

Assessing enablers for smart technologies in maritime and shipping logistics: a GINA approach

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Abstract

Purpose – This study aims to assess the key enablers facilitating the adoption of smart technologies in maritime and shipping logistics using the Grey Influence Analysis (GINA) approach. As maritime supply chains become digitalised at a fast pace, technologies such as Artificial Intelligence, Internet of Things, Blockchain, Big Data analytics and Digital Twins have become significant drivers of efficiency, sustainability and resilience in operations; however, their successful implementation is contingent on an interconnected set of technological, environmental, economic, ecological and social enablers.

Design/methodology/approach – The paper identifies the major enablers influencing the adoption of smart technology in maritime logistics through an extensive literature review and professional validation. Expert opinion was collected using a structured questionnaire, and the GINA methodology was applied to identify causal relationships and determine the relative importance of each enabler. This methodology enables the analysis of a large number of responses without information loss, addressing the shortcomings of conventional approaches such as Interpretive Structural Modelling and DEMATEL.

Findings – The findings identify the most potent enablers that play a significant role in the digital transformation of maritime logistics systems.

Practical implications – The insights generated will inform policymakers, port actors and logistics managers of the strategic areas of interest for investment and for devising sustainable, smart logistics ecosystems.

Originality/value – By integrating intelligent technologies with a rigorous causal analysis approach, the paper contributes to the current body of knowledge on maritime digitalization.

Keywords Smart technologies, Maritime logistics, Shipping industry, Digital transformation, GINA, Supply chain sustainability, Enablers analysis

Paper type Research article

List of abbreviations

AI	Artificial Intelligence
IoT	Internet of Things
GINA	Grey Influence Analysis
TOE	Technology-Organization-Environment (framework)
ISM	Interpretive Structural Modelling
DEMATEL	Decision-Making Trial and Evaluation Laboratory
MCDM	Multi-Criteria Decision-Making
5G	Fifth-Generation (wireless network)
RFID	Radio-Frequency Identification

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1. Introduction

Maritime logistics is one of the fundamental pillar of the global economy, facilitating the movement of goods across the various international markets as well as enabling global trade integration. Shipment and port services form a crucial part of the supply chain systems because a substantial proportion of the global trade is conducted through the utilization of the maritime transport system (Shang *et al.*, 2025). The effectiveness, reliability and connectivity of maritime logistics determines the sustainability of the economies, competitiveness of the world and the sustainability of the trade. Maritime supply chains are becoming increasingly complex with the process of globalization which is increasingly engaging additional cargo, stakeholders, and dynamism in accordance with the market requirements.

The rapid advancement of the digital technologies has led to the emergence of the smart technologies in the maritime logistics. The introduction of technologies (Artificial Intelligence (AI), Internet of Things (IoT), Blockchain, Big Data analytics, and Digital Twins) alters the traditional shipping and port activities into intelligent, automatized, and data-driven solutions. These technologies give real-time monitoring of cargo and vessels, predictive maintenance, automatic decision-making and improved communication among the stakeholders. Smart ports have been the order of the day where digitalization can be used to enhance efficiency in every task reducing delays and enhancing services (Issa *et al.*, 2025; Zeng *et al.*, 2025). This change has also been enhanced by Industry 4.0 since it has promoted connectivity, automation, and intelligent control systems in the maritime world (Alavi-Borazjani *et al.*, 2025).

Despite technological advancements, many of the maritime supply chains still rely on traditional as well as the fragmented operational models characterized by manual documentation, lack of real-time visibility, and the inefficient coordination among stakeholders (Akbari *et al.*, 2022). These inefficiencies cause delays, increased operating costs as well as reduced responsiveness to disruption such as port congestion, environmental uncertainties as well as world crisis. Digital transformation has therefore been a requirement to ensure that it modernizes the maritime logistics in the areas of transparency, coordination and optimization of resource utilization. The efficient flow of information through the use of smart technologies provides it, supply chain visibility creates sustainable and resilient logistics processes.

Although the value of smart technologies is large, there are certain challenges with their application in the maritime logistics. The implementation cost is very high, the digital infrastructure is not there and technical expertise is not as pervasive as an impediment to many organizations (Andres *et al.*, 2025). There also exists the problem of data security, privacy and interoperability across different systems that are impediments to the ease of integration of technology. This makes the process of adoption complicated by the fact that it is not amenable to organizational change, complexities of regulation and lack of standardization. Maritime is a highly conservative industry that in most cases lacks adaptation to the new digital-based systems of operation, particularly in developing economies (Andres *et al.*, 2025; Zeng *et al.*, 2025).

