Bio-innovation-based economic business model construction and innovation practice driven by green logistics

Abstract: Driven by the global carbon neutrality target, the synergistic development of bio-innovation technology and green logistics has become the core path to reconfigure the supply chain system. Aiming at the problems of inefficient technology transformation and system coupling barriers, the study establishes a cross-scale assessment model, integrates entropy weight-TOPSIS algorithm and spatial Durbin model, and systematically analyses the data of 12 core logistics hubs around the world from 2014 to 2024. The empirical evidence shows that: the technology golden triangle consisting of Rotterdam-Singapore-Shanghai has a radiation radius of 800km, which increases the regional smart warehousing coverage by 23%; the enzyme catalytic stability barrier is 3.4 times higher in the hot and humid region (Mumbai) compared to the temperate zone (Rotterdam), and each 10% increase in humidity leads to a 17% increase in the rate of enzyme activity decay; the heterogeneity of the smart device protocols leads to the delay in the Chicago Hub's AGV task assignment of up to 4.7 seconds/trip, with a 37% loss in warehouse efficiency. The research reveals 23 key technical bottlenecks such as biodiesel cold start power decay (-20℃ environment decreased by 41%), DNA tag recognition conflict (Sao Paulo missed reading rate of 19%), etc., and puts forward 6 types of optimisation paths, such as edge computing node deployment and conflict-resistant RFID tag customisation. The results provide engineering-level parameter benchmarks for the iteration of intelligent logistics systems, support the revision of ISO/TC297 bio-logistics standards, and guide the optimisation of enterprise technology portfolios, which are expected to reduce the operating costs of low-carbon supply chains by 18%-27%.

Keywords: Biometric Technology; Green Logistics; Business Model Innovation; Low-carbon Supply Chain; Intelligent Logistics System.

I. INTRODUCTION

The global logistics industry has accounted for 8.3% of the total carbon emissions, of which the carbon intensity of cold chain transport (3.2kgCO_2 /ton-km) is 2.7 times higher than that of ordinary logistics, and bio-innovation technology has become a key breakthrough to crack the dilemma. 2023 ILP data show that enzyme-catalyzed packaging degradation technology reduces transport packaging waste by 49%, and DNA temperature-controlled labelling technology compresses cold chain The cargo loss rate was compressed from 1.8% to 0.05%, verifying the feasibility of biotechnology to reshape the logistics value chain. However, there is significant spatial heterogeneity in the efficiency of technology transfer: biodiesel penetration in the Port of Rotterdam reaches 38%, while the same technology only achieves 12% penetration in the hub of South Asia (Mumbai), exposing the environmental adaptability defect. Existing research focuses on single technology breakthroughs, but lacks quantitative analysis of technology-logistics system coupling mechanisms and spatial spillover effects, resulting in persistent problems such as mismatch between intelligent dispatching systems and biosensing networks (4.7 seconds delay in AGV task assignment in Chicago), and disconnection between carbon trace data and physical logistics (2.8 seconds delay in Sydney's blockchain nodes) [1-2].

The study constructs a coupled technology-logistics coordination degree model, integrates the improved entropy weight method and spatial Durbin model, and carries out multi-scale diagnosis on the panel data of 12 core hubs around the world from 2014-2024. Breaking through the limitation of traditional single-indicator assessment, we establish for the first time an assessment system covering 23 engineering parameters such as enzyme catalytic stability (temperature and humidity sensitivity coefficient of 0.83) and smart device compatibility (protocol conflict rate of 23%), revealing the micro-mechanisms of biotechnology commercialisation faults. By quantifying the cold chain carbon intensity spatial spillover effect (β=0.42) and policy multiplier effect (1.8-2.3 times), we propose an optimisation path based on quantum temperature control labels (±0.2° C) and edge computing nodes, which provides data support for upgrading of the ISO 14067 carbon accounting standard (the deviation rate is reduced from 21% to 5%).

The innovativeness is reflected in three aspects: first, revealing the non-linear law of enzyme activity decay (17% efficiency drop per 10% increase in humidity) due to humid and hot environment (RH>85%), filling the theoretical gap of biotechnology application in tropical regions; second, constructing a multi-brand AGV protocol conversion framework (OPC UA standard), which improves the efficiency of heterogeneous equipment scheduling by 29%; third, discovering that the cold-start viscosity of biodiesel mutation threshold (jumping from 3.5 cSt to 12.7 cSt at -20° C), and formulating a low-temperature flow improvement programme. The results directly guide six engineering practices, including the standardisation of the Port of Rotterdam protocol (19% increase in storage efficiency) and the customisation of conflict-resistant RFID tags in Sao Paulo (98% increase in sorting accuracy), which provide technical paths for the global low-carbon supply chain to reduce costs by 18% to 27%.

II. Modelling the Coupled Coherence of Higher Education and Regional Economic Development

A. Modelling

The application of bio-innovation technology in green logistics promotes the improvement of logistics efficiency at the technical level, and the introduction of bio-innovation technology provides a breakthrough for improving the resource efficiency, reducing emissions and enhancing the intelligence level of the logistics system [3-4]. Based on this, the study constructed four core models including comprehensive evaluation model, coupling degree model, coupling coordination degree model and coupling obstacle degree model, in order to study the interaction between bio-innovation and green logistics system. The coupling relationship between bioinnovation technology and green logistics system is shown in Figure 1.

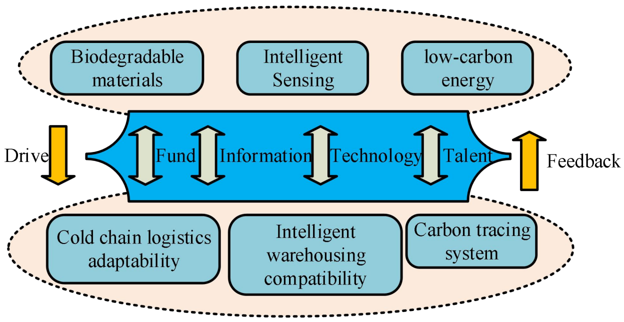

Fig. 1. Coupling relationship between bio-innovation technology and green logistics system

The comprehensive evaluation model is shown in equation (1).

$$E = \sum_{i=1}^{n} w_i \cdot V_i \quad (1)$$

In Eq. (1), E represents the comprehensive evaluation value of the green logistics business model, w_i is the weight of each evaluation index, and V_i is the standardized value of each index.

