.137***	0.126
	(-3.196)	(1.566)
tech_z		0.070**
		(2.196)
_cons	0.000	-0.000
	(0.000)	(-0.000)
N	48	48
R^2	0.488	0.286
F	13.048	3.997

Note: ***p < 0.01, **p < 0.05, *p < 0.10

Interpretation of Results: The results show that the digital economy has a significant direct effect on the green development of reverse logistics (λ_1=0.175, $p < 0.10$), and that green technological innovation has a significant partial mediation effect (λ_2=0.070, $p < 0.05$). The Sobel test further confirms the mediation effect: Estimated indirect effect is approximately 0.107. This accounts for approximately 41.5% of the total effect (0.258). The result is significant at the 10% level (Z = 1.874, p = 0.0609) Analysis of the sign consistency between direct and indirect effects shows they are in the same direction, further validating the presence of partial mediation. In other words, digital economy development not only directly promotes the green transformation of reverse logistics, but also indirectly empowers it through the pathway of green technological innovation. Therefore, the theoretical framework of both Hypothesis 2 and Hypothesis 3 is empirically supported.

4. Conclusion and policy recommendations

4.1. Research conclusions

Based on panel data from 2011 to 2022 for four provinces in the Yangtze River Delta, this study constructs an innovative and systematic evaluation index system for the development level of the digital economy and the green development of reverse logistics. Using benchmark regression and mediation effect models, it empirically verifies the enabling pathways of the digital economy. The key conclusions are as follows:

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4.1.1. The digital economy significantly promotes the green development of reverse logistics through direct empowerment.

Benchmark regression results show that each 1-standard-deviation increase in digital economy development (de_z) raises the green reverse logistics level (gdl_z) by 0.258 standard deviations ($p < 0.01$). This positive impact remains robust after multiple tests (e.g., FGLS coefficient: 0.117, $p < 0.10$), indicating that the digital economy improves green transformation through enhanced resource allocation efficiency and targeted green investment. This supports Hypothesis 1.

4.1.2. Green technological innovation plays a significant partial mediating role.

The mediation model shows that digital economy development indirectly enhances reverse logistics green development through green innovation. The coefficient for the digital economy's impact on green innovation is 1.529 ($p < 0.01$), and the effect of green innovation on reverse logistics is 0.070 ($p < 0.05$), giving an indirect effect of approximately 0.107, accounting for 41.5% of the total effect. The direct effect of the digital economy remains significant after introducing the mediator. This validates the dual-pathway mechanism of direct transmission and mediated empowerment, confirming Hypothesis 2.

4.1.3. Regional disparities and technology diffusion gaps coexist.

Reverse logistics green development levels across the four provinces show a gradient pattern, with Shanghai significantly outperforming Anhui. This suggests that the digital economy's effects are amplified by synergistic policies and infrastructure advantages in core cities, while peripheral areas face "low-efficiency lock-in" due to weak digital infrastructure and low innovation capacity.

4.2. Policy recommendations

In light of the above conclusions, the following targeted policy recommendations are proposed:

(1) Build a tiered digital infrastructure network and establish cross-regional technology collaboration mechanisms. The research findings indicate that the digital economy has a significant direct enabling effect on the green development of reverse logistics, primarily by improving resource allocation efficiency and supporting green transformation. Therefore, to address the inadequate digital infrastructure coverage in provinces such as Anhui and Zhejiang, priority should be given to deploying IoT sensing devices and blockchain data platforms at key nodes like electronic waste recycling centers and remanufacturing hubs. A Yangtze River Delta Digital Collaboration Fund should be established to provide targeted support for less developed areas. Additionally, by leveraging big data platforms, dynamic matching of remanufacturing capacity in Shanghai and Jiangsu with recycling demand in Anhui and Zhejiang should be carried out to optimize cross-regional transportation route planning. Given the partial mediating role of green technological innovation, it is recommended to establish a Yangtze River Delta Green Technology Collaborative Innovation Center, anchored in innovation hubs like Zhangjiang in Shanghai and Suzhou Industrial Park. The center should focus on overcoming key technical bottlenecks such as enhancing the precision of intelligent sorting robots and the application of hydrogen-powered transportation equipment, thereby accelerating green technology innovation and diffusion. Meanwhile, a "technology equity + tax synergy" mechanism should be implemented for SMEs in Anhui and Zhejiang, whereby Shanghai's leading green patents are authorized via a cross-provincial

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technology transfer platform to these enterprises, with complementary policies such as super deductions for R&D expenses to encourage the adoption of green technologies.

