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Enhancing Port Shipping Synergy Through Bayesian Network: A Case of Major Chinese Ports

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Abstract: Port shipping collaboration is vital to greener, more resilient trade, yet decisions remain siloed and uncertain. This study develops a Bayesian network model grounded in empirical data from major Chinese ports, aiming to systematically analyze and enhance port shipping collaborative capacity. The methodology integrates expert knowledge and structural learning algorithms to construct a Directed Acyclic Graph (DAG), representing complex multi-stakeholder interactions among port enterprises, shipping companies, customers, and governmental bodies. Through forward and backward probabilistic inference, the study quantifies how coordinated improvements yield substantial synergistic benefits. Five leverage points stand out: customer engagement in green supply chains, perceived service quality, port digital information integration, multilateral trading maturity, and strict policy enforcement. A newly revealed feedback loop between digital integration and enforcement extends Emerson et al.'s collaborative governance framework, highlighting “digital-era connectivity” as a critical governance dimension and offering managers a focused, evidence-based action agenda.

Keywords: Bayesian network; port shipping collaboration; digital transformation; probabilistic modeling



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1. Introduction

Driven by rapid growth in trade volumes, strengthened decarbonization regulations, and accelerating maritime digital transformation, global maritime trade has entered a period of dynamic transformation [1]. As a cornerstone of the global logistics system, the port shipping industry not only facilitates efficient cross-regional movement of goods but also plays a crucial role in promoting sustainability, innovation, and resilience in global supply chains. Over the past decade, numerous global ports have focused on enhancing physical handling capacities and expanding service scopes. However, with the continuously rising complexity of international trade, these conventional approaches struggle to effectively address multidimensional challenges, such as volatile market demand and stringent environmental requirements. They are also inadequate for fostering coordinated solutions among key stakeholders. Recent research has indicated that isolated upgrades to operational components, such as adding berths or deploying standalone digital platforms, do not necessarily enhance overall system performance. Conversely, substantial evidence demonstrates that collaboration among port enterprises, shipping companies, customers, and governments yields significant and sustainable benefits [2]. These benefits include logistical process optimization, reduced carbon footprints, and improved policy coordination efficiency [3]. Such a systemic perspective aligns closely with the concept of “collaborative governance”, which emphasizes shared responsibilities among all stakeholders.

Nevertheless, promoting effective collaboration among multiple stakeholders in the port-shipping industry faces considerable challenges [4]. For instance, although port enterprises and shipping companies rely heavily on integrated scheduling and energy-efficiency management, they often lack quantifiable decision support models [5]. Meanwhile, customers are increasingly demanding greener, timelier, and more reliable services, yet existing customer engagement mechanisms remain underdeveloped [6]. While governments hold influential positions through fiscal subsidies and regulatory policy-making, insufficient recognition of stakeholders' differentiated demands hinders expected collaborative outcomes [7]. Given these complex interactions, traditional linear analysis or single-factor assessments fall short in uncovering inherent nonlinearities and uncertainties within the system.

To address these gaps, this research introduces the Bayesian network (BN)—a powerful modeling and inference tool—to analyze multi-agent collaborative networks. The objective is to explore effective strategies for enhancing collaborative capacity in the port shipping industry under dynamic conditions. Specifically, this research aims to answer the following questions:

- (1) How can BNs be utilized to construct accurate models representing the complex structure of collaborative systems within the port shipping industry?
- (2) How can probability distributions simulate the dynamic and uncertain nature of governance factors, and how can Bayesian inference be applied to reveal underlying collaboration mechanisms?
- (3) Under multi-stakeholder participation, which key factors significantly impact collaborative performance?
- (4) How can empirical data and inference results be effectively combined to propose viable optimization pathways and policy recommendations for collaborative development in the port shipping industry?

The aim of this study is to develop a BN-based approach to enhance port shipping collaborative capacity. In summary, we construct a BN model with empirical data and find that synchronized, moderate improvements across stakeholders yield greater synergy than isolated large-scale actions.

The main innovations of this research include:

- (1) **Introducing the concept of collaborative development based on a BN:** The research constructs and visualizes a multi-agent collaboration system centered around four major subsystems—port enterprises, shipping companies, customers, and governments—to clearly depict their complex interactions.
- (2) **Proposing a data knowledge-driven structural learning approach:** By integrating expert prior knowledge with empirical data, this method addresses BN limitations associated with small datasets and the risk of overfitting.
- (3) **Simulating dynamic collaborative processes using probability distributions and Bayesian inference:** Under uncertainty, this approach quantitatively assesses cumulative effects resulting from improvements at individual or combined nodes within the network.
- (4) **Providing practical value through empirical case studies:** This research conducts empirical analyses on representative Chinese ports, delivering tailored policy and managerial recommendations that offer feasible pathways toward green, digital, and collaborative industry development.

Based on these objectives and innovations, the remainder of this research is structured as follows: Section 2 reviews the relevant literature on collaborative development in the port shipping industry; Section 3 describes the BN modeling and inference methodologies

employed; Section 4 develops a collaborative capability evaluation model and conducts BN inference analysis, using major Chinese ports as empirical cases; Section 5 synthesizes results from forward and backward inferences, analyzing key influencing factors and their underlying mechanisms.; Section 6 proposes collaborative development strategies and policy implications tailored specifically to different stakeholders; and Section 7 concludes the research and outlines directions for future study.

2. Literature Review

This section synthesizes the scholarship most relevant to port shipping collaboration, highlighting the research gaps our study addresses.

2.1. Port Shipping Industry

The port shipping industry plays a critical role in global trade and regional economic development. It serves as a vital hub that integrates multiple resource flows, including goods, information, and capital. With the continuous expansion of maritime trade and concurrent drivers of decarbonization and digital transformation, demands from governments, port enterprises, and shipping companies are steadily increasing. These demands focus on infrastructure construction, innovation in operational models, and environmental protection.

Previous studies have predominantly examined the coupling relationship between port throughput capacity and shipping network efficiency. Typical topics include berth configuration strategies, automated container terminal operations, channel dredging, and environmental governance within port areas [8,9]. Traditionally, business interactions between port enterprises and shipping companies have been largely unidirectional. These interactions have emphasized improvements in cargo-handling efficiency and berth utilization while neglecting systematic considerations of customer needs and policy environments [10]. Although infrastructure expansions and technological upgrades driven by single-objective optimization can temporarily improve operational efficiency, such approaches often encounter limitations. These limitations arise from inadequate attention to external stakeholders and inefficient policy coordination across regions [11].

Addressing these challenges involves examining interaction mechanisms among shipping companies, customers, and governments. It also necessitates in-depth exploration of data sharing and information transparency. Given the simultaneous progression of digitalization and decarbonization, balancing port throughput capacity with ecological requirements has become an urgent and pivotal issue [12].

2.2. Collaborative Development in the Port Shipping Industry

The concept of collaborative development in the port shipping industry has emerged partly as a response to limitations inherent in traditional “vertical management” or “single-entity centralized decision-making” models. Existing research confirms that under rapid market fluctuations, diverse regional policies, and increasingly stringent environmental standards, unilateral actions by either governments or enterprises seldom lead to significant system-wide improvements [13]. In contrast, multi-agent collaboration can better leverage shipping networks, regulatory policies, and customer-related information. This approach opens new opportunities for resource integration, data interoperability, and innovative benefit-sharing mechanisms [14].

Drawing insights from the collaborative governance literature, this research defines the collaborative capability system within the port shipping industry into four subsystems: port enterprises, shipping companies, customers, and governments. A collaborative devel-

opment framework (Figure 1) is established to further identify critical factors within each subsystem clearly and systematically.

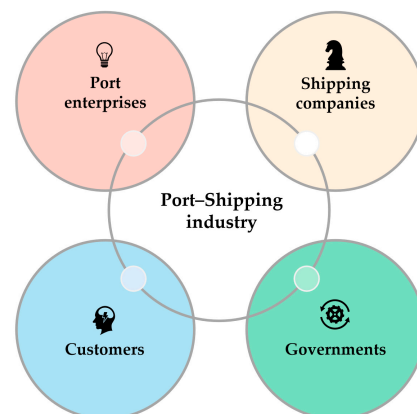


Figure 1. Collaborative development framework.

Port enterprises are widely regarded as key hubs within global logistics and maritime trade networks, performing critical functions such as cargo consolidation, warehousing, and multimodal transportation integration [15]. Previous studies at the port level have often focused on indicators like throughput capacity and operational efficiency. Conventional wisdom suggests that improving port infrastructure or expanding capacity directly enhances cargo-handling efficiency [16] and service timeliness [17]. However, given the increasing complexity of global logistics, reliance solely on infrastructure (“hard power”) is insufficient. Ports today must also address pressures from artificial intelligence applications [18], environmental compliance, and cross-regional collaboration [19]. Shipping companies typically have a deeply interdependent relationship with port enterprises. Nevertheless, effective collaboration is frequently hindered by information asymmetry or unequal benefit distribution [20]. Furthermore, because shipping companies primarily prioritize reducing operational costs [21] and maintaining schedule reliability [22], improvements in energy efficiency or service innovation are often confined internally without an effective coordination mechanism. Consequently, these internal optimizations rarely achieve significant benefits across the entire supply chain [23]. Customers represent a crucial demand-side driver for collaborative development in the port shipping industry. They encompass cargo owners and logistics service providers and ultimately extend to end consumers [24]. Research highlights that proactively responding to customers’ growing demands for greener and smarter logistics solutions can stimulate coordinated transformations across port infrastructure and shipping service models [25]. Conversely, neglecting these evolving demands could reinforce path dependency, encouraging continued reliance on traditional operational methods [26]. Governments hold a pivotal role in the port shipping industry through macro-level regulation and institutional development. They influence corporate behavior and market dynamics primarily through cross-regional policy coordination, regulatory enforcement, and financial incentives such as subsidies [27]. Previous research extensively discusses how governments provide public services to support port shipping collaboration. Typical measures include developing green shore-power infrastructure and enforcing vessel emissions control [28]. However, within complex multi-stakeholder interactions, governmental interventions risk limited effectiveness if policymakers underestimate implementation challenges faced by enterprises or overlook the diverse demands of customers. This oversight may inadvertently result in ineffective policy implementation or new administrative barriers [29]. The identification of development factors within this collaborative framework is summarized in Table 1.