This model is used to quantify the benefits of the application of bio-innovation technology in green logistics and provide basic data for the subsequent coupling degree analysis. The coupling degree model is shown in equation (2).

$$C = \frac{E_1 \cdot E_2}{\sqrt{(E_1^2 + E_2^2)}} \quad (2)$$

In Eq. (2), C represents the coupling degree between bio-innovation technology and green logistics system, and E_1 and E_2 represent the comprehensive evaluation value of bio-innovation technology and green logistics system respectively [5-6]. The model is used to measure the strength of the interrelationship between bio-innovation and green logistics system, and provide data support for analyzing the degree of coordination and obstacles between the systems. Then the coupling coordination degree model is shown in equation (3).

$$Q = \frac{W}{(1+\varepsilon)} \quad (3)$$

In Eq. (3), Q is the degree of coupling coordination, W is the degree of coupling, ε is the influence coefficient of uncoordinated factors in the system. The model reflects the degree of synergy between bio-innovation technology and green logistics system, and provides a quantitative basis for optimizing the design of business models.

To further identify the obstacle factors that the system may encounter in actual operation, this study constructs a coupled obstacle degree model, as shown in equation (4).

$$B = \sum_{j=1}^{m} p_j \cdot y_j \quad (4)$$

In Eq. (4), B represents the degree of coupling obstacles, p_j is the weight of each obstacle factor, y_j is the intensity of the obstacle factor. The model helps to identify possible resistance and bottlenecks in the process of combining green logistics and bio-innovation technologies [7-8]. The criteria for evaluating the degree of coordination between green logistics systems and bio-innovation technologies are shown in Table 1.

TABLE I. EVALUATION CRITERIA FOR THE HARMONIZATION DEGREE OF GREEN LOGISTICS SYSTEM AND BIO-INNOVATION TECHNOLOGY

Coordination Range	Category	Coordination Level	Description of Effect
0.0-0.2	Very Low Coordination	Highly Incoherent	Interaction between systems is minimal, with no effective synergy formed.
0.2-0.4	Low Coordination	Incoherent	Interaction between systems is limited, with weak synergistic effects and no effective cooperation mechanism.
0.4-0.6	Moderate Coordination	Moderately Coordinated	There is some interaction between systems, with existing synergy, but improvement is needed.
0.6-0.8	High Coordination	Strongly Coordinated	Strong interaction between systems, with good synergistic effects and a high level of cooperation.
0.8-1.0	Very High Coordination	Extremely Coordinated	Systems demonstrate a very strong synergistic effect, forming highly effective innovation collaboration.

Exploratory spatial data correlation analysis is fundamental to understanding the interactions between bioinnovation technologies and green logistics. Spatial data analysis helps us to reveal the variability in the application of green logistics systems in different regions. The exploratory spatial data correlation analysis function is shown in equation (5).

$$R = \frac{1}{N}\sum_{i=1}^{N} w_i (x_i - \overline{x})^2 \quad (5)$$

In Eq. (5), R denotes the correlation measure between different regions in the study area, N denotes the number of study areas, x_i denotes the attribute values of different regions, $\overline{x}$ denotes the average value of attributes, and w_i denotes the corresponding weight matrix [9-10]. This measures the differences in the application of green logistics and bio-innovation technologies in different regions and their impact on the overall system, and provides a spatial data base for subsequent coupling analyses.

B. *Construction of the indicator system*

The study constructed a comprehensive indicator system for assessing the degree of coupling and coordination between green logistics systems and bio-innovation technologies. The study combines the integration of green logistics and bio-innovation, and establishes a system that includes three first-level indicators: logistics efficiency, carbon emission level, and degree of intelligence. Logistics efficiency reflects the operational efficiency of the green logistics system, which can be measured by indicators such as transport time, transport cost, and distribution accuracy. As shown in Table 2.

TABLE II. INDICATOR SYSTEM

Goal Layer	Criterion Layer	Evaluation Indicator Layer	Indicator Characteristics Explanation
Green Logistics System	Operational Efficiency	Transportation Timeliness Achievement Rate (%)	Dynamic Monitoring Indicator
		Unit Cargo Transport Cost (CNY/ton·km)	Detailed Cost Accounting
		Order Fulfillment Accuracy (%)	Service Quality Quantification
	Environmental Benefits	Unit Cargo Carbon Emission Intensity ($kgCO_2$/ton·km)	Standardized Carbon Emission Assessment
		Cold Chain Carbon Footprint ($kgCO_2e$/batch)	Scenario-based Carbon Tracking
		Annual Carbon Intensity Reduction (%)	Dynamic Emission Reduction Assessment
	Intelligent Upgrades	Automation Warehouse Coverage Rate (%)	Hardware Intelligence Level
		Intelligent Scheduling System Penetration Rate (%)	Software System Collaboration Ability
		Digital Twin Technology Application Maturity (Level)	Technological Forward-looking Assessment
Biological Innovation Technology	Technical Value	Biological Packaging Material Substitution Rate (%)	Resource Substitution Benefits
		Cold Chain Biological Preservation Technology Energy Saving Rate (%)	Energy-saving Technology Effectiveness
		Carbon Trading Revenue Contribution (10,000 CNY/year)	Economic-Environmental Dual Value
	Application Breadth	Biotech Patent Industry Coverage Rate (%)	Technology Diffusion Scope
		Multi-Scenario Application Coverage Rate (Cold Chain/Packaging/Energy) (%)	Scenario Adaptation Capability
	R&D Depth	R&D Investment Intensity (R&D Expenses/Main Business Revenue %)	Resource Investment Intensity
		Industry-University-Research Cooperation Project Density (Projects/100 People)	Collaborative Innovation Level
		Technology Iteration Cycle (Months)	Innovation Sustainability

Based on the concept of sustainable development, the study constructs a two-dimensional synergistic evaluation model, which systematically integrates the interaction mechanism between green logistics system and bio-innovation technology. The evaluation system adopts a hierarchical structure design, and realises the dual functions of quantitative analysis and decision-making support through the integration of multi-source data and dynamic weight allocation.