It is also worth noting that AI-based predictive analytics is not the only technological pathway available to maritime and shipping stakeholders. Complementary and, in some contexts, alternative technologies – such as robotic process automation for documentation and customs processing, cloud-based port community systems for data sharing, cybersecurity and encryption frameworks for safeguarding digital infrastructure, and automated identification and tracking systems (e.g. RFID and satellite-based AIS) – are also being adopted across the industry. This study focuses on AI, IoT, Blockchain, Big Data analytics and Digital Twins because these five technologies recur most consistently across the maritime digitalization

literature as the primary drivers of smart-port and smart-shipping transformation; however, the enablers identified in this study are expected to be broadly applicable to the adoption of these complementary technologies as well.

In order to overcome these challenges and successful transition into smart technologies in maritime logistics, it is necessary to identify the most significant enablers that will increase the use of smart technologies in maritime logistics. The enablers, which can accelerate the rate of digital transformation, include technological preparedness, infrastructure, policy support, economic stimulus, environmental consciousness and partnership with stakeholders. The connection between these enablers is important to know the strategies and priorities to invest in to find out the effective ones (Parnell, 2016). The paper is therefore intended to examine these enablers using the grey influence Analysis (GINA) procedure of determining their weight and effect. The policy makers and port administrations, the logistics managers will also find the conclusions helpful to develop an efficient, sustainable, and intelligent system of maritime logistics.

The adoption of digital technologies into the maritime and shipping logistics has turned into a very significant concern in order to ensure the efficiency, sustainability, and stability of the global supply chains (Aparicio *et al.*, 2012). Some of the technologies that can change the traditional maritime operations into data-driven and smart systems include Artificial Intelligence (AI), Internet of Things (IoT), blockchain, digital twins, and big data analytics. However, there has been inconsistency and low adoption of these technologies in the industry despite the immense benefits they have on the industry. The key cause of this gap is the lack of a systematic cognition of the enablers, which can help it to be adopted.

Many technological, environmental, economic, ecological, and social enablers that influence integration of smart technologies have been discovered in the current literature. Most of the literature however focuses on identifying these factors separately and fails to take into account the new complex relationships and causal dependencies of the factors with each other. The maritime logistics systems as they exist in the real world are not operating independently of one another; they are dynamically interacting with one another with certain factors influencing other ones reinforcing them or rendering them dependent. The absence of a structured causal analysis framework fails to enable the decision-makers to emphasize on the key enablers and allocate the resources in the most efficient method possible.

In addition, traditional, or classical methods of analysis, such as regression analysis methods or simple statistical analysis methods, cannot adequately capture the complexity of cause-effect relationships of different interdependent factors. Even rather common methods as ISM and DEMATEL presuppose the processes of data aggregation that may lead to the information loss, especially with large data sets (Bongomin *et al.*, 2020). This creates an acute research gap in the application of powerful and data-conservative methods of analyzing the enabler relationships in the adoption of smart technology in the maritime industry.

Therefore, there is a pressing need to have a wide and systematic causation design approach that can successfully accommodate the relationships of effects among enablers (Ennouri, 2026). The likelihood of sealing this gap will assist the policy makers, researchers and industry players to have a more accurate understanding of the forces that drive the smart technology adoption and develop more effective implementation strategies in the maritime logistics.

While several studies have examined technology-adoption enablers in supply chain and logistics contexts individually, this study is among the first to apply the Grey Influence Analysis (GINA) technique specifically to the maritime and shipping logistics sector, integrating technological, environmental, economic, ecological and social dimensions of smart-technology adoption within a single causal framework. This cross-dimensional, information-preserving approach distinguishes the present study from prior maritime digitalization research that has relied on either descriptive enabler lists or aggregation-prone multi-criteria decision-making (MCDM) techniques such as ISM and DEMATEL.

1.1 Research gap

1.1.1 Limited application of GINA in maritime logistics. Such smart technologies as Artificial intelligence, Internet of Things, blockchain, and digital twins have already overwhelmed the existing body of knowledge about the maritime and shipping logistics. However, the lack of studies that make use of the sophisticated procedures of causal analysis, namely the Grey Influence Analysis (GINA), can also be identified in the specified field. Most of the earlier works have based their works on classical multi-criteria decision-making tools such as Interpretive Structural Modelling (ISM) and DEMATEL that could involve data aggregation processes which could lose valuable information.