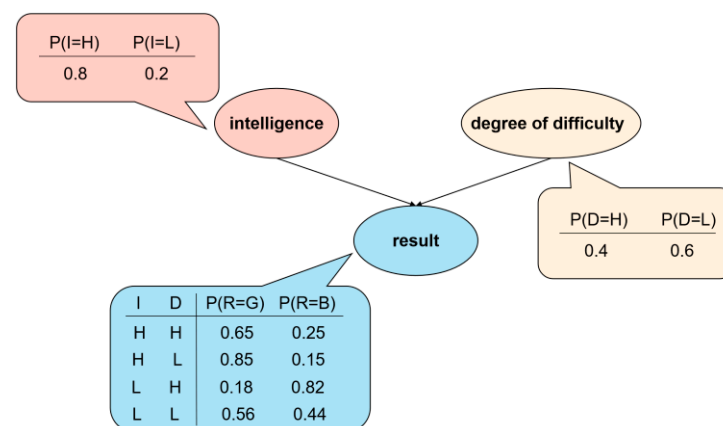
Table 1. A summary of collaborative system and factors.

Collaborative System	Collaborative Factors	Year	Ref.
Port enterprises	Cargo handling efficiency	2009	[16]
	Service timeliness	2020	[17]
	Infrastructure management and technological innovation	2022	[18]
	Environmental sustainability	2025	[19]
Shipping companies	Shipping route and capacity optimization	2014	[21]
	Ship management	2024	[22]
	Service quality	2022	[23]
	Carbon emission accounting	2025	[19]
Customers	Green supply chain	2017	[25]
	Customer engagement approach	2020	[24]
	Customer satisfaction	2022	[26]
Governments	Policy support	2023	[27]
	Public resource services	2024	[28]
	Multilateral collaboration	2024	[29]

2.3. Bayesian Network Model

A BN is an effective inference tool based on known network structures [30]. It provides a Directed Acyclic Graph (DAG), describing dependency relationships among variables [31]. This network can be represented as a binary tuple $B = \langle G, \theta \rangle$. $G = \langle V(G), E(G) \rangle$ denotes a DAG, where $V(G)$ is a set of nodes representing random variables. These variables abstract any phenomena, outcomes, or states within a given problem. $E(G)$ is a set of directed edges indicating causal dependencies between nodes. The parameter set θ specifically refers to the Conditional Probability Tables (CPTs), quantitatively expressing the dependencies among nodes via conditional probabilities.

For illustration, Figure 2 portrays a rudimentary Bayesian network with only three nodes, in which “intelligence” and “degree of difficulty” serve as the parent nodes to “result” [32]. Model development necessitates the establishment of both network topology and conditional probabilities associated with each variable, frequently grounded in empirical data [33] or expert opinion. Panahi et al. [34] utilized Bayesian networks to introduce an evaluation methodology for gauging the resilience of port infrastructure. Nonetheless, this methodology is encumbered by certain limitations, such as data intensiveness and the presupposition of variable independence.

**Figure 2.** Bayesian network structure.

2.4. Summary

In summary, there is consensus within academia and industry regarding the necessity of collaborative development in the port shipping industry. Nevertheless, existing research exhibits gaps in fully elucidating collaborative mechanisms, identifying key influencing factors, and dynamically modeling system interactions. Most studies either focus on single-entity improvements related to environmental impacts or operational efficiency, or they investigate the partial impacts of specific technological interventions. Such approaches struggle to account comprehensively for complex causal relationships and systemic uncertainties among multiple stakeholders. Methodologically, techniques such as interviews, qualitative approaches, and decision science tools demonstrate limited capacity in handling nonlinear and uncertain characteristics inherent in collaborative systems [35–37]. Furthermore, given the increasingly dynamic nature of collaborative development in the port shipping industry, there is a pressing need for research methodologies capable of capturing multi-agent interaction mechanisms, simulating evolutionary trajectories, and accurately assessing the influences of key nodes.

Addressing these identified gaps, this research employs a BN to construct a comprehensive model of the collaborative development system in the port shipping industry. The research provides an in-depth analysis of how port enterprises, shipping companies, customers, and governments interact across dimensions such as environmental compliance, digital transformation, policy frameworks, and service innovation. Through forward and backward inference analyses, critical influencing factors and evolutionary mechanisms are identified and assessed. This approach not only introduces a novel quantitative research paradigm but also offers actionable decision-making references for managers and policy-makers in the port shipping industry. These references aim to enhance resource allocation, technological upgrades, and stakeholder coordination.

3. Methodology

Section 3 outlines the methodological pipeline adopted in this study—from data collection and Bayesian network (BN) construction to parameter estimation and inference experiments. Each step is explicitly aligned with the aim of quantifying multi-stakeholder interactions under uncertainty.

3.1. Research Framework

Figure 3 illustrates the research framework developed in this research. First, through a literature review and expert interviews, the functional roles and key indicators for multiple stakeholders—including port enterprises, shipping companies, customers, and governments—are identified. An improved K2 algorithm, combined with expert refinement, is then employed to construct a DAG, representing the multi-agent collaborative mechanism. Subsequently, parameter estimation for nodes' prior and conditional probabilities is performed, using questionnaire surveys and field investigation data. This facilitates capturing multidimensional causal relationships under uncertainty via the BN. Next, forward inference is applied to analyze the collaborative development mechanism. Backward inference is conducted to identify key factors that must be prioritized to achieve high-level collaborative capability. Finally, based on empirical results and inference insights, practical recommendations are provided for industry and policy. Moreover, future research directions are discussed, considering model applicability and data limitations.

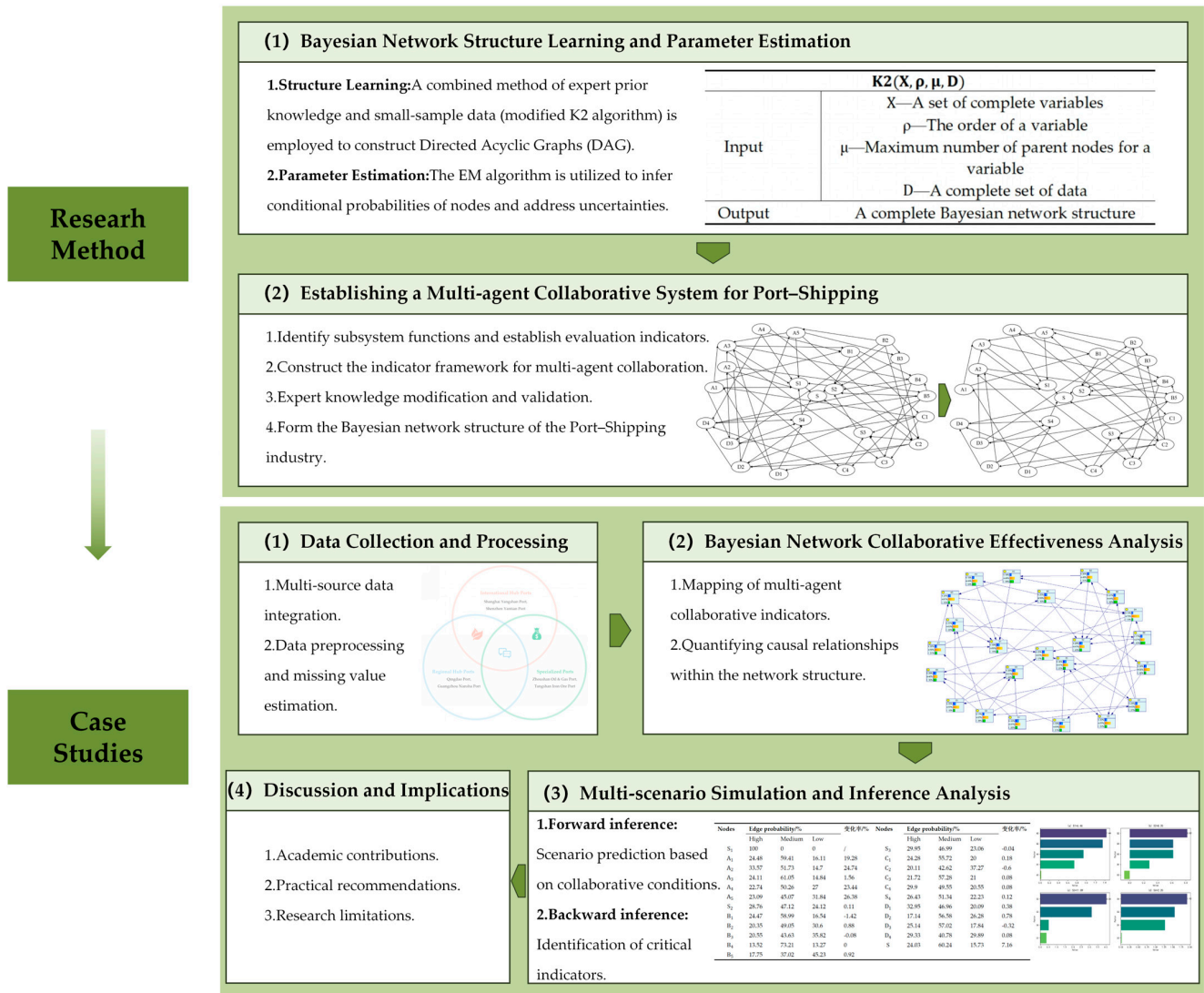


Figure 3. The developed research framework.

3.2. BN Fundamentals

Governed by Bayesian principles, the Joint Probability Distribution (JPD) of a BN comprises n variables, as described in Equation (1):

$$P(A_1, A_2, A_3, \dots, A_n) = P(A_1 | A_2, A_3, \dots, A_n) P(A_2 | A_3, A_4, \dots, A_n) P(A_{n-1} | A_n) P(A_n) \quad (1)$$

Equation (1) can be simplified in the following manner, as shown in Equation (2):

$$P(A_1, A_2, A_3, \dots, A_n) = \prod_{i=1}^n P(A_i | A_{i+1}, A_{i+2}, \dots, A_n) = \prod_{i=1}^n P(A_i | \text{Parents}(A_i)) \quad (2)$$

The internal causal mechanisms and their corresponding magnitudes within the BN are captured through the use of IF-THEN logical functions, elaborated in Equation (3).

$$R_k : \text{IF} \{C_1^k, C_2^k, \dots, C_p^k\}, \text{ THEN} \{(\beta_1^k, S_1), (\beta_2^k, S_2), \dots, (\beta_q^k, S_q)\} \quad (3)$$

In Equation (3), R_k denotes the k th rule of the system. Confidence levels, represented by β_d ($d = 1, 2, \dots, q$), are mapped to states C_d ($d \in q$), thereby converting p conditional attributes $\{C_1, C_2, \dots, C_p\}$ into q distinct states $\{S_1, S_2, \dots, S_q\}$.