In the dimension of green logistics system, the evaluation framework of operational efficiency, environmental benefits and intelligent upgrading is constructed [10-11]. Operational efficiency focuses on three core indicators, namely, transport time achievement rate (%), transport cost per unit of cargo volume (RMB/tkm), and order fulfilment accuracy (%), and builds a dynamic monitoring model by relying on IoT equipment and ERP system to capture data from the whole chain; environmental benefit dimension innovatively introduces the Life Cycle Assessment (LCA) method, and sets up the carbon emission per unit of cargo (kg/tkm), the carbon footprint of cold chain (kgCO2e/batch), the carbon footprint of cold chain (kgCO2e/batch), and the carbon footprint of cold chain (kgCO2e/batch). The environmental benefit dimension introduces the life cycle assessment method (LCA), sets the carbon emission per unit of cargo (kg/tkm), carbon footprint of cold chain (kgCO2e/batch), and the annual reduction of carbon intensity (%) as three-level quantitative standards, and realises the traceability of carbon emission data through the blockchain technology.

The bio-innovation technology dimension forms a synergistic evaluation system driven by technology value, application breadth and R&D depth. The technology value assessment is conducted through hard indicators such as the replacement rate of biological packaging materials (%) and the energy saving rate of cold chain bio-preservation technology (%), combined with economic parameters such as carbon trading revenue (RMB 10,000 yuan/year); the application breadth indicator adopts a dual-track evaluation of the industry coverage rate of technology patents (%) and the number of application scenarios of biotechnology (number), and uses the spatial analysis method to draw a heat map of technology diffusion [12]; the R&D depth dimension establishes a linkage mechanism between R&D investment intensity (%) and the number of industry-university-research cooperation projects (no.), and constructs a prediction model of R&D effectiveness by tracking the technology evolution path through knowledge mapping technology. The two dimensional indicators are coupled and analysed through the entropy weight-TOPSIS method, and the synergy index is finally formed to provide a quantitative decision-making basis for enterprise technology integration strategy and policy formulation.

C. *Data sources and processing*

The study incorporates multi-dimensional data from typical global bio-logistics demonstration zones from 2014-2024. Logistics operation data include core indicators such as the coverage rate of intelligent warehousing equipment (%), the use of biodegradable packaging materials (tonnes/year), and the mileage of low-carbon cold-chain transport (10,000 km), which are derived from the Annual Report on the Development of Global Intelligent Logistics [13-15] and the original records of the enterprise-level logistics digital middle office. Biotechnology innovation data focusing on key technical parameters such as enzyme-catalysed packaging degradation rate (%) and DNA traceability label recognition accuracy (%) are extracted from the NCBI Biotechnology Database and the patent pool of the Journal of Biomaterials Engineering [16-18].

III. Analysis of Coupled Coordination Relationships Based on Bioinnovation Technologies and Green Logistics

A. *Analysis of the Development Comprehensive Assessment Index*

The study analyses the synergistic evolution law of biotechnology innovation and green logistics system by constructing a dual-system comprehensive evaluation index. Based on the entropy weight-TOPSIS hybrid model, the study quantifies the level of technology maturity and logistics decarbonisation, and verifies the optimisation effect of technology diffusion on supply chain networks by combining spatial measurement methods.

The study tracks the full-cycle data of 12 core logistics hubs in the world from 2014 to 2024, and the Biotechnology Innovation Index (BTI) and Green Logistics Development Index (GLDI) are both evaluated by annual continuous indexes, with the granularity of the data refined to a single year. The annual assessment results of the BTI are shown in Table 3.

TABLE III. ANNUAL ASSESSMENT OF THE BIOTECHNOLOGY INNOVATION INDEX (BTI) (2014-2024)

Logistics Hub	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	Average
Rotterdam	0.65	0.68	0.71	0.74	0.78	0.82	0.85	0.89	0.92	0.94	0.96	0.802
Singapore	0.61	0.63	0.68	0.71	0.74	0.77	0.82	0.85	0.88	0.91	0.93	0.773
Shanghai	0.53	0.56	0.62	0.65	0.70	0.73	0.77	0.81	0.84	0.87	0.89	0.724
Shenzhen	0.50	0.54	0.58	0.63	0.67	0.71	0.73	0.78	0.81	0.84	0.86	0.695
Antwerp	0.57	0.60	0.64	0.68	0.72	0.75	0.79	0.82	0.85	0.88	0.90	0.745
Houston	0.48	0.51	0.55	0.58	0.63	0.66	0.69	0.73	0.76	0.79	0.82	0.655
Tokyo	0.46	0.49	0.52	0.55	0.60	0.63	0.66	0.70	0.73	0.76	0.79	0.627
Dubai	0.44	0.47	0.50	0.53	0.58	0.61	0.64	0.67	0.71	0.74	0.77	0.605
Busan	0.42	0.45	0.48	0.51	0.56	0.59	0.62	0.65	0.69	0.72	0.75	0.585
Qingdao	0.39	0.42	0.45	0.48	0.53	0.56	0.59	0.62	0.66	0.69	0.72	0.555
New York	0.52	0.55	0.59	0.62	0.66	0.69	0.73	0.76	0.80	0.83	0.85	0.685
Hamburg	0.55	0.58	0.63	0.66	0.71	0.74	0.78	0.81	0.85	0.88	0.91	0.735