(2) Design differentiated carbon governance mechanisms and enhance interregional policy coordination. Based on differences in provincial carbon intensities, the Yangtze River Delta Emissions Trading System should introduce special quotas for reverse logistics. Carbon tax revenues can be earmarked for cloud-based environmental R&D in Zhejiang. An interprovincial ecological compensation fund should be established, requiring Shanghai and Jiangsu to transfer 5% of their environmental budgets annually to Anhui and Zhejiang. These funds would support low-carbon infrastructure like smart recycling bins, reducing the regional gap in decarbonization capacity and promoting coordinated green development.

(3) Deepen digital-market integration mechanisms to mobilize multi-stakeholder participation. To fully leverage the digital economy's impact, a "Yangtze River Delta Reverse Logistics Carbon Credit Platform" should be created. This platform would connect consumer participation with financial incentives, enabling carbon point accumulation. Additionally, green bonds dedicated to reverse logistics should be issued to attract capital for high-impact projects (e.g., Anhui's new energy disassembly bases, Zhejiang's low-carbon packaging R&D). This would ease financial constraints in less-developed areas and foster a "technology-capital-policy" synergy for green transformation.

References

[1] Govindan K, Soleimani H, Kannan D. Reverse logistics and closed-loop supply chain: A comprehensive review to explore the future [J]. European journal of operational research, 2015, 240(3): 603-626.
[2] Saberi S, Kouhizadeh M, Sarkis J, et al. Blockchain technology and its relationships to sustainable supply chain management [J]. International journal of production research, 2019, 57(7): 2117-2135.
[3] Dekker R, Bloemhof J, Mallidis I. Operations research for green logistics–An overview of aspects, issues, contributions and challenges [J]. European journal of operational research, 2012, 219(3): 671-679.
[4] Ivanov D, Dolgui A, Sokolov B. Cloud supply chain: Integrating Industry 4.0 and digital platforms in the "Supply Chain-as-a-Service" [J]. Transportation research part E: logistics and transportation review, 2022, 160: 102676.
[5] Brandenburg M, Govindan K, Sarkis J, et al. Quantitative models for sustainable supply chain management: Developments and directions [J]. European journal of operational research, 2014, 233(2): 299-312.
[6] Savaskan R C, Van Wassenhove L N. Reverse channel design: the case of competing retailers [J]. Management science, 2006, 52(1): 1-14.
[7] Zhu Q, Sarkis J, Lai K. Examining the effects of green supply chain management practices and their mediations on performance improvements [J]. International journal of production research, 2012, 50(5): 1377-1394.
[8] Kristoffersen E, Mikalef P, Blomsma F, et al. The effects of business analytics capability on circular economy implementation, resource orchestration capability, and firm performance [J]. International journal of production economics, 2021, 239: 108205.
[9] Rasool F, Greco M, Morales-Alonso G, et al. What is next? The effect of reverse logistics adoption on digitalization and inter-organizational collaboration [J]. International journal of physical distribution & logistics management, 2023, 53(5/6): 563-588.
[10] Sahal R, Breslin J G, Ali M I. Big data and stream processing platforms for industry 4.0 requirements map** for a predictive maintenance use case [J]. Journal of manufacturing systems, 2020, 54: 138-151.
[11] Agarwal S, Kumar N, Tyagi M, et al. Integrating soft computing techniques for optimizing green vehicular communications and networking in circular digital supply chain [J]. Journal of science and technology policy management, 2025.
[12] Wang X, Li Y, Tian L, et al. Government digital initiatives and firm digital innovation: Evidence from China [J]. Technovation, 2023, 119: 102545.
[13] Yang G, Nie Y, Li H, et al. Digital transformation and low-carbon technology innovation in manufacturing firms: The mediating role of dynamic capabilities [J]. International journal of production economics, 2023, 263: 108969.
[14] Qiao L, Huo D, Sun T, et al. Cross-border e-business and air quality: A quasi-natural experiment from the perspective of natural resources [J]. Sustainability, 2025, 17(7).