In this research, particular emphasis is placed on two essential functions of BN:

- (1) Modeling Function: Decomposing and characterizing the complex collaborative system within the port shipping industry.
- (2) Inference Function: Capturing dynamic interaction mechanisms and investigating factors influencing the collaborative capability of the port shipping industry.

Compared with deterministic system dynamics simulations or black box, purely data-driven algorithms (e.g., random forest or XGBoost classifiers), BNs provide three unique advantages for multi-stakeholder port shipping problems: (i) explicit causal directionality that managers can interpret and validate; (ii) seamless fusion of sparse empirical observations with structured expert priors, which is essential when historical data are patchy or proprietary; and (iii) exact probabilistic inference that simultaneously propagates aleatory and epistemic uncertainty through the network. These properties allow BNs to capture the systemic complexity of port shipping collaboration more faithfully than alternative modeling families, even when formal performance benchmarks are not feasible within the scope of a single study.

By analyzing four primary stakeholders—port enterprises, shipping companies, customers, and governments—a BN model is constructed. The network intuitively reveals the complex internal structure of the port shipping collaborative system, enhancing comprehension and visualization. Due to inherent uncertainties and dynamic characteristics of collaboration within this industry, BNs effectively manage stochastic uncertainties arising from individual factors and their interactions via prior and conditional probabilities. Through adjusting node probabilities, the network dynamically simulates stakeholder behaviors in collaborative governance. It also quantitatively associates influencing factors through probabilistic inference, uncovering uncertain relationships. Therefore, a BN is particularly suitable for studying collaborative capability in the port shipping industry.

3.3. Hybrid Data-Knowledge Structure Learning

BN structure learning refers to the process of determining network structures using datasets [38]. Because empirical port shipping data are often sparse or proprietary, integrating expert knowledge is essential for robust BN structure learning. Accordingly, we employ a data-knowledge hybrid approach to build the DAG that represents port shipping collaborative governance. Section 4.3 provides a detailed explanation of this method.

The algorithm identifies the optimal parent node set for each node by employing a search strategy in conjunction with a scoring function, thereby yielding the most robust network architecture. The algorithm requires the specification of two parameters: the nodal sequence and the maximum allowable number of parent nodes. These constraints prevent a preceding node from acting as a parent to subsequent nodes and restrict the number of parent nodes to a predefined maximum. The intricacies of the scoring function are elaborated in Equation (4).

$$\max[P(G, D)] = C \prod_{i=1}^n \max_{\Pi^i} \left[\prod_{j=1}^{q_j} \frac{(r_i - 1)!}{(N_{ij} + r_i - 1)} \prod_{k=1}^{r_i} N_{ijk}! \right] \quad (4)$$

In Equation (4), the variable G symbolizes the network's structural framework, while D represents the dataset employed for structural learning. r_i specifies that node X_i can exist in r different states, and q_j enumerates the q possible state combinations for its parent nodes. $\prod^i$ delineates the set of parent nodes corresponding to the i th node X_i . Table 2 details the input and output variables associated with the K2 algorithm.

Table 2. Inputs and outputs of the K2 algorithm.

K2 (X, ρ , μ , D)	
Input	X—A set of complete variables
	ρ —The order of a variable
	μ —Maximum number of parent nodes for a variable
	D—A complete set of data
Output	A complete Bayesian network structure

The K2 algorithm was chosen because it strikes a practical balance between model fit and parsimony while allowing expert guidance. Constrained parent limits tame over-fitting on small datasets, and expert-defined node ordering narrows the search space, so K2 can recover plausible structures with modest computation.

3.4. Parameter Learning

The Expectation-Maximization (EM) algorithm is widely used in BN parameter learning for such incomplete data because it iteratively maximizes likelihood while inputting gaps, yielding unbiased conditional probability estimates before convergence. This research employs the EM algorithm to transform incomplete data into complete data through a two-stage process: the E-step and the M-step. In the E-step, expected values are calculated, whereas the M-step focuses on optimization. After several iterations, the algorithm converges, providing estimates for unknown parameters. Specifically, the E-step involves calculating the lower bound of the log-likelihood function. Let X represent the unknown variables, Y the observed variables, and D the training set. By defining $q(X = x|Y)$ as the probability associated with $X = x$ when Y is the observed value, we can derive Equation (5):

$$\sum_x q(X = x|Y) = 1 \quad (5)$$

Suppose the log-likelihood function L is defined as in Equation (6):

$$L(\theta) = \sum_m \log \sum_n P(X = x_i, Y = D) \quad (6)$$

Let L denote the log-likelihood function, X the set of unknown variables, Y the observed variables, and D the dataset. Assuming $P(X = x_i, Y = D)$ is a convex function with an extremum, Jensen's inequality yields Equation (7):

$$\begin{aligned} L &= \sum_m \log \sum_n q(X|Y) \times \frac{P(X = x_i, Y = D)}{q(X|Y)} \\ &\geq \sum_m \sum_n q(X|Y) \times \frac{P(X = x_i, Y = D)}{q(X|Y)} \end{aligned} \quad (7)$$

The EM algorithm effectively calculates a lower bound for the parameters during the E-step and updates them to their maximum values during the M-step. Let $q(X = x|Y) = P(X|\theta_t)$ and θ_t represent the unknown parameters in the current iteration, and θ_{t+1} signify the parameters for the next iteration. Solving for the lower bound L essentially involves determining the parameters for the next iteration under the given current parameters. Let the lower bound of L be $Q(\theta_{t+1}|\theta)$, expressed in Equation (8):

$$Q(\theta_{t+1}|\theta) = \sum_m \sum_n P(X|\theta_t) \log P(X, D|\theta_{t+1}) \quad (8)$$

In accordance with the methodology in maximum likelihood estimation, the parameters $\hat{\theta}_t$ are found when $Q(\theta_{t+1}|\theta)$ is maximized, as shown in Equation (9):

$$\hat{\theta}_t = \frac{EN_{ijk}}{EN_{ij}} \quad (9)$$

In Equation (9), EN_{ijk} represents the data in the dataset D that satisfies $X_i = x_{ik}$ and $P_a(X_i) = P_a(X_i)_j$, the data corresponding to the parent node j when node i takes its k th value.

Take node X_i with conditional probability $P(X_i|\text{Parents}(X_i))$ as an example:

(1) Frequency counting:

Count occurrences N_{ijk} of each possible state x_{ik} of node X_i under each combination of parent nodes π_{ij} .

For instance, if X_i has parent nodes A and B , count all frequencies for combinations such as $(A = a, B = b)$.

(2) Calculating conditional probabilities:

The conditional probability is estimated by normalizing the frequencies, as shown in Equation (10):

$$P(X_i = x_{ik}|\pi_{ij}) = \frac{N_{ijk} + \alpha}{\sum_{k'} (N_{ijk'} + \alpha)} \quad (10)$$

Here, α is a smoothing factor (Laplace smoothing), introduced to avoid zero probability problems. If data are sufficient, α can be set to 0.

(3) Constructing CPT:

The computed probabilities are inserted into the CPT. For example, if node X_i has 3 states and its parent nodes have 4 combinations, the resulting CPT is a 4×3 matrix.

3.5. Probabilistic Reasoning and Scenario Simulation

BN inference calculates the posterior probabilities of target nodes based on prior probabilities and available evidence. It includes two primary methods: forward inference and backward inference. When identifying critical subsystems and collaborative mechanisms between subsystems, forward inference elucidates how multiple subsystems interact and collectively influence the ultimate target. It also clarifies subsystem roles within urban community governance more quickly and accurately by altering subsystem states. Conversely, backward inference simplifies data analysis, reducing uncertainty and complexity when identifying critical parameters and conducting holistic system analysis. Backward inference begins from known targets and rapidly narrows the problem scope, making it easier to identify parameters directly influencing these targets. Thus, analyzing every parameter and their complex relationships becomes unnecessary. GeNIe is a software tool for BN modeling and inference, offering a user-friendly interface that significantly facilitates inference processes. BN inference in this research is conducted using GeNIe.

4. BN Model for Port Shipping Collaboration

The BN developed here is the study's core instrument for tackling fragmented collaboration—the key challenge identified in Section 1. By representing ports, shipping lines, customers, and regulators as interconnected nodes, the model (i) captures how decisions by any stakeholder ripple through the system and (ii) quantifies which joint actions yield the largest synergy gains. The remainder of Section 4 explains how the BN was built and how each component links to real-world governance levers.

4.1. Order Parameter Framework

4.1.1. Unpacking Synergistic Development Competencies

Collaborative development, a key paradigm for modernizing the port shipping system, illustrates how multiple stakeholders—including port enterprises, shipping companies, customers, and governments—can achieve significant improvements in system efficiency through dynamic collaboration. This is particularly important given the dual challenges of globalized supply chains and low-carbon transitions. However, ambiguity in defining the specific objectives, pathways, and practical outcomes of this development model presents substantial barriers. These barriers affect mechanism design, policy tool selection, and effectiveness evaluation in both theoretical and practical contexts.

Based on the Integrated Framework for Collaborative Governance (IFCG) proposed by Emerson et al., several scholars have attempted to analyze collaborative governance in the port shipping industry. They emphasize that collaborative capability should encompass institutionalized participation mechanisms, incentives for shared benefits, and joint action capabilities [39]. Cleave et al. further suggested that the goals of collaborative port development include governance restructuring, optimized resource allocation, and integrated economic, environmental, and social benefits [40]. Nonetheless, practical challenges—such as mismatches in stakeholder responsibilities, data barriers, or conflicting policies—often hinder the full realization of expected collaborative effects.

Drawing upon the collaborative governance framework in Figure 4 and existing research, this research defines the collaborative development capability of the port shipping industry as follows: the integrated capacity of the network governance structure—comprising port enterprises, shipping companies, customers, and governments—to achieve collaborative development, address industry challenges, optimize resource aggregation, and create public value through dynamic cross-subsystem interactions. As illustrated in Figure 4, this framework clarifies the logic and constraints of potential collaborative effects. It also provides target-oriented decision support for optimizing port shipping policies.