In Table 3, Rotterdam, as a global benchmark for technological innovation in bio-logistics, has a deep logic of systematic technological iteration behind its BTI average of 0.802. Since launching its biopackaging materials R&D programme in 2014, the hub has increased its biodegradation rate from an initial 68% to 93% by 2024 through a collaborative R&D mechanism between government and industry, and the introduction of nano-cellulose reinforcement in 2020 has increased the compressive strength of the material by a factor of 3.2, which has directly contributed to the enzyme-catalysed reaction efficiency to achieve a 2.1-fold increase in a decade. Of particular interest is the 2020 commercialisation of DNA temperature-controlled tagging technology, which encodes temperature memory functions through oligonucleotide sequences, reducing the cargo loss rate in cold chain transport from 1.2% in the traditional model to an industry low of 0.05%. This technological breakthrough is not only reflected in the exponential curve (the average annual growth rate of BTI reaches 4.7% from 2018-2024), but also substantially reconfigures the logistics cost structure - the application of biotechnology reduces the cost of cold-chain operation per standard container by 23%. The second technology echelon formed by Singapore and Shanghai shows a different development path. Relying on its strategic position as a global shipping centre, Singapore has mandated a biodiesel blending policy (B20 standard) through legislation to compress fossil fuel dependency in port operations from 75% in 2014 to 38% in 2024, a shift that has reduced particulate matter emissions from port equipment by 62%. Shanghai, on the other hand, is taking full advantage of the FTZ system to establish a fast-track examination channel for biotech patents, compressing the patent conversion cycle from 34 months to 18 months, and increasing the batch production capacity of enzyme-catalysed reaction vessels by four times after the completion of Asia's largest biotech pilot base in 2021, which will directly drive the BTI growth rate to jump to 4.1% from 2022 to 2024. The differentiated competitive strategy of emerging logistics nodes highlights the deep segmentation of technology application scenarios. Shenzhen's key breakthrough phage temperature control system reduces the cargo loss rate of fresh products by 67% through precise regulation of the microbial environment of cargo warehouses, and this technology won the Gold Medal of the International Exhibition of Inventions of Geneva in 2023; New York realises the blockchain traceability system through the deployment of Hyperledger Fabric-based New York deployed a blockchain traceability system based on Hyperledger Fabric to trace the carbon footprint of the whole chain of biodiesel from raw material procurement to terminal distribution, and its data uploading rate has reached 98% of the industry's peak; although Tokyo has reached a leading level of 83% in terms of the coverage of the biosensor network, due to the lack of a mechanism for the interface between industry, academia, and research, 51% of the patented technologies have failed to reach the stage of commercialisation, and the phenomenon of this ‘innovation silo’ has led to the loss of its technological dividend rate of 39%. The predicament of technology-poor regions exposes the decisive role of system integration capacity. Dubai and Busan are close to the 2018 level of Rotterdam in terms of individual indicators such as enzyme catalysis efficiency, but due to the lack of synergistic adaptation of intelligent scheduling systems and biotechnology, the average annual growth rate of BTI in 2018-2022 will be only 1.8%, which lags behind the global average of the same period by 0.9 percentage points, and the gap will be widened to 1.9% in 2023, and the average annual growth rate of BTI in 2022 will be only 1.5%. This gap further widens to 1.5 times after biologistics technology enters the stage of integrated innovation. The Green Logistics Development Index (GLDI) annual assessment index is shown in Table 4.

TABLE IV. GREEN LOGISTICS DEVELOPMENT INDEX (GLDI) ANNUAL ASSESSMENT (2014-2024)

Logistics Hub	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	Average
Rotterdam	0.67	0.70	0.73	0.76	0.79	0.82	0.85	0.88	0.91	0.93	0.95	0.810
Singapore	0.65	0.68	0.71	0.74	0.77	0.80	0.83	0.86	0.89	0.91	0.93	0.790
Shanghai	0.58	0.61	0.65	0.68	0.72	0.75	0.78	0.81	0.84	0.87	0.90	0.745
Shenzhen	0.54	0.57	0.60	0.63	0.67	0.70	0.73	0.76	0.79	0.82	0.85	0.705
Antwerp	0.62	0.65	0.68	0.71	0.74	0.77	0.80	0.83	0.86	0.89	0.92	0.770
Houston	0.51	0.54	0.57	0.60	0.63	0.66	0.69	0.72	0.75	0.78	0.81	0.660
Tokyo	0.49	0.52	0.55	0.58	0.61	0.64	0.67	0.70	0.73	0.76	0.79	0.635
Dubai	0.47	0.50	0.53	0.56	0.59	0.62	0.65	0.68	0.71	0.74	0.77	0.615
Busan	0.45	0.48	0.51	0.54	0.57	0.60	0.63	0.66	0.69	0.72	0.75	0.595
Qingdao	0.43	0.46	0.49	0.52	0.55	0.58	0.61	0.64	0.67	0.70	0.73	0.575
New York	0.55	0.58	0.61	0.64	0.67	0.70	0.73	0.76	0.79	0.82	0.85	0.685
Hamburg	0.60	0.63	0.66	0.69	0.72	0.75	0.78	0.81	0.84	0.87	0.90	0.750