1.1.2 Lack of structured causal relationship modelling. The second gap in the literature that is necessary is the gap of having no systematic and complete causal relationships modelling in enablers of smart technology adoption in the maritime logistics setting. Though several studies have managed to identify some of the key factors that influence digital transformation, they pay the tendency of assuming that these factors are independent variables, which forget to remember the interdependence that exists between these variables.

1.1.3 Need for an integrated and holistic framework. The current literature also suggests fragmentation of the research of smart technology intake, in which technological, environmental, economic, ecological, and social facets of the same are often examined in divergence. This is not such an approach that considers maritime logistic systems as a whole with various parts interacting with one another to deliver concurrent effects. There is the urgent need of a unified framework that would enable incorporation of all these dimensions within one model that could be referred to as the analytical model.

1.2 Theoretical framework

This study is anchored in an extended Technology–Organization–Environment (TOE) framework, a widely adopted theoretical lens for understanding technology adoption in organizational settings. The TOE framework emphasizes that adoption decisions are influenced by technological characteristics, organizational readiness and resources, and the external environmental context (regulatory, market, and competitive pressures). To better capture the sustainability imperatives in maritime logistics, we extend the framework with explicit ecological and social dimensions. This integrated multi-dimensional perspective underpins the categorization of the 21 enablers into technological, environmental, economic, ecological, and social groups and guides the causal analysis of their interrelationships using GINA.

1.3 Research objectives

- (1) To identify key enablers of smart technologies in maritime logistics
- (2) To analyze causal relationships among enablers using GINA
- (3) To rank the most influential enablers

1.4 Research questions

- (1) What are the key enablers facilitating the adoption of smart technologies in maritime logistics, and how can they be categorized across technological, environmental, economic, ecological, and social dimensions?
- (2) How do these enablers influence each other through causal relationships?
- (3) Which enablers exert the strongest causal influence (driving power) on the adoption of smart technologies, as identified through the GINA methodology?

2. Literature review

The literature underpinning this study was identified through a structured search of Scopus, Web of Science, and Google Scholar, using combinations of the keywords “smart technology adoption”, “maritime logistics”, “digital transformation”, “enablers”, “Grey Influence Analysis”, “ISM”, and “DEMATEL”, restricted primarily to peer-reviewed journal articles published between 2019 and 2026, with earlier foundational sources retained where conceptually necessary (e.g. [Aparicio et al., 2012](#); [Parnell, 2016](#)). Sources were screened for direct relevance to technology-adoption enablers in maritime, logistics, or closely comparable supply-chain settings, and were cross-checked against recent systematic reviews to minimize the risk of overlooking significant work in the field.

2.1 Digital transformation in maritime logistics

Digitalization is bringing transformative change to the maritime logistics industry. Technologies such as big data analytics, blockchain, and artificial intelligence are fundamentally reshaping operational efficiency and decision-making processes ([Zeng et al., 2025](#)). Digitalization promotes greater openness, reduces operational costs, and improves supply chain visibility. However, significant impediments remain, including high implementation costs, lack of standardized structures, cybersecurity threats, and resistance to organizational change. Government support, development of technological infrastructure, and cultivation of a skilled workforce are identified as critical contributors to successful digital transformation.

Smart technologies are redefining maritime logistics by enabling efficiency, automation, and sustainability. Internet of Things (IoT), artificial intelligence, and data analytics transform traditional port operations into intelligent and interconnected systems. Intelligent ports improve cargo management, reduce turnaround times, optimize resource utilization, and deliver positive environmental outcomes through reduced emissions and energy consumption. Evidence from automated container terminals confirms that such automation can increase terminal productivity, reduce costs and improve environmental sustainability ([Kon et al., 2020](#)).

Marine ports are undergoing radical transformation through the integration of electrification, IoT, 5G connectivity, and green energy, leading to smarter, more interconnected, and sustainable operations ([Issa et al., 2025](#)). These technologies enable real-time monitoring, more efficient energy use, and substantial reductions in carbon emissions.

Digital shipping corridors require key success factors such as technological infrastructure, regulatory alignment, stakeholder collaboration, and data standardization ([Alavi-Borazjani et al., 2025](#)). These corridors enhance data exchange, eliminate operational inefficiencies, and improve supply chain transparency. Public-private partnerships are essential to stimulate innovation and investment while addressing challenges such as lack of international standards, cybersecurity threats, and interoperability issues.

2.2 Role of specific smart technologies

Digital twin technology marks a new era in industrial innovation by enabling real-time simulation, monitoring, and optimization of physical systems ([Hasan and Crawford, 2025](#)). Digital twins create virtual replicas of physical assets, supporting predictive maintenance, performance analysis, and proactive issue identification to optimize operational efficiency and decision-making across industries.