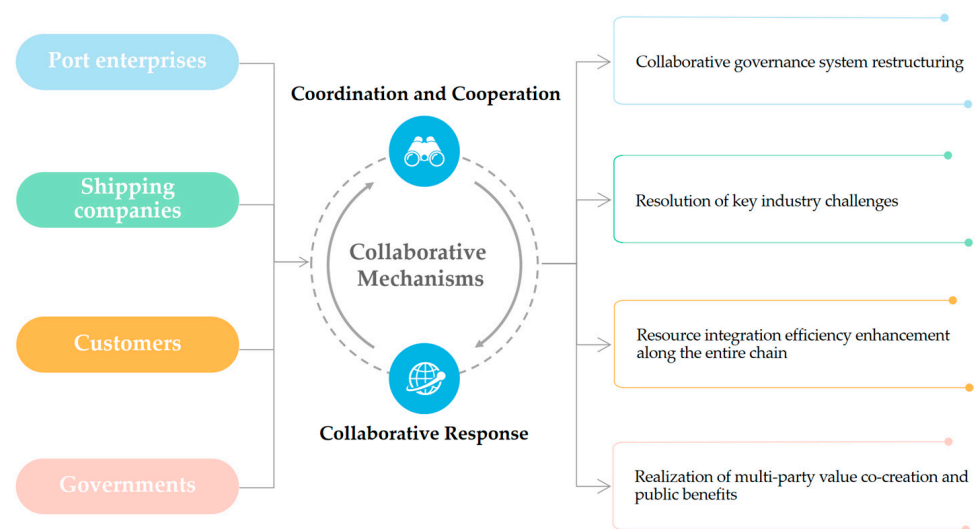


Figure 4. Collaborative interaction framework in the port shipping system.

4.1.2. Linking Order Parameters to a Graphical Model

In BN modeling, nodes represent critical factors driving collaborative capability. This research identifies influencing factors of collaborative capability through an order parameter system, mapping these factors onto network nodes. The construction process for the order parameter system is as follows:

(1) Preliminary Screening

Based on the collaborative framework of port enterprises, shipping companies, customers, and governments shown in Figure 1, and the port shipping development factors summarized in Table 1, 21 order parameters were initially extracted.

(2) Delphi Expert Knowledge Integration

A two-round Delphi survey was conducted with 15 purposely selected experts (five senior port managers, four liner-shipping strategists, three academics, and three government regulators; mean experience = 15 years). Round 1 collected open-ended factor suggestions; Round 2 asked the same panel to rate the 23 preliminary factors on a 5-point relevance scale. After two rounds, a consensus was reached. The resulting 18 factors are listed in Table 3.

Table 3. Governance factors and indicator system for port shipping collaboration.

Collaborative System	Subsystems	Order Parameters	Ref.
S	Port enterprises (S ₁)	Port infrastructure capacity (A ₁)	[41]
		Port digital information level (A ₂)	[20]
		Port operational efficiency (A ₃)	[18]
		Port diversified service capability (A ₄)	[19]
		Application rate of low-carbon technologies (A ₅)	[21]
	Shipping companies (S ₂)	Compatibility of shipping networks (B ₁)	[23]
		Ship energy efficiency management level (B ₂)	[24]
		Transparency of carbon emission accounting (B ₃)	[21]
		Reliability and timeliness of shipping services (B ₄)	[19]
		Coordination of regional blockchain transportation (B ₅)	[42]
	Customers (S ₃)	Logistics demand forecast accuracy (C ₁)	[43]
		Green supply chain participation (C ₂)	[21]
		Customer satisfaction and service quality evaluation (C ₃)	[28]
		Willingness to engage in port shipping optimization (C ₄)	[26]
	Governments (S ₄)	Cross-regional policy coordination (D ₁)	[30]
		Completeness and enforcement of policies (D ₂)	[44]
		Fiscal support and subsidy levels (D ₃)	[29]
		Maturity of multilateral trading mechanisms (D ₄)	[36]

(3) Final System Output

The finalized order parameter system for collaborative capability in the port shipping industry (S) includes 18 order parameters across four subsystems, as summarized in Table 3.

4.2. Data Acquisition and Pre-Processing Procedures

Collaborative development data in the port shipping industry were collected from multiple heterogeneous sources, primarily including expert ratings from international maritime organizations and structured data from operational annual reports of shipping companies. To ensure objectivity, a three-level scale (“Low”, “Medium”, and “High”) was employed to evaluate 23 key indicators, minimizing potential bias and subjectivity.

The research team selected 6 representative ports from three major port clusters (Yangtze River Delta, Guangdong–Hong Kong–Macao region, and Bohai Rim), as shown in Figure 5.

A total of 317 valid data samples were collected, covering multiple stakeholders, including port enterprises (23%), shipping companies (35%), logistics service providers (28%), and customs regulatory authorities (14%). A data quality control matrix and anomaly detection algorithm (Figure 6) were applied, resulting in the retention of 298 high-quality datasets with an effective rate of 94.01%. This comprehensive dataset captures the multi-scale characteristics of port shipping collaborative development, providing robust support

for subsequent modeling. BN modeling based on this dataset thus demonstrates broad applicability within the port shipping industry.

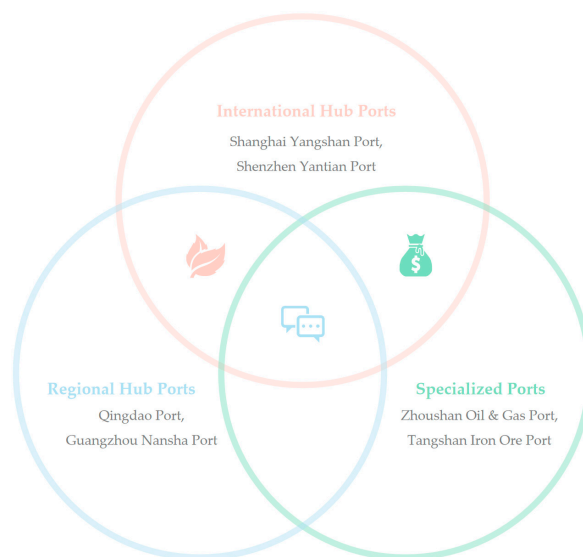


Figure 5. Representative ports.

```

1  def maritime_data_cleaning(df):
2
3      iso_forest = IsolationForest(contamination=0.05)
4      outliers = iso_forest.fit_predict(df)
5
6      df_clean = df[(outliers == 1) & (df.completeness > 0.85)]
7
8      maritime_std = MaritimeSTDChecker()
9      return maritime_std.transform(df_clean)

```

Figure 6. Anomaly detection algorithm.

4.3. Experimental Design for Structure Learning

4.3.1. Node Sequence and Prior Structural Information Design

The order parameter system of collaborative development capability in the port shipping industry also exhibits a hierarchical structure, where lower-level indicators significantly influence higher-level indicators. By extracting effective information from the order parameter system to design the node sequence and prior structural information, the structure learning performance of the K2 algorithm can be optimized, enhancing model accuracy and data utilization efficiency.

(1) Node Sequence

In the BN for port shipping collaborative capacity, allowing subsystem nodes (e.g., S_1, S_4) to directly point to order parameter nodes (e.g., A_1, B_1) conflicts with actual collaborative development logic. Consequently, this research prescribes a node-ordering approach based on the priority of these order parameters to circumvent unproductive network structure searches and thereby improve search efficiency, model accuracy, and data utilization. In practice, order parameter nodes (e.g., port operational efficiency A_3 or completeness and enforcement of policies D_2) are placed before subsystem nodes, while the target node (overall port shipping synergy S) is positioned at the same hierarchical level as the subsystem nodes (S_1, S_2, S_3, S_4) but sorted randomly. The final node sequence is thus defined as:

$$(A_1, \dots, A_5, B_1, \dots, B_5, C_1, \dots, C_4, D_1, \dots, D_4), (S, S_1, S_2, S_3, S_4), S$$

(2) Prior Structural Information

Port shipping systems often exhibit cyclical or iterative dependencies, yet a BN—being a DAG—cannot directly capture such circular relationships. To address this limitation, this research utilizes a tiered structure derived from the order parameter system (Figure 7) as the input framework when initializing the DAG via the K2 algorithm. Concretely, subsystem nodes and their corresponding order parameter nodes are assigned to different layers, with each subsystem directly depending on its own order parameter nodes. These order parameter nodes function as intermediary variables for complex inter-subsystem interactions, re-routing such dependencies to the order parameter layer, thus mitigating circular reliance and streamlining the network’s overall structure.

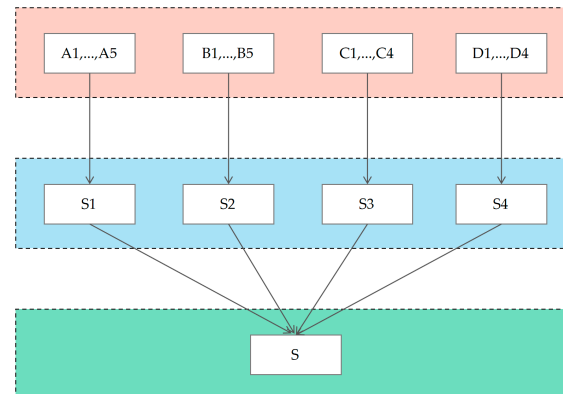


Figure 7. Tiered structure derived from the order parameter system, used to initialize the Bayesian network.

4.3.2. Improved Design for Node Ordering and Prior Structural Information

Traditional K2 algorithms cannot directly incorporate prior structural information into their search strategy, nor can they fully utilize expert insights. To integrate expert knowledge with data-driven approaches more effectively, this research refines both the algorithm’s input and search strategy, proposing the “K2-PSI” (K2 with Prior Structure Integration) method. This approach resolves the issue of representing iterative dependencies when constructing a BN for port shipping collaborative capacity. Specifically:

(1) Input Enhancement: Layered Prior Structure Embedding

Let the node set $Z = X_1, X_2, \dots, X_{23}$ correspond to the 23 order parameters, each having three states—low, medium, and high ($r_i = 3$). The dataset D comprises $m = 298$ records. Each core node can have up to five parent nodes, whereas auxiliary nodes are capped at three parents.

At the input stage, the prior tiered structure is introduced to the K2 algorithm in the form of “prior node sets.” Denote by PN_i the set of prior order parameter nodes for a given subsystem i . As illustrated in Figure 7, $PN_{S_1} = [A_1, A_2, A_3, A_4, A_5]$, $PN_{S_2} = [B_1, B_2, B_3, B_4, B_5]$, $PN_{S_3} = [C_1, C_2, C_3, C_4]$, and $PN_{S_4} = [D_1, D_2, D_3, D_4]$ serve as “preceding” node groups for S_1, S_2, S_3 , and S_4 , respectively. Cross-subsystem, or “overstepping”, pointers are disallowed to prevent violations of the DAG’s acyclicity constraint.