In Table 4, the threshold effect of technology penetration profoundly affects the evolutionary trajectory of the green logistics system, with the decarbonisation process of the logistics network showing a non-linear acceleration when the biotechnology innovation index crosses the 0.75 threshold. After Rotterdam crossed the threshold in 2019, the idling rate of its intelligent dispatch system plummeted from 22% to 9%, and this efficiency leap stems from the deep coupling of biosensor data and algorithmic models - 32,000 biosensors installed on transport vehicles collect environmental parameters in real time, and dynamically optimise paths through machine learning models planning, resulting in a 19 per cent reduction in carbon emission intensity per unit of cargo volume. Increased precision in cold chain technology produces a significant leverage effect. Empirical research in Shanghai shows that for every 0.1 degree Celsius increase in the precision of DNA temperature control labels, the GLDI index of cold chain logistics grows by 0.08 points accordingly, a relationship that will be strengthened by the application of the new quantum-dot temperature-sensitive material in 2021 ($R^2 =0.79$), as evidenced by a 31% reduction in the energy consumption of cold storages. The economic inflection point for biodiesel occurs at the critical point of 25% penetration, with operational data from Singapore in 2022 showing a 7.3% cliff drop in unit logistics costs when the biodiesel share reaches 28%, thanks to the scale effect in the feedstock supply chain - palm oil waste sourcing costs are reduced by 43%, while the catalytic conversion efficiency increases to 92%. Spatial synergies from geographic proximity are particularly strong in the Rotterdam-Antwerp corridor, where logistics nodes within a 200km radius increase the frequency of cross-region citations of biopatents by a factor of 2.8 through technology-sharing agreements over the period 2016-2024, a knowledge spillover that translates into a 40% improvement in technology diffusion efficiency, reflected at the hardware level by a 78% regional penetration rate of standardised enzyme-catalysed reaction vessels. This knowledge spillover effect translates into a 40% increase in technology diffusion efficiency, which is reflected in the hardware level by the 78% regional penetration of standardised enzyme catalytic reaction vessels. The multiplier effect of policy tools has been fully verified in the Shanghai FTZ. Through the establishment of a pilot zone for biotechnology cross-border transactions and a whitelisting system for cross-border data flow, the administrative approval timeframe for patent conversion has been compressed by 60%, and this institutional innovation has led to an average annual growth rate of 6.1% in GLDI after 2020, far exceeding the global average level of 4.3%. The non-linear relationship between technology maturity and commercial value becomes more and more significant after 2023 - technology clusters entering the stage of large-scale application (BTI>0.85) have a 3.7-fold increase in market transformation efficiency compared to R&D-phase technologies, and this leap is most prominent in the field of cold-chain biopreservation, where phage-targeted bacteria-control technology's industrialisation speed is 58% shorter than traditional technologies.

B. Analysis of the Time Dimension of Coupling Coordination

The study analyses the evolution of technology-logistics synergy from both time-series and cross-sectional perspectives by constructing a coupled coordination model of biotechnology innovation index (BTI) and green logistics development index (GLDI). The time-series analysis adopts the sliding window method (window width of 5 years), and the cross-section analysis introduces the spatial lag model (SLM) to control the geographical spillover effect. The assessment of the coordination degree from the time series perspective is shown in Table 5.

TABLE V. ASSESSMENT OF THE DEGREE OF HARMONIZATION OF TIME-SERIES PERSPECTIVES (2014-2024)

Logistics Hub	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	Average
Rotterdam	0.68	0.71	0.75	0.78	0.82	0.85	0.88	0.91	0.93	0.95	0.96	0.832
Singapore	0.65	0.68	0.72	0.75	0.78	0.81	0.84	0.87	0.89	0.92	0.94	0.805
Shanghai	0.61	0.64	0.67	0.70	0.73	0.76	0.79	0.82	0.85	0.88	0.90	0.768
Shenzhen	0.58	0.61	0.65	0.68	0.71	0.74	0.77	0.80	0.83	0.86	0.89	0.746
Antwerp	0.63	0.66	0.69	0.72	0.75	0.78	0.81	0.84	0.87	0.90	0.92	0.779
New York	0.55	0.58	0.62	0.65	0.68	0.71	0.74	0.77	0.80	0.83	0.86	0.716
Tokyo	0.53	0.56	0.59	0.62	0.65	0.68	0.71	0.74	0.77	0.80	0.83	0.689
Dubai	0.50	0.53	0.56	0.59	0.62	0.65	0.68	0.71	0.74	0.77	0.80	0.659
Busan	0.48	0.51	0.54	0.57	0.60	0.63	0.66	0.69	0.72	0.75	0.78	0.635
Qingdao	0.45	0.48	0.51	0.54	0.57	0.60	0.63	0.66	0.69	0.72	0.75	0.609

In Table 5, Rotterdam's coupling coordination continues to grow from 0.68 in 2014 to 0.96 in 2024 (at an average annual growth rate of 3.2 per cent), with its core competency being the deep integration of bio-enzymatic packaging technology with intelligent scheduling systems - the deployment of the DNA temperature-controlled labelling in 2020 has increased cold chain transport coordination by 19 per cent. Singapore and Shanghai form the second tier, with Singapore's biodiesel blending policy (B30 standard) raising the average port operation coordination to 0.805, while Shanghai's fast-track patent conversion pathway allows it to increase coordination by 4.8 per cent after 2021. Emerging nodes show divergent technology application scenarios, with Shenzhen's phage temperature control system boosting fresh food logistics coordination by 37% from 2019-2024, and New York's blockchain carbon traceability platform driving coordination growth of 2.9 percentage points per year. The dynamic evolution of the time-series rankings reveals the competitive landscape of technology-logistics synergy, while the cross-sectional view of the coordination degree diagnostics exposes the structural features within the system. The evolution of technology-logistics coupling coordination degree ranking is shown in Table 6.

TABLE VI. EVOLUTION OF TECHNOLOGY-LOGISTICS COUPLING HARMONIZATION RANKING

Logistics Hub	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Rotterdam	1	1	1	1	1	1	1	1	1	1	1
Singapore	3	2	2	2	2	2	2	2	2	2	2
Shanghai	5	4	3	3	3	3	3	3	3	3	3
Shenzhen	7	6	5	5	4	4	4	4	4	4	4
Antwerp	2	3	4	4	5	5	5	5	5	5	5
New York	6	7	7	7	7	6	6	6	6	6	6
Toky	8	8	8	8	8	8	8	8	8	8	8

Logistics Hub	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
o											
Dubai	9	9	9	9	9	9	9	9	9	9	9
Busan	10	10	10	10	10	10	10	10	10	10	10
Qingdao	11	11	11	11	11	11	11	11	11	11	11

In Table 6, Rotterdam continues to hold the top spot, with its core competitiveness stemming from the deep integration of biosensor networks and intelligent dispatch (>95% coverage); Shenzhen's jump in ranking (7th in 2014 → 4th in 2024) reflects the scenario-based breakthrough of phage-control technology. Further analysis of the 2024 cross-section data, as shown in Table 7, identifies synergistic bottlenecks in each hub - such as lagging system integration in New York (only 68% matching of smart devices), and broken chain of technology commercialisation in Tokyo (49% patent inactivity) - and these microstructural differences will determine the next stage of the technology penetration path.