Complementary technologies such as IoT for real-time monitoring, blockchain for secure data sharing, and big data analytics provide the data-rich environment necessary for intelligent, automated, and sustainable maritime operations. Digital platforms have also demonstrated potential in improving efficiency and sustainability in related sectors; for instance, digital solutions in water utilities have reduced losses and enhanced resource management through smart metering and analytics. Text-mining and machine-learning analyses of the blockchain literature similarly show that blockchain integration with IoT is central to secure, transparent and sustainable supply chain operations ([Hirata et al., 2021](#)).

2.3 Human, organizational, and sustainability factors

The human element remains central to successful Industry 4.0 implementation in maritime contexts. Operational preparedness and personnel flexibility are critical in Green Digital Shipping Corridors (GDSC), where automation, IoT, and data-driven systems are primary but inadequate training, digital illiteracy, and resistance to change can hinder progress (Emad *et al.*, 2025).

Logistics 4.0 further illustrates how automation, robotics, and data analytics can improve efficiency, speed, and accuracy in warehousing and inventory control, though challenges such as high investment costs, lack of skilled labor, and resistance to technology adoption persist (Karunarathna *et al.*, 2019).

2.4 Enablers of smart and sustainable technology integration

Recent studies have identified and evaluated specific enablers that drive the adoption of smart and sustainable technologies in maritime and logistics settings. A comprehensive review of digital twins in sustainable supply chains demonstrates how IoT, AI/ML, blockchain, and cloud computing enable predictive maintenance, process simulation, and emission reductions to meet operational and environmental objectives (Bandara and Buics, 2024).

Enablers of blockchain adoption in logistics supply chains, particularly in emerging economies, include secure data sharing, trust building, smart contracts, and IoT integration. ISM-DEMATEL analysis confirms blockchain's strong positive impact on transparency and automation (Samad *et al.*, 2023).

Sustainable enablers of green logistics, evaluated via fuzzy DEMATEL and ISM, include green vehicles, pollution control technology, cost-effective logistics, green port operations, green procurement, circular economy practices, waste disposal, CSR, and stakeholder cooperation (Shoaib *et al.*, 2023).

In the context of green supply chain management in Indian manufacturing, fuzzy analysis highlighted reverse logistics, circular economy practices, low-environmental-content materials, resource scarcity management, and consumer pressure for green products as significant contributors to waste minimization and long-term sustainability (Nayak *et al.*, 2023).

During pandemics, integrated MCDM approaches identified AI/ML for automation, real-time IoT monitoring, 5G connectivity, and logistics optimization as key resilience parameters for ports and shipping control (Liu *et al.*, 2023). Machine learning and discrete-event simulation techniques have likewise been used to optimize supply chain operations towards sustainability, demonstrating the value of data-driven methods for logistics decision-making (Le and Xuan-Thi-Thu, 2024).

IoT implementation in maritime freight further underscores enablers such as real-time monitoring, 5G infrastructure, cloud-based scalability, and integration with AI systems, which collectively enhance visibility and operational efficiency.

Evidence of IT- and digitalization-driven enablement is also well documented in agricultural and agri-food supply chains, offering transferable insights for maritime logistics. Kumar *et al.* (2015) identified information-technology enablement issues at the farmer level in the sugar supply chain and proposed e-application-based solutions to strengthen coordination between farmers and processors. Similarly, Sharma *et al.* (2022) examined disruptions in the Himalayan horticulture produce supply chain, using the kiwi fruit value chain in Uttarakhand as a case study, and proposed a sustainable business model to improve farmer revenue. Building on this, Sharma *et al.* (2024) developed a digital ecosystem framework for sustainable fruit supply chains in Uttarakhand, highlighting differential technology adoption between large and small farmers. These cross-sectoral studies reinforce the premise that digital and IT-enablement factors, though studied extensively in agri-food contexts, remain comparatively under-explored in maritime and shipping logistics, further substantiating the research gap addressed in this study.

2.5 Identification and categorization of enablers

The identification of enablers constitutes a critical phase of this research. The enablers were derived through a systematic review of literature and validated through expert consultation to ensure both theoretical and practical relevance.

The identified enablers are categorized into five major dimensions: technological, environmental, economic, ecological, and social. This classification ensures a holistic representation of the maritime logistics ecosystem.