(2) Search Strategy Enhancement: K2-PSI-port

Improvement of search strategy: Before executing the greedy search strategy, the algorithm checks if the node X_i has prior parent nodes. If it does, these nodes are added to the parent node set of X_i before executing the search strategy. If not, the search strategy is executed directly. This process seeks the optimal parent node set for X_i . Finally, the algorithm outputs the parent node sets for all nodes. The process of the K2 algorithm for integrating prior hierarchical structural information is shown in the K2-PSI-port algorithm (Figure 8).

Input: Node set, node order, dynamic parent node limit u_{core}/u_{aux} , prior parent node set PN_i , multi-source database D , weight matrix W
Output: Parent node set and weights for each node

```

1: Procedure K2-PSI-Port
2: For  $i = 1 \rightarrow n$  do
3:   If  $i \in \text{core nodes}$ , then  $u = u_{core}$ ; else  $u = u_{aux}$ 
4:    $\pi_i := PN_i$  // Initialize prior parent nodes
5:    $P_{old} := g_{new}(i, \pi_i, W)$ 
6:   OKToProceed := true
7:   While OKToProceed and  $|\pi_i| < u$  do
8:      $z := \text{argmax}_{z \in \text{Pred}(X_i) - \pi_i} [g_{new}(i, \pi_i \cup \{z\}, W)]$ 
9:      $P_{new} := g_{new}(i, \pi_i \cup \{z\}, W)$ 
10:    If  $P_{new} > P_{old}$  then
11:       $P_{old} := P_{new}$ 
12:       $\pi_i := \pi_i \cup \{z\}$ 
13:    Else
14:      OKToProceed := false
15:    End If
16:  End While
17:  If conflict exists ( $\pi_i$  does not conform to expert rule base) then
18:    Trigger expert review, update  $PN_i$  or  $W$ 
19:  End If
20:  Output node  $x_i$ 's parent nodes  $\pi_i$  and weight  $W$ 
21: End For
22: End Procedure

```

Figure 8. Flow diagram of the K2-PSI port algorithm.

Visualize the output results of K2-PSI port algorithm, which yield the initial DAG, as shown in Figure 9. From the connections between the subsystem nodes in Figure 9, it can be observed that there are only three direct dependency relationships among these four subsystems (S_1 – S_4), and there is a close relationship between the order parameters. This result confirms the effectiveness of the hierarchical prior structure designed in this paper, which successfully guides some of the cyclic dependencies between subsystems to the sequence parameter level.

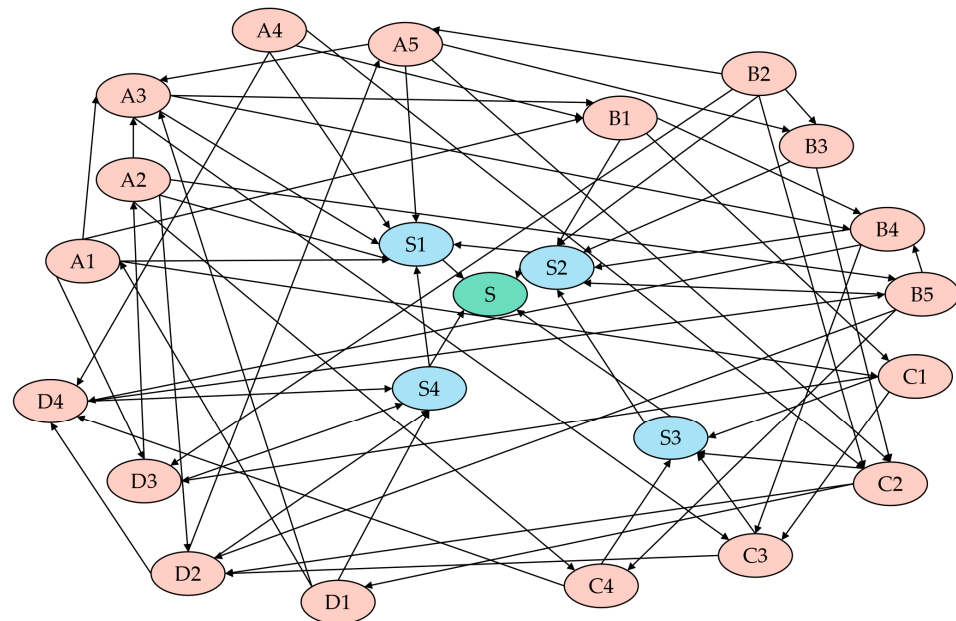


Figure 9. Initial Bayesian network structure generated by the K2-PSI port algorithm.

To enhance accuracy in reflecting real-world conditions, expert knowledge was utilized to refine the initial DAG. Five experts individually evaluated each directed edge shown in Figure 9. Edges identified by at least three experts as needing modification were adjusted accordingly. The experts unanimously agreed that overly strong interactions among order parameters in the initial DAG weakened direct causal relationships among subsystems. Thus, these direct subsystem causalities, recognized as weak causal links, were removed. Additionally, inconsistencies with domain knowledge suggested potential overfitting due to insufficient data.

Accordingly, unreasonable directed edges were removed, and improperly directed edges were reversed based on expert feedback. Specifically, 11 edges were removed, and 11 edges were reversed. The final refined DAG, as shown in Figure 10, clearly illustrates the complex relationships among governance entities and factors, effectively depicting the internal structure of the collaborative system.

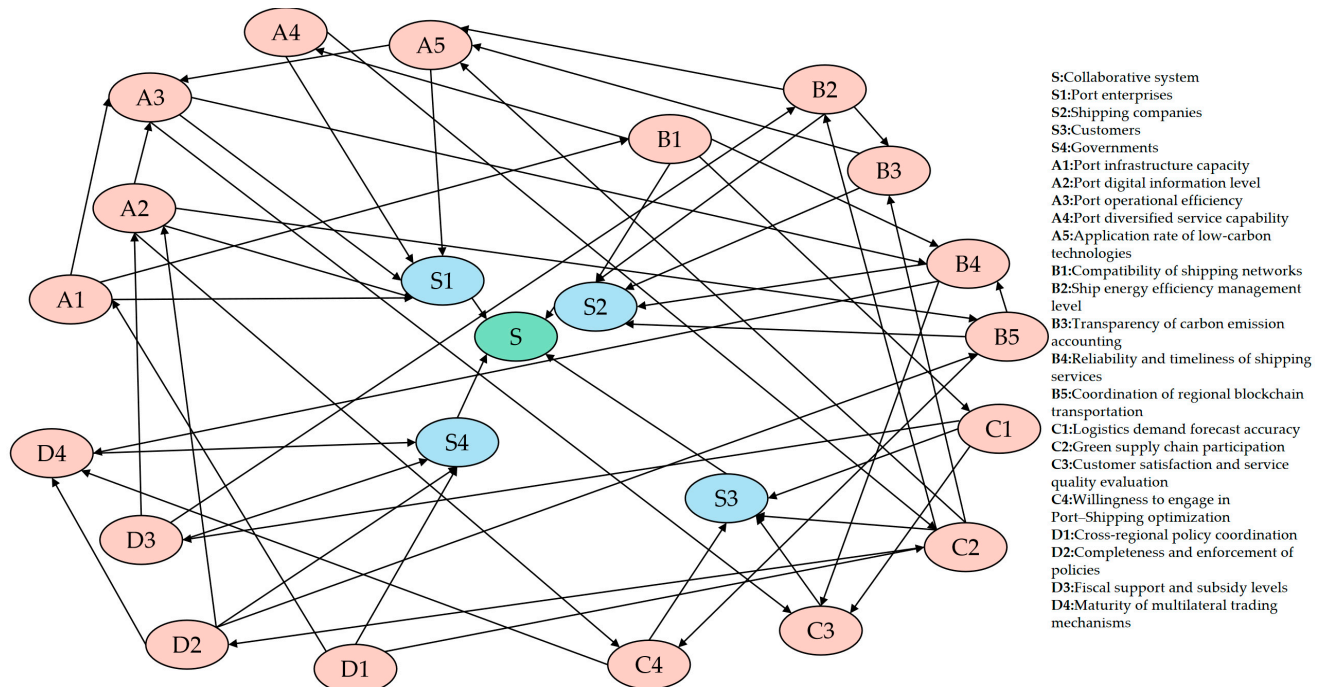


Figure 10. Final refined Bayesian network (DAG) after incorporating expert feedback and adjustments.

4.3.3. DAG Analysis

To provide deeper insights into the internal structure of port shipping synergy, this research constructs a DAG that visualizes the multilayered interactions among port enterprises, shipping companies, customers, and governments. Each subsystem node (S_1 – S_4) is linked to its respective order parameter nodes (e.g., A_1 – A_5 , B_1 – B_5), and certain key variables also exhibit cross-connections, reflecting the complex coupling mechanisms in collaborative governance. For instance, an improvement in the port enterprise subsystem's digital information integration (A_2) strongly influences other subsystems by facilitating initiatives like regional blockchain-based logistics (shared with the shipping subsystem) and enabling cross-regional policy coordination (connecting to the government subsystem). A higher level of port digitalization thus leads to more synchronized operations between ports and shipping lines, which in turn boosts overall collaborative performance. Another important causal path originates from the customers subsystem: high customer participation in green supply chain programs (C_2) and demand for better service quality (C_3) put positive pressure on ports and shipping companies to adopt greener practices and enhance service standards. This demand-pull effect is represented in the DAG by directed links from customer-related nodes to improvements in port operations and shipping services. On the policy side, strict environmental policy enforcement (D_2) and robust fiscal support (D_3) in the government subsystem emerge as top-down drivers that propagate through the network, compelling corresponding enhancements in both port and shipping subsystems.