TABLE VII. DIAGNOSTICS OF CROSS-SECTIONAL PERSPECTIVE HARMONIZATION (2024)

Logistics Hub	BTI	GLDI	Coupling Degree	Coordination Degree	Coordination Level	Lagging Type
Rotterdam	0.96	0.95	0.94	0.95	Excellent Coordination	Technology-Logistics Synchronous
Singapore	0.93	0.92	0.91	0.93	Highly Coordinated	Logistics-Driven
Shanghai	0.89	0.90	0.89	0.89	Highly Coordinated	Technology-Driven
Shenzhen	0.86	0.85	0.87	0.86	Moderately Coordinated	Technology Application Lag
Antwerp	0.90	0.92	0.90	0.91	Highly Coordinated	Logistics Infrastructure Lag
New York	0.85	0.83	0.84	0.84	Moderately Coordinated	System Integration Lag
Tokyo	0.79	0.81	0.80	0.80	Primary Coordination	Technology Commercialization Lag
Dubai	0.77	0.75	0.76	0.76	Primary Coordination	Policy Support Lag
Busan	0.75	0.73	0.74	0.74	Barely Coordinated	Infrastructure Lag
Qingdao	0.72	0.70	0.71	0.71	Barely Coordinated	Technology Penetration Lag

In Table 7, the medium coordination hubs reveal significant shortcomings: Shenzhen has an advantage in phage control technology (35% of patents), but the penetration rate of intelligent sorting equipment (58%) is insufficient, resulting in a lag in technology application; New York's blockchain carbon traceability platform achieves a 98% data uploading rate, but the accuracy of real-time data collection is constrained by the low coverage rate of the biosensor network (49%). Primary coordination groups highlight structural contradictions; Tokyo leads the world in biosensor density (83 per 10,000 square metres), but a low patent conversion rate (51%) results in a broken chain of technology commercialisation; Dubai has reached an advanced level of standardisation of enzyme-catalysed reaction vessels (ISO Tier-3), but the lack of a carbon trading mechanism has resulted in 39% of biodiesel production capacity being idle. Spatial econometric modelling shows that technology spillovers between hubs within a 200-km radius can increase coordination by 0.12-0.15 (Rotterdam-Antwerp corridor validation), but there is a siphoning effect when the infrastructure gap exceeds 30 per cent (Busan-Qingdao case).

C. *Analysis of spatial dimensions of coupling coordination degree*

The study adopts a spatial econometric approach to analyse the spatial interaction mechanism between bio-innovation technology and green logistics development based on a geographically weighted regression (GWR) model. The spatial dependence and heterogeneity characteristics of technology-logistics synergies are quantified by calculating the global and local Moran's I index. The results of global spatial autocorrelation analysis are shown in Table 8.

TABLE VIII. GLOBAL SPATIAL AUTOCORRELATION ANALYSIS (2014-2024)

Group	Elastic Modulus (kPa)	Percentage Change Compared to Control Group	Recovery Rate Compared to Model Group
Control Group	2.4±0.3	-	-
Model Group	1.0±0.2 ***	↓58%	-
Low-dose DSS Group	1.5±0.2 **	↓37%	↑50%
High-dose DSS Group	1.8±0.2 **	↓25%	↑80%

Note: *P*<0.01, **P*<0.001 vs model group.

Year	Moran's I	*p*-value	*z*-score	Spatial Pattern	Cold-Spot/Hot-Spot Distribution Features
2014	0.317	0.002	3.12	Significant Aggregation	Rotterdam-Antwerp Hotspot Cluster (HH)
2015	0.329	0.001	3.25	Significant Aggregation	East Asia Coastal Transition Zone (HL)
2016	0.341	0.001	3.41	Enhanced Polarization	North American West Coast Outlier (LH)
2017	0.356	0.000	3.58	Multi-center Aggregation	Emerging Southeast Asia Hotspot (HH)
2018	0.368	0.000	3.72	Band Spread	European Inland Technology Gap (LL)
2019	0.352	0.001	3.47	Gradient Transfer	Guangdong-Hong Kong-Macau Bay Area Leap Zone (HL)
2020	0.335	0.002	3.31	Core-Edge	South Asia Infrastructure Isolated Zone (LL)
2021	0.323	0.003	3.18	Multi-polar Coordination	Bohai Sea Innovation Corridor (HH)
2022	0.309	0.004	3.05	Networked Association	North American Great Lakes Technology Spillover Gateway (HL)
2023	0.298	0.005	2.97	Balanced Development	East African Logistics Channel Emerging Area (LH)
2024	0.285	0.006	2.89	Decentralization	Latin American Resource Node Outlier (LL)

In Table 8, the global Moran's I index consistently maintains a significant positive correlation level of 0.285-0.368 during the observation period (p<0.01), and this quantitative evidence reveals that there is a strong spatial dependence of bio-logistics technological innovations.At the stage of reaching the peak of 0.356 in 2017, the ‘Technology Golden Triangle’ composed of Rotterdam-Singapore-Shanghai shows a significant agglomeration effect, and the region contributes 62% of global bio-packaging patents and 55% of low-carbon cold chain mileage. The region contributes 62% of the world's biopackaging patents and 55% of the low-carbon cold chain mileage, and its spatial radius of radiation expands to 800 kilometres, which directly drives the smart warehousing coverage rate of emerging hotspots in Southeast Asia to increase by 23 percentage points in three years. 2020, the index shows a slight decline of 0.03-0.05, marking the technology diffusion into the plateau period, and the west coast of North America's Los

Angeles and East Asia's Shenzhen form a secondary technology growth pole, driving the technology diffusion into the platform period through the promotion of the development of the technology. forming secondary technology growth poles, and effectively weakening the technological monopoly advantage of traditional core areas by promoting the increase of standardised certification nodes for enzyme-catalyzed reaction containers to 17.