DOI: 10.54254/2754-1169/2025.LH25131

[15] Gharibi K, Abdollahzadeh S. A mixed-integer linear programming approach for circular economy-led closed-loop supply chains in green reverse logistics network design under uncertainty [J]. Journal of enterprise information management, 2025, 38(1): 1-31.
[16] Li W, Cui W, Yi P. Digital economy evaluation, regional differences and spatio-temporal evolution: Case study of Yangtze River economic belt in China [J]. Sustainable cities and society, 2024, 113: 105685.
[17] Ma J, Li Z. Measuring China’s urban digital economy [J]. Natl acc rev, 2022, 4: 329-61.
[18] Gao Q, Cheng C, Sun G, et al. The impact of digital inclusive finance on agricultural green total factor productivity: Evidence from China [J]. Frontiers in ecology and evolution, 2022, 10: 905644.
[19] Hammer J, Pivo G. The triple bottom line and sustainable economic development theory and practice [J]. Economic development quarterly, 2017, 31(1): 25-36.
[20] Chen G, Chen J. Reverse logistics network model of dual-channel recycling boxes based on genetic algorithm optimization: A multi-objective and uncertain environment perspective [J]. Sustainability, 2023, 15(5): 4408.
[21] Zhang M, Sun M, Bi D, et al. Green logistics development decision-making: Factor identification and hierarchical framework construction [J]. IEEE access, 2020, 8: 127897-127912.
[22] Graham S, Graham B, Holt D. The relationship between downstream environmental logistics practices and performance [J]. International journal of production economics, 2018, 196: 356-365.
[23] Du K, Cheng Y, Yao X. Environmental regulation, green technology innovation, and industrial structure upgrading: The road to the green transformation of Chinese cities [J]. Energy economics, 2021, 98: 105247.
[24] Li Y, Xu H, Li H, et al. Environmental Regulation, Opening up to the outside world, and regional green industry development: Policy effects and optimization strategies [J]. Finance research letters, 2025: 106837.
[25] Dasaklis T K, Voutsinas T G, Tsoulfas G T, et al. A systematic literature review of blockchain-enabled supply chain traceability implementations [J]. Sustainability, 2022, 14(4): 2439.
[26] Serrano W. The blockchain random neural network for cybersecure IoT and 5G infrastructure in smart cities [J]. Journal of network and computer applications, 2021, 175: 102909.
[27] Yalabik B, Petruzzi N C, Chhajed D. An integrated product returns model with logistics and marketing coordination [J]. European journal of operational research, 2005, 161(1): 162-182.
[28] Feng D, Bao W, Yang Y, et al. How do government policies promote greening? Evidence from China [J]. Land use policy, 2021, 104: 105389.
[29] Hall J, Lacasa I D, Günther J. Path dependence and QWERTY's lock-in: Toward a veblenian interpretation [J]. Journal of economic issues, 2011, 45(2): 457-464.
[30] Yang X, Lei G, Wang X. Can the development of digital construction reduce enterprise carbon emission intensity? New evidence from Chinese construction enterprises [J]. Frontiers in ecology and evolution, 2023, 11: 1250593.
[31] Zhang H. Efficient adjusted joint significance test and sobel-type confidence interval for mediation effect [J]. Structural equation modeling: A multidisciplinary journal, 2025, 32(1): 93-104.
[32] Chen Y, Tang J. The impact of carbon emission intensity on high-quality economic development: An empirical study from 284 prefecture-level cities in China [J]. Polish journal of environmental studies, 2025, 34(1).