According to Bayesian theory, if $P(S_1|A_1, \dots, A_5)$ denotes the probability distribution of S_1 under specific order parameter states—and similarly $P(S_2|B_1, \dots, B_5)$, $P(S_3|C_1, \dots, C_4)$, and $P(S_4|D_1, \dots, D_4)$ represent prior distributions for other subsystems—then the overall joint probability for the target node SSS can be expressed as shown in Equation (11):

$$\begin{aligned}
& P(S, S_1, S_2, S_3, S_4, A_1, \dots, A_5, B_1, \dots, B_5, C_1, \dots, C_4, D_1, \dots, D_4) \\
& = P(A_1, \dots, A_5)P(S_1|A_1, \dots, A_5)P(B_1, \dots, B_5)P(S_2|B_1, \dots, B_5)P(C_1, \dots, C_4)P(S_3|C_1, \dots, C_4)P(D_1, \dots, D_4) \\
& \quad P(S_4|D_1, \dots, D_4)P(S|S_1, S_2, S_3, S_4) = P(A_1, \dots, A_5, B_1, \dots, B_5, C_1, \dots, C_4, D_1, \dots, D_4) \\
& \quad P(S_1|A_1, \dots, A_5)P(S_2|B_1, \dots, B_5)P(S_3|C_1, \dots, C_4)P(S_4|D_1, \dots, D_4)P(S|S_1, S_2, S_3, S_4)
\end{aligned} \quad (11)$$

Such a decomposition effectively captures inter-subsystem coupling and, through forward and backward inference, identifies both the pathways and magnitudes of critical interactions. This network design retains hierarchical structure and clear visualization, overcoming the limitations of conventional BNs in handling cyclical dependencies and improving explanatory power in real-world systems. In the DAG, each edge denotes a probabilistic dependency derived from expert-informed structure learning; it signals influence, not deterministic causation.

From an internal perspective within each subsystem, every specific indicator not only directly affects that subsystem but may also exert indirect influence through interactions with other indicators. For instance, within the port enterprise subsystem (S_1), port operational performance (A_1) and port digital information level (A_2) exhibit a strong probabilistic dependency; through their interlinked effects, A_1 and A_2 together shape port efficiency (A_3) via a nonlinear interaction.

4.4. BN Parameter Estimation

The Expectation-Maximization (EM) algorithm was adopted for parameter estimation. Given the known network structure, this approach determines the conditional probability values of network nodes based on survey data on port shipping collaborative governance. Specifically, using survey data on collaborative governance capabilities, probabilities of each node in “Low”, “Medium” and “High” states were calculated to form a CPT. CPTs effectively quantify causal relationships within the network, explicitly indicating the impacts of governance factors on collaborative capability.

To ensure alignment with practical conditions in port shipping operations, this research integrates expert interviews and empirical data to determine the marginal probability of each node’s state. These aggregated results are summarized in Figure 11, which reveals the baseline probability distribution for each indicator. As shown in Figure 11, several core capability indicators already have a high likelihood of being in the “High” state (reflecting strong baseline performance in those areas), whereas other indicators remain predominantly in a “Medium” state, suggesting room for improvement. This probabilistic profile provides a useful context for the inference analysis that follows.

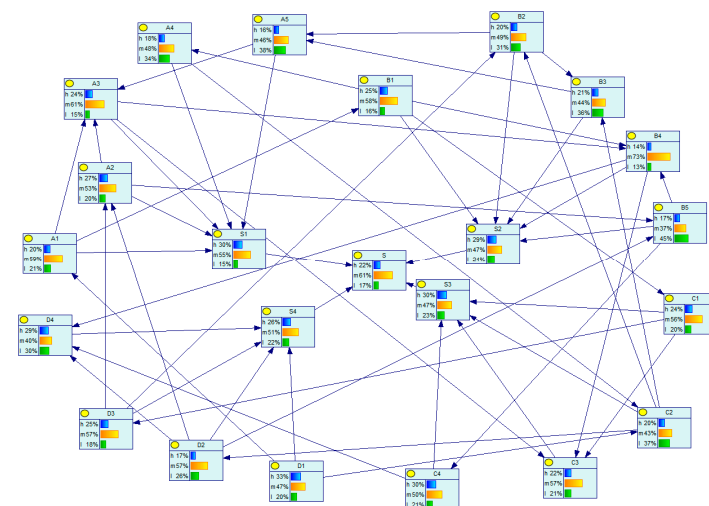


Figure 11. The marginal probabilities of nodes in the Bayesian network.

5. BN Model for Collaborative Development in the Port Shipping Industry

With the BN calibrated, Section 5 applies the model to analyze collaborative performance. We report forward and backward inference results and translate them into practical leverage points for managers and policymakers.

5.1. Scoring Framework for Node State Transition Analysis

Previous practices often relied solely on a simplistic “low-medium-high” classification to define node states, which fails to capture the distinct contributions of various node indicators to overall collaborative capacity. To thoroughly investigate the key drivers of port shipping collaborative development, this research builds upon conventional BN inference methods and incorporates the unique characteristics of port shipping operations and collaborative mechanisms. Accordingly, an innovative approach to quantifying node states is proposed, including a differentiated scoring system that more accurately reflects the impact of node state changes on overall synergy (Table 4).

Table 4. Quantitative indicators for node state changes.

Node Type	Low	Medium	High	Nodes
Core Capability Indicators	2	4	6	S, S ₁ , S ₂ , S ₃ , S ₄
Technology/Policy/Collaboration Indicators	1	3	5	A ₁ , A ₂ , ..., D ₃ , D ₄

For technology- and policy-related indicators, this research applies a scoring scheme of 1, 3, and 5 points (low–medium–high). However, for core capability indicators—given their more pronounced effect on synergy—the scoring scale is adjusted to 2, 4, and 6 points (low–medium–high).

In real-world port shipping collaboration, each node exhibits varying degrees of importance. To quantify their overall scores, this research proposes a novel weighting and state transition method grounded in operational priorities. The core formulas are as follows:

- (1) The Pre-Adjustment Node Score (Score_{before}) is calculated according to Equation (12):

$$\text{Score}_{\text{before}} = \sum_{i=1}^n \left(P_{\text{high}} \times W_{\text{high}} + P_{\text{medium}} \times W_{\text{medium}} + P_{\text{low}} \times W_{\text{low}} \right) \quad (12)$$

Here, P_{high} , P_{medium} , and P_{low} denote the probabilities of a node being in high, medium, or low states before adjustment, whereas W_{high} , W_{medium} , and W_{low} represent the weights assigned to these respective states.

- (2) The Post-Adjustment Node Score (Score_{after}) is given by Equation (13):

$$\text{Score}_{\text{after}} = \sum_{i=1}^n \left(P'_{\text{high}} \times W_{\text{high}} + P'_{\text{medium}} \times W_{\text{medium}} + P'_{\text{low}} \times W_{\text{low}} \right) \quad (13)$$

Here, P'_{high} , P'_{medium} , and P'_{low} denote the probabilities of the node being in each state after adjustment. Increasing the probability of the high state (for instance) would require a corresponding decrease in the medium or low states, reflecting the benefits of improving the node's condition.

- (3) The Node Score Change Rate (Changes) can be computed according to Equation (14):

$$\text{Change}_S = \frac{\text{Score}_{\text{after}} - \text{Score}_{\text{before}}}{\text{Score}_{\text{before}}} \times 100\% \quad (14)$$

By comparing node scores before and after state optimization, it is possible to evaluate each node's relative contribution to enhancing overall port shipping synergy.

5.2. Forward Inference Analysis

Utilizing evidence-based causal inference helps reveal the dynamic relationships between subsystems and assess how changes in subsystem behavior impact the collaborative development capability of the port shipping industry. To achieve this, this research employs forward inference to examine how modifications to specific subsystem inputs influence the overall system. The rate of score variation indicates the extent to which each subsystem affects overall collaborative capability.

5.2.1. Analysis of the Port Enterprise Subsystem (S_1)

The inference results for changes in the port enterprise subsystem are presented in Table 5. Within the port enterprise subsystem (S_1), improvements typically bring the most immediate benefits to shipping companies (S_2) and governments (S_4), while exerting relatively limited influence on customers (S_3). This outcome partly reflects the tendency of traditional port enterprises to focus on close collaboration with the shipping sector and regulatory agencies in order to secure throughput, vessel turnover, and compliance. However, they pay insufficient attention to customer needs and engagement, resulting in minimal changes to C_3 and C_4 in the inference results.

Table 5. Reasoning for port enterprise subsystem change.

Nodes	Edge Probability/%			Change Ratio/%	Nodes	Edge Probability/%			Change Ratio/%
	High	Medium	Low			High	Medium	Low	
S_1	100	0	0	/	S_3	29.95	46.99	23.06	− 0.04
A_1	24.48	59.41	16.11	19.28	C_1	24.28	55.72	20	0.18
A_2	33.57	51.73	14.7	24.74	C_2	20.11	42.62	37.27	− 0.6
A_3	24.11	61.05	14.84	1.56	C_3	21.72	57.28	21	0.08
A_4	22.74	50.26	27	23.44	C_4	29.9	49.55	20.55	0.08
A_5	23.09	45.07	31.84	26.38	S_4	26.43	51.34	22.23	0.12
S_2	28.76	47.12	24.12	0.11	D_1	32.95	46.96	20.09	0.38
B_1	24.47	58.99	16.54	− 1.42	D_2	17.14	56.58	26.28	0.78
B_2	20.35	49.05	30.6	0.88	D_3	25.14	57.02	17.84	− 0.32
B_3	20.55	43.63	35.82	− 0.08	D_4	29.33	40.78	29.89	0.08
B_4	13.52	73.21	13.27	0	S	24.03	60.24	15.73	7.16
B_5	17.75	37.02	45.23	0.92					

When the port enterprise subsystem (S_1) significantly enhances its capabilities, the level of port digital information (A_2) accordingly rises, thereby more effectively boosting the coordination of regional blockchain transportation (B_5). Higher degrees of digitalization facilitate real-time data sharing and intelligent scheduling, reducing information asymmetry between shipping companies and governments and prompting more cross-regional and multiagency initiatives. Against the backdrop of rising decarbonization and environmental priorities, an elevated application rate of low-carbon technologies (A_5) not only helps secure government subsidies (D_3) and policy support but may also attract deeper collaboration from shipping companies, promoting more eco-friendly routing and vessel retrofitting.

5.2.2. Analysis of the Shipping Company Subsystem (S_2)

The inference results for changes in the shipping company subsystem are presented in Table 6.

Table 6. Reasoning for shipping company subsystem change.