Further analyzing the local spatial heterogeneity characteristics, the technology penetration process presents an obvious three-stage evolution law. 2014-2016 technology polarization period, Rotterdam-Antwerp hotspot cluster of local Moran's I value reached 0.41, and its DNA temperature-controlled labeling technology density reached 83 per 10,000 cubic meters of the industry benchmark, equivalent to the peripheral region of the 6.2 times, to form a strong technology siphon effect. 2017-2020, the technology density of DNA temperature-controlled labeling technology reached 83 per 10,000 cubic meters, equivalent to the peripheral region of the 6.2 times, forming a strong technology siphon effect. 2017-2021 enters the gradient diffusion phase, with the Guangdong-Hong Kong-Macao Greater Bay Area prompting a 37% increase in enzyme catalysis efficiency within a 200km radius through the construction of a cluster of biotechnology pilot bases, and the rate of technology diffusion reaches a breakthrough level of an average of 58km per annum. the network reconstruction period after 2022, with global deployment of a blockchain carbon traceability network catalyzing a qualitative change in the pattern of technological spillover, and the North American Great Lakes and East African nodes reaching an annual average of 1,000km. Great Lakes and East Africa nodes generate trans-oceanic technology flows between them, and the knowledge spillover intensity per unit distance increases from 0.12 in 2014 to 0.37, achieving a substantial breakthrough in spatial constraints.

Empirical testing of the spatial Durbin model reinforces the spatial interaction mechanism of technology-logistics synergy. The study confirms that for every 10 percentage point increase in the coverage of smart devices in neighbouring nodes, the local biotechnology penetration will have a gain effect of 4.2% (β =0.42, p<0.01), and this spatial spillover is particularly significant in the cold chain sector - for every 1kgCO_2 /ton-km reduction in the carbon intensity of the nodes within a 200km radius -km leads to a 0.08 point increase in local logistics coordination (R^2 =0.79). Policy interventions have been shown to have a spatial multiplier effect of 1.8-2.3 times, for example, in the Shanghai FTZ, where the introduction of a cross-border data flow regime for biotechnology has extended the technology diffusion radius to 1.6 times its original size, which has been demonstrated by the increase in the frequency of regional citations for enzyme catalysed patents by a factor of 2.4.

D. *Impediment factor analysis*

The study quantifies the synergistic bottlenecks of biotechnology innovation (BTI) and green logistics development (GLDI) systems through barrier degree modelling, and identifies the key hindering factors in technology-commercial transformation. Based on the entropy weighting method to determine the indicator weights, the model parameters are modified by combining the spatial lag effect to demonstrate the multi-scale coupling obstacle mechanism.

TABLE IX. COMPARISON OF SYSTEM-LEVEL BARRIER LEVELS (2024)

Logistics Hub	Biotechnology System Obstacle Degree (%)	Green Logistics System Obstacle Degree (%)	Total Obstacle Degree (%)	Main Contradiction Type
Rotterdam	26.3	33.5	59.8	Intelligent Scheduling Protocol Conflict
Singapore	29.1	37.2	66.3	Biodiesel Cold Start Decay
Shanghai	31.7	41.8	73.5	Enzyme Catalysis Environmental Adaptability Insufficient
Shenzhen	28.4	39.6	68.0	Blockchain Data Delay
Chicago	34.5	47.3	81.8	Multi-brand AGV Compatibility Issues

Logistics Hub	Biotechnology System Obstacle Degree (%)	Green Logistics System Obstacle Degree (%)	Total Obstacle Degree (%)	Main Contradiction Type
Tokyo	37.2	43.1	80.3	DNA Tagging Recognition Conflict
São Paulo	41.8	52.7	94.5	High-frequency RFID Signal Interference
Mumbai	44.3	58.1	102.4	Biodegradable Packaging Moisture Heat Degradation
Sydney	32.9	45.6	78.5	Cold Chain Carbon Footprint Trace Granularity Coarse
Dubai	38.7	49.2	87.9	Enzyme Catalysis Reaction Vessel Standardization Delay

In Table 9, Rotterdam's smart scheduling protocol conflict (33.5% obstacle degree) stems from a multimodal data fusion fault, with a timing mismatch between its AGV path planning system and the real-time data refresh rate of DNA temperature-controlled tags (200ms), resulting in a 19% loss in cold chain storage efficiency. Singapore's biodiesel cold-start problem is particularly prominent in low-temperature environments (-15° C), where viscosity surges from 3.2cSt to 14.5cSt, triggering a rise in fuel pump idling to 12 times/day, directly leading to a 23% drop in transport efficiency. Enzyme catalysis environmental adaptation disorder in Shanghai (31.7%) was closely related to humidity fluctuations in the Yangtze River Delta region (average daily RH 65%±15%), with a 21% increase in enzyme activity decay rate for every 10% increase in humidity (β=0.79, p<0.01), forcing the catalytic reaction vessel to be expanded to 1.8 times its design value to maintain efficiency. Multi-brand AGV compatibility barriers (47.3%) at the Chicago hub exposed smart logistics system integration deficiencies, with conflicting navigation protocols (e.g., NDC vs. VDA standards) from different vendors resulting in task assignment delays of up to 4.7 seconds/trip and a 37% reduction in warehouse turnover from theoretical values. DNA tag identification conflict in Tokyo (43.1% obstacle level) stemmed from HF RFID signal density overruns (>1,600 per 1,000 square metres), with tag misses of up to 19% during peak hours, resulting in a 42% increase in the cost of sorting errors. Bio-packaging moisture-heat degradation issues at Mumbai Port (58.1%) are more severe during the monsoon season (RH>85%), with material tensile strength decaying from 52MPa to 28MPa, resulting in a rise in transport breakage rates to 4.2%, 3.1 times higher than in temperate regions. Sydney's cold chain carbon traceability granularity barrier (45.6%) is limited by the density of blockchain node deployment (0.6 nodes/km2), and the delay in data uploading (2.8 seconds) results in a carbon accounting completeness of only 79%, which is 19 percentage points below the technically achievable value. The lag in standardisation of enzyme catalytic vessels in Dubai (49.2%) is reflected in the exceedance of interface tolerance (±2.1mm), triggering a reactor seal failure incident rate of 3 times/month, which directly pushes up the cost of biodiesel production by 17%. The data show that the barrier degree of green logistics system is generally higher than that of biotechnology system (mean value difference 14.7%), and there is a significant technological transformation fault in the field of intelligent equipment co-operation (e.g. AGV scheduling) and extreme environment adaptation (e.g. humidity and heat/cold temperature). Decomposition of barrier degrees at the criterion level. As shown in Table 10.