3. Research methodology

3.1 Data collection

The data for this study were collected using a structured questionnaire designed to capture the influence relationships among the identified enablers. A five-point Likert scale was used to measure the degree of influence between enablers. A purposive sampling strategy was employed to recruit experts with substantial experience (minimum 5–10 years) in maritime logistics, port operations, shipping management, or digital supply chain technologies. Participants were selected based on their professional roles (directors, senior managers, executives, and academics/researchers) and expertise in smart technologies or sustainability initiatives, ensuring both practical and theoretical perspectives.

A total of 35 valid responses were collected from academicians and industry experts specializing in maritime logistics, supply chain management, and digital technologies. The diversity of respondents ensured the inclusion of both theoretical insights and practical perspectives, enhancing the reliability of the dataset.

3.1.1 Reliability and validity of the instrument. The questionnaire was pilot-tested with five domain experts prior to full deployment to check clarity, relevance, and face validity of the enabler items, and was refined based on their feedback. Content validity was further supported by deriving all 21 enablers from a systematic literature review and cross-verifying them with the same expert panel used for data collection, consistent with the recommended validation approach for grey-systems and MCDM-based studies (Rajesh, 2023). Because GINA operates on interval grey numbers rather than crisp averages, it inherently preserves the variability and internal consistency of individual expert judgments, reducing the reliability concerns associated with the premature averaging used in conventional ISM/DEMATEL approaches.

3.2 GINA methodology

The study employs the Grey Influence Analysis (GINA) method to analyze the causal relationships among the 21 enablers. GINA is a novel multi-criteria decision-making technique grounded in grey system theory and grey input–output models (Rajesh, 2023). It is particularly effective for handling uncertain, incomplete, and complex datasets while preserving the complete variability of expert judgments without any information loss during aggregation.

Unlike conventional approaches such as Interpretive Structural Modelling (ISM) and the Decision-Making Trial and Evaluation Laboratory (DEMATEL), which typically rely on small expert panels and average (crisp or fuzzy) responses leading to significant data loss GINA can accommodate a large number of responses by representing them as grey numbers. The methodological foundation of GINA follows the eleven-step procedure proposed by Rajesh (2023), which was implemented exactly as described below.

Step 1: Identification of Enablers

The 21 enablers were identified through a systematic literature review and validated by domain experts.

Step 2: Determine the Influence Relations between the Enablers

Expert opinions were collected via a structured questionnaire. Each of the 35 experts rated the direct influence of every enabler on every other enabler on a five-point Likert scale:

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- (1) 1 = Very Low influence
- (2) 2 = Low influence
- (3) 3 = Medium influence
- (4) 4 = High influence
- (5) 5 = Very High influence

Step 3: Cleaning and Sorting of the Responses

All 35 responses were carefully screened and cleaned by removing incomplete or inconsistent entries.

Step 4: Conversion of Linguistic Values into Grey Values

Linguistic ratings were converted into interval grey numbers using the standard grey conversion table (Rajesh, 2023):

$$1 \text{ (Very Low)} \rightarrow (1, 3)$$

$$2 \text{ (Low)} \rightarrow (2, 5)$$

$$3 \text{ (Medium)} \rightarrow (4, 7)$$

$$4 \text{ (High)} \rightarrow (6, 9) \quad 5 \text{ (Very High)} \rightarrow (8, 10)$$

Each pairwise influence relation is denoted as:

$$\otimes f_{ij} = \left(\underline{\otimes f_{ij}}, \overline{\otimes f_{ij}} \right)$$

Step 5: Aggregate the Relationships in Greyscales

The 35 individual grey matrices were aggregated using the grey addition operator (Deng, 1989). The aggregated grey influence for each cell is:

$$\sum_{l=1}^n \otimes f_{ij}^l = \left(\sum_{l=1}^n \underline{\otimes f_{ij}^l}, \sum_{l=1}^n \overline{\otimes f_{ij}^l} \right)$$

where:

$$n = 35$$

Step 6: Whitenization of Grey Scores into Crisp Values

The aggregated grey values were whitenized into three crisp models (Rajesh, 2023):

- *Critical model*: lower-bound values of the aggregated influences
- *Ideal model*: upper-bound values of the aggregated influences
- *Typical model*: average of the lower-bound and upper-bound values

Step 7: Evaluate the Direct Influence Coefficient

The direct influence coefficient matrices (B^p), where:

$$p = 1 \text{ (Critical)}, p = 2 \text{ (Ideal)}, p = 3 \text{ (Typical)}$$

were computed as:

$$b_{ij}^p = \frac{f_{ij}^p}{\sum_{i=1}^{21} f_{ij}^p}$$

for:

$$i, j = 1, 2, \dots, 21$$

Step 8: Determine the Complete Influence Matrix