Nodes	Edge Probability/%			Change Ratio/%	Nodes	Edge Probability/%			Change Ratio/%
	High	Medium	Low			High	Medium	Low	
S ₁	29.72	55.32	14.96	0.12	S ₃	29.94	47	23.06	−0.06
A ₁	20.18	58.01	21.81	−0.72	C ₁	24.03	55.98	19.99	−0.32
A ₂	26.78	53.09	20.13	0.3	C ₂	20.1	43.04	36.86	0.14
A ₃	23.69	61.37	14.94	0.52	C ₃	21.45	57.55	21	−0.52
A ₄	17.99	47.93	34.08	−0.22	C ₄	30	49.39	20.61	0.16
A ₅	16.00	46.88	37.12	1.64	S ₄	26.43	51.31	22.26	0
S ₂	100	0	0	/	D ₁	33.11	46.50	20.39	0.1
B ₁	28.83	53.74	17.43	5.52	D ₂	16.99	56.52	26.49	0
B ₂	23.33	52.6	24.07	19.9	D ₃	25.17	57.29	17.54	0.34
B ₃	20.85	43.98	35.17	1.82	D ₄	28.84	40.81	30.35	−1.22
B ₄	16.08	73.39	10.53	10.66	S	24.98	59.67	15.35	9.78
B ₅	19.93	40.5	39.57	16.6					

Shipping companies must interface with port enterprises (S₁) for berthing, cargo handling, and intermodal transport details, while also attending to customers' (S₃) sensitivity regarding timeliness, safety, and cost. Their operational efficiency and reliability not only directly affect port workflows but also indirectly shape customer satisfaction and engagement in overall supply chain services. When S₂ achieves a high-level state, it provides robust support for upstream port enterprises (S₁) and often drives government agencies toward green-shipping policies, while simultaneously stimulating greater demand for high-quality, sustainable logistics among customers (S₃).

Shipping operations are widely considered a major source of carbon emissions and energy consumption. When ship energy efficiency management (B₂) and the transparency of carbon emission accounting (B₃) both reach elevated levels, governments are more inclined to offer policy or subsidy support (D₃) and to encourage broader involvement in monitoring and refining green shipping services. Maintaining high performance in timeliness and reliability (B₄) further raises customer satisfaction and participation in port shipping optimization (C₃, C₄). In addition, shipping companies should prioritize the coordination of regional blockchain transportation (B₅) by enabling real-time sharing and verification of shipping documents with port enterprises, customers, and governments, thus achieving end-to-end visibility and strengthening collaborative efficiency.

5.2.3. Analysis of the Customer Subsystem (S₃)

The inference results for changes in the customer subsystem are presented in Table 7. The customer subsystem (S₃) exerts the most significant positive impact on node S, reaching 10.2%—underscoring its critical role in modern supply chains. Customers' (S₃) preferences regarding delivery speed, costs, and eco-friendly attributes directly influence the operational and policy priorities of port enterprises (S₁), shipping companies (S₂), and governments (S₄). When customers actively connect with port and shipping sectors by furnishing more precise forecasts (C₁) and specifying clearer green service needs (C₂), port enterprises and shipping companies can better identify improvement pathways, collectively advancing the overall collaborative system.

When the customer subsystem (S₃) operates at its maximum potential, green supply chain participation (C₂) can surge by 54%, while customer satisfaction and service quality evaluation (C₃) may rise by 43%. This finding shows that stronger customer commitment to eco-friendly transport and carbon reductions (C₂) frequently motivates governments (S₄) to introduce targeted incentives or regulations—such as green subsidies or tax incentives—and spurs port and shipping sectors to enhance low-carbon technologies (A₅, B₂, and B₃). Customer satisfaction and service quality evaluation (C₃) directly shape how rapidly and

in what direction port shipping enterprises refine their operations; if satisfaction remains low for an extended period, port and shipping enterprises lack clear insights into service defects, and government agencies (S_4) also lack reference data for timely policy adjustments. Moreover, more accurate logistics demand forecasts (C_1) enable port enterprises (S_1) to optimize berth allocation, scheduling, and equipment usage in advance, thereby mitigating congestion, reducing empty-load rates, and elevating overall turnover efficiency.

Table 7. Reasoning of customer subsystem change.

Nodes	Edge Probability/%			Change Ratio/%	Nodes	Edge Probability/%			Change Ratio/%
	High	Medium	Low			High	Medium	Low	
S_1	29.68	55.38	14.94	0.08	S_3	100	0	0	/
A_1	20.04	58.73	21.23	0.16	C_1	27.05	53.57	19.38	6.94
A_2	27.28	52.46	20.26	1.04	C_2	33.51	43.16	23.33	54.02
A_3	22.86	61.77	15.37	−2	C_3	34.38	53.69	11.93	43.48
A_4	17.88	47.38	34.74	−1.76	C_4	33.08	47.37	19.55	8.44
A_5	15.98	46.12	37.9	0.04	S_4	27.80	51.45	20.75	5.82
S_2	28.72	47.11	24.17	0	D_1	32.71	46.60	20.69	−1.3
B_1	24.92	58.41	16.67	−0.78	D_2	20.9	58.28	20.82	19.22
B_2	20.13	49.04	30.83	−0.02	D_3	25.06	57.37	17.57	0
B_3	20.36	43.73	35.91	−0.64	D_4	29.66	40.23	30.11	0.9
B_4	12.92	73.44	13.64	−1.88	S	25.48	58.88	15.64	10.2
B_5	17.24	37.52	45.24	−0.12					

5.2.4. Analysis of the Government Subsystem (S_4)

The inference results for changes in the government subsystem are presented in Table 8.

Table 8. Reasoning of government subsystem change.

Nodes	Edge Probability/%			Change Ratio/%	Nodes	Edge Probability/%			Change Ratio/%
	High	Medium	Low			High	Medium	Low	
S_1	29.7	55.37	14.93	0.14	S_3	30.38	46.7	22.92	1.10
A_1	19.79	58.75	21.46	−0.8	C_1	24.24	55.67	20.09	−0.1
A_2	27.09	52.63	20.28	0.62	C_2	21.64	42.24	36.12	4.7
A_3	23.53	61.46	15.01	0.06	C_3	21.77	57.23	21	0.12
A_4	17.97	48.05	33.98	−0.06	C_4	29.75	49.59	20.66	−0.44
A_5	16.00	46.1	37.9	0.08	S_4	100.00	0	0	/
S_2	28.74	47.10	24.16	0.06	D_1	52.38	33.64	13.98	51.46
B_1	25.15	58.34	16.51	0	D_2	24.08	50.87	25.05	17.12
B_2	20.28	48.8	30.92	0.1	D_3	24	58.29	17.71	−2.34
B_3	20.58	43.62	35.8	0.02	D_4	34.64	47.24	18.12	34.84
B_4	13.28	73.23	13.49	−0.86	S	24.38	59.21	16.41	6.46
B_5	17.21	37.5	45.29	−0.28					

Among the four subsystems, the government subsystem (S_4) exhibits the smallest positive effect, at only 6.46%. In a port shipping synergy system, changes in government policies or actions often benefit the customer subsystem (S_3) first—such as incentives for green logistics or mechanisms to boost customer engagement, which must be carried out by port enterprises and shipping companies. At the same time, infrastructure projects, technology subsidies, and legal frameworks also favor port enterprises (S_1) and shipping companies (S_2), as these measures align closely with industry needs. However, focusing excessively on collaboration with S_1 and S_2 while disregarding customer demands may constrain C_4 and hamper the full synergistic potential of D_1 – D_4 .

When the government subsystem (S_4) reaches its highest state, cross-regional policy coordination (D_1) significantly increases, making governments more inclined to coordinate

interregional logistics processes, port oversight, and shipping strategies to better address both industrial and public needs. The maturity of multilateral trading mechanisms (D_4) rises by 34.84%, second only to the shift in D_1 . By proactively engaging with port enterprises, shipping companies, and customers—often through multilateral consultation platforms—governments can promote joint technological innovations and low-carbon initiatives, thereby expanding both commercial and societal value. A well-established regulatory framework (D_2), combined with rigorous enforcement, further strengthens the confidence of port and shipping enterprises in the business environment, encouraging them to invest in port infrastructure and green upgrading (A_1 , A_5 , B_2). Nonetheless, if fiscal support and subsidies (D_3) do not increase proportionally, governments may need to refine funding mechanisms to better incentivize active participation from social organizations and sustain momentum for port shipping collaboration.

5.3. Backward Inference Analysis

To determine which factors are most critical for enhancing port shipping collaborative capacity (S), we set the overall synergy node S to a “high” state (100%) in the Bayesian network model, then applied backward inference. By observing how each indicator node’s state probabilities changed under $S = \text{“high”}$ (as illustrated in Figure 12), we identified the elements that contribute the most to overall synergy. The results show that green supply chain participation (C_2), customer satisfaction and service quality (C_3), the maturity of multilateral trading mechanisms (D_4), completeness and enforcement of policies (D_2), and the port digital information level (A_2) exhibit the most significant changes. Prioritizing these five components is associated with the largest expected uplift in overall synergy according to the model.

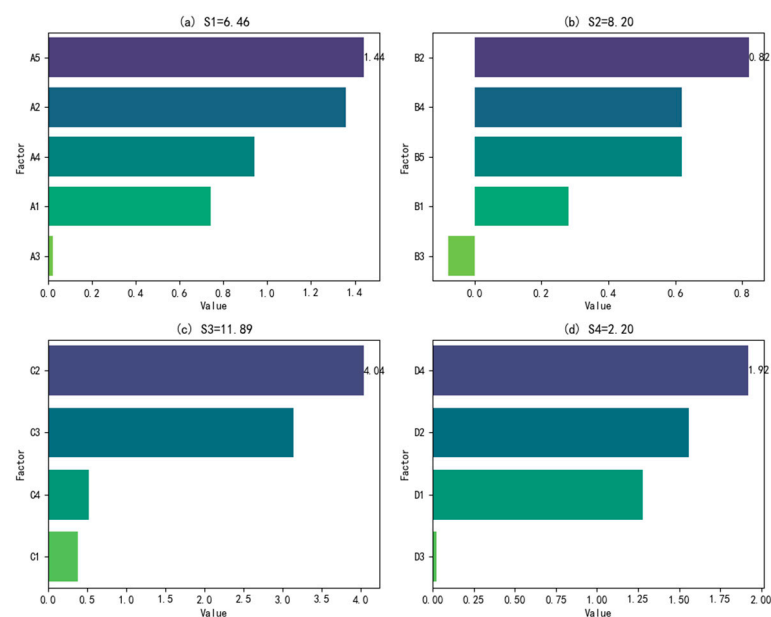


Figure 12. Reasoning for the collaborative ability of port shipping change.

Specifically, C_2 and C_3 reflect the customer subsystem’s (S_3) pull for more eco-friendly logistics and higher service quality; when both factors reach high levels, they effectively incentivize port and shipping enterprises to decarbonize, improve efficiency, and reduce costs. Meanwhile, D_4 and D_2 originate from the government’s subsystem (S_4), with D_4 offering more avenues for new business and subsidies through multilateral platforms, and D_2 ensuring a stable, enforceable institutional environment that underpins collaborative development. Finally, the port digital information level (A_2) in the port enterprise subsystem

(S_1) was associated with a measurable improvement in the precision of information sharing and operational scheduling.