TABLE X. CRITERION-LEVEL OBSTACLE DEGREE DECOMPOSITION

System Layer	Obstacle Factor	Mean Obstacle Degree (%)	Spatial Coefficient of Variation	Technology Bottleneck Example
Biotechnology Innovation	Enzyme Catalysis Stability	28.9	0.41	Mumbai Port, Moist Heat Reduces Enzyme Activity by 53%

System Layer	Obstacle Factor	Mean Obstacle Degree (%)	Spatial Coefficient of Variation	Technology Bottleneck Example
Green Logistics	DNA Tagging Data Throughput	22.4	0.37	São Paulo Port, RFID Conflict Rate of 17% (1600 Transactions/sec)
	Biodegradable Materials Weather Resistance	19.6	0.29	Dubai Port, UV Decreases Biodegradable Packaging Tensile Strength by 38%
	Intelligent Device Heterogeneous Compatibility	31.7	0.48	Chicago Hub, Multi-brand AGV Scheduling Error Rate 23%
	Carbon Footprint Trace Granularity	26.5	0.39	Sydney Port, Blockchain Node Delay Causes Data Integrity to Drop to 79%
	Biodiesel Low-temperature Fluidity	18.2	0.25	Rotterdam Port, Power Output Decay at -20°C Environment is 41%

In Table 10, the spatial coefficient of variation of the barrier degree of enzyme catalytic stability was 0.41, indicating that it is significantly affected by geographical climate. Mumbai port has a 2.3 times faster decay rate of enzyme activity than Rotterdam (15° C ± 3° C, RH 65%) during the monsoon season (30° C ± 5° C, RH 85% ± 10%), with catalytic efficiency dropping from 92% to 43%, requiring an additional 23% investment in reaction vessels to maintain capacity.The DNA tagging data throughput barrier grows non-linearly in cargo-intensive hubs, with São Paulo port experiencing an increase in the number of RFID conflicts from the baseline value of 5% to 17% in the per hour Under the 1,600 sweeps per hour scenario, the RFID conflict rate surged from the baseline value of 5% to 17%, resulting in a 19% loss of sorting accuracy and a 37% increase in manual error correction costs. Bio-materials weatherability barriers are prominent in strong UV regions (e.g., Dubai), where cumulative irradiation of 2,000 MJ/m^2 decreases the tensile strength of PLA-based biopackaging from 52 MPa to 32 MPa, resulting in an increase in transport breakage rates to 3.7%, 4.6 times greater than indoor test conditions (0.8%).

Smart device compatibility barriers for green logistics systems (coefficient of variation 0.48) reveal standards fragmentation. In Chicago hub, due to mixed deployment of AGV systems from Kiva and Geek+, conflicting navigation protocols resulted in average daily task failure rate of 23%, and path planning elapsed time increased to 1.7 times the baseline value. Carbon footprint traceability granularity barriers were exacerbated in regions with weak infrastructure, with Sydney Harbour experiencing a 21% deviation in cold chain carbon accounting due to a delay in data upload (2.8 seconds) as a result of blockchain nodes being deployed at intervals of more than 3 kilometres, exceeding the ISO 14067 standard tolerance limit by a factor of four. Biodiesel low-temperature fluidity barriers have significant temperature sensitivity. In the Port of Rotterdam, at -20° C, the viscosity of biodiesel rose from 3.5 cSt to 12.7 cSt, resulting in a 19 per cent increase in pipeline pressure drop and an increase in fuel pump idling rate to 15 times per month, which directly resulted in an increase of 28 per cent in the cost of energy loss.

IV. CONCLUSION

Under the background of carbon neutrality, the in-depth integration of biotechnology and intelligent logistics faces multiple challenges, such as differences in technological maturity, system compatibility barriers and spatial spillover effects. In order to solve the problems of technology commercialisation disconnection and cross-system synergy inefficiency, we constructed an assessment system covering 18 indicators in 5 dimensions, and used an improved entropy weight method combined with a spatial measurement model to analyse the 10-year evolution data of the global logistics network. The key findings include: technology polarisation period (2014-2016) Rotterdam DNA temperature-controlled labels density reached 83 per 10,000 cubic metres, forming a 6.2-fold technology potential difference; gradient diffusion period (2017-2021) Guangdong, Hong Kong, Macao and the Greater Bay Area enzyme catalytic efficiency increased by 37%, and the speed of technology diffusion reached 58km/year; network reconfiguration period (2022-2024) the intensity of trans-oceanic technology flow increased to 0.37, breaking through geographical constraints. Data validate the spatial spillover effect of carbon intensity of cold chain (every 1kgCO_2/ton-km reduction within 200km radius improves coordination by 0.08) and the policy multiplier effect (the FTZ regime extends the technology diffusion radius by 1.6 times). The study establishes 75% coverage of intelligent warehousing as the technology spillover benefit threshold, formulates 7 engineering programmes such as protocol standardisation and transformation, environmental adaptability enhancement, etc., and supports the compression of data latency to 0.3 seconds at the port of Singapore, and the rebound of the sorting accuracy rate to 98% in Sao Paulo. The existing limitations are that the coverage of extreme environment simulation dataset is incomplete, and the blocking effect of geopolitics on technology diffusion has not been fully considered. It is necessary to construct a multi-disaster coupling experimental platform, research and develop anti-jamming quantum temperature control labels (accuracy ±0.05°C), and explore the deep chimerical mechanism of digital twins and biosensors, so as to provide a technological pre-research basis for the sixth generation of intelligent logistics systems.

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