Although individual nodes exhibit score change rates mostly between 0.5% and 4%, suggesting relatively minor absolute shifts, small adjustments across multiple nodes can accumulate into a notable synergy, significantly raising S overall. Consequently, port enterprises, shipping companies, customers, and governments should aim to form a collective force rather than adopting fragmented, localized strategies. When shipping companies (S_2) attain a high level, they interact positively with active customer feedback (S_3) and specialized government support (S_4). However, fully unleashing the potential of port enterprises (S_1)—and thus stimulating system-wide synergy—requires simultaneous enhancements of key factors such as B_1 , B_2 , and B_5 , along with improvements in C_3 and C_4 . Consistent with the forward inference findings, the customer subsystem (S_3) stands out for its particularly strong influence on S , further affirming the central position of customers in port shipping collaboration. Small, simultaneous adjustments across multiple stakeholders accumulate into notable synergy gains, which implies that ports, shipping companies, customers, and governments should act in concert rather than in isolation to maximize collaborative benefits.

6. Discussion and Policy Implications

Building on the quantitative findings, this section interprets their managerial and policy significance and situates them within existing collaborative governance research.

6.1. Establishing a Unified Objective and Enhancing Synergistic Effects

Building on the inference results, we find that improvements in basic throughput capacity, digitalization, and service diversification at port enterprises (subsystem S_1) directly promote overall synergy (S). However, simply expanding facilities or upgrading technologies on the port side alone does not fully boost collaboration with shipping companies (S_2) and customers (S_3). This underscores the need for ports to integrate capacity expansion with digital data-sharing in close coordination with shipping companies and customers, in order to fully leverage technological advancements. To maximize contributions to total collaborative capacity, port enterprises must strengthen both “hardware” (physical infrastructure) and “software” (digital and organizational mechanisms) while actively linking with the other subsystems.

First, when planning new terminals or expanding berths, port enterprises should coordinate schedules and routing with shipping companies—such as harmonizing shipping timetables and dispatch information—and leverage cross-regional policy support from governments (S_4) to balance construction with environmental requirements.

Second, improvements in port digital information level (A_2) must go beyond internal logistics efficiency and provide transparent, convenient data interfaces for customers (S_3), enabling them to swiftly track port operations and offer feedback. This in turn fosters greater demand-side acceptance of green and intelligent logistics. When ports and customers exchange information seamlessly, port operational efficiency (A_3) and diversified service capability (A_4) can be more accurately validated and refined.

Finally, ports should align their application rate of low-carbon technologies (A_5) with government ecological initiatives, seeking policy subsidies and piloting emerging technologies—such as blockchain—to bolster energy efficiency management connections with shipping companies (S_2). Under the momentum of green logistics, this also helps translate environmental values into market gains alongside customers. Only by placing equal emphasis on physical infrastructure (“hardware”) and collaborative mechanisms, and

by forging common goals with other stakeholders, can ports truly serve as the cornerstone of overall port shipping synergy.

6.2. Identifying Stakeholder Differences and Optimizing Resource Allocation

Shipping companies (S_2) demonstrate a notably strong impact on overall collaborative capacity in forward inference, particularly through key indicators such as compatibility of shipping networks (B_1), ship energy efficiency management (B_2), and coordination of regional blockchain transportation (B_5). If shipping companies focus solely on internal scheduling or vessel dispatch without effectively coordinating with port enterprises (S_1) and governments (S_4), or without addressing the transport demands and service feedback of customers (S_3), they cannot sustain overall synergy enhancement. This reinforces the need for shipping companies to not only optimize energy usage but also to actively respond to client expectations in terms of personalized services and sustainable logistics solutions.

According to backward inference outcomes, shipping companies should deepen collaboration in two areas. First, they need close interaction with port enterprises to share information and synchronize schedules, translating the operational advantages of high-efficiency vessels into efficient port operations and higher customer satisfaction. Second, they should proactively accommodate customers' preferences for green supply chains (C_2), service quality (C_3), and specialized requirements in their route planning and strategic development, steering shipping networks and bills of lading data toward lower carbon emissions and greater transparency. This approach not only attracts government incentives—such as fiscal support and subsidies (D_3)—but also garners broader social approval. By maintaining strong communication with S_1 , S_3 , and S_4 , and by harnessing digital tools like big data, artificial intelligence, and blockchain, shipping companies can elevate their own operational performance while advancing industry-wide decarbonization and upgrading efforts.

6.3. Flexibly Adjusting Customer Engagement Mechanisms

Within BN inferences, the customers subsystem (S_3) exhibits a strong “demand-pull” effect, especially through indicators such as green supply chain participation (C_2) and customer satisfaction and service quality evaluation (C_3), which exert substantial pressure on port enterprises (S_1) and shipping companies (S_2) to innovate in technologies and services. However, the large and diverse customer base also complicates communication and governance. Achieving a genuine boost from S_3 thus requires addressing both “breadth” and “depth.” This dynamic can be further strengthened if customers actively use established feedback channels to express expectations for service excellence and sustainability.

On one hand, governments (S_4) and enterprises can gather and respond to customer input via multiple channels, such as online platforms, periodic surveys, and complaint-reporting mechanisms, thereby enhancing customer influence in areas like low-carbon logistics and digital operations. On the other hand, during critical decision-making and implementation—for instance, launching new green routes or piloting blockchain transportation—stakeholders should involve key customer segments or primary interest groups in more focused discussions to ensure practical viability and market alignment. By adopting a “broad-first, then-deep” participation strategy, organizations can capture diverse demands and identify hidden challenges without compromising decision efficiency. When customers maintain high satisfaction (C_3) and continue to engage (C_2 , C_4), their cumulative push for port shipping synergy grows stronger, making improvements by S_1 and S_2 more targeted and driving positive feedback loops through market choices and reputation.

6.4. Strengthening the Government's Coordinating Role in Collaborative Governance

In both forward and backward inference results, the government subsystem (S_4) plays a clear “macro-level coordinator” role. Governments leverage policy and regulatory tools—including fiscal support, subsidies, and cross-regional coordination—to streamline resource flows and align stakeholder interests in port shipping systems. By offering cross-regional platforms and legal guarantees through well-crafted incentives and regulations, governments foster collaboration among all parties.

First, governments should employ top-level design to introduce tiered and differentiated support policies that ensure adequate investment in infrastructure, environmental protection, and digital transformation for port enterprises and shipping companies, while also meeting green logistics (C_2) and service demands (C_3) from the customer subsystem.

Second, governments need to strengthen legal and regulatory frameworks (D_2) to create a stable environment for innovations—such as blockchain transportation, energy efficiency management, and digital operations—and to use cross-regional policy coordination (D_1) to reduce local administrative barriers, allowing route planning and port expansion to achieve both low-carbon and high-efficiency objectives on a broader scale.

Finally, governments should appropriately redefine their role at the operational level: rather than micromanaging the activities of enterprises and customers, they can utilize policy instruments and public platforms to facilitate multi-stakeholder collaboration, assist S_1 and S_2 in upgrading technologies and operations, and help S_3 establish structured feedback mechanisms and participation channels. Only by integrating macro-level planning with grassroots flexibility can governments maintain stability, efficiency, and sustainability in this complex collaborative system.

7. Conclusions

Addressing challenges in multi-stakeholder coordination, resource misallocation, and dual pressures of low-carbon and digital transformations within port shipping, this research develops a comprehensive BN model. Through forward and backward inferences, it elucidates the key interactive mechanisms among port enterprises (S_1), shipping companies (S_2), customers (S_3), and governments (S_4). The findings indicate that when stakeholders undertake moderate yet synchronized enhancements in hardware, technology, and policy, they generate stronger synergistic effects than large-scale investments made by any single actor in isolation. Moreover, core indicators—such as green supply chain participation, maturity of multilateral trading mechanisms, and port digital information level—demonstrate high sensitivity and amplification effects, underscoring the importance of prioritizing these aspects in policy-making and corporate reforms. Cross-regional policy coordination and rigorous regulatory enforcement also prove critical to balancing economic benefits with environmental goals; effectively integrating these factors with enterprise upgrades and customers' low-carbon demands can notably accelerate the greening and digitization of port shipping systems.

Based on the above inferences, this research proposes feasible recommendations for multi-stakeholder governance. Port enterprises should integrate capacity expansion with digital data-sharing in collaboration with shipping companies and customers to fully leverage technological dividends. Shipping companies must focus on energy efficiency management and strengthen responses to customer demands—both in customization and green logistics. Customers, in turn, should actively utilize feedback channels to advocate for higher service quality and environmental performance. Governments can offer cross-regional platforms and legal guarantees through differentiated incentives and regulatory frameworks, thus fostering collaboration among all parties. From a theoretical standpoint, our results align with collaborative governance scholarship that stresses the superiority

of coordinated, cross-boundary action over single-actor initiatives. The BN reveals that digital information integration at ports and stringent policy enforcement reinforce one another, illustrating the shared motivation and joint capacity loop described in the IFCG. This coupling between digital infrastructure and policy extends the IFCG by highlighting connectivity in the data era as an emerging dimension of collaborative governance.

While BNs are well suited for capturing the nonlinear, uncertain interactions of multi-stakeholder systems, limitations remain concerning data completeness and the risk of overfitting. Future research should enlarge sample sizes, experiment with dynamic BNs, and undertake rigorous sensitivity or learning curve analyses to enhance predictive accuracy and overall model robustness. Furthermore, we recognize the importance of aligning the BN model with tangible operational performance metrics and validating its predictions against real-world outcomes. Although external validation of our BN has not been carried out in this study, we have now added a discussion of how the model's synergy insights relate to key port performance indicators. For example, improved port shipping coordination predicted by the BN would likely shorten vessel turnaround times and increase berth utilization by reducing delays and optimizing schedules. Similarly, higher collaborative efficiency—such as through synchronized operations and green initiatives—should translate into lower carbon emissions, as ships spend less time idling and resources are used more effectively. We emphasize that future work should validate these expectations by comparing the BN's probabilistic predictions with actual operational data (e.g., observed turnaround times, berth occupancy rates, and emissions), which will be crucial to confirm the model's practical applicability. Overall, by implementing relatively small yet simultaneous improvements across multiple dimensions, the port shipping industry can more rapidly achieve efficiency, resilience, and sustainability, thereby laying a solid foundation for a green and efficient global maritime ecosystem.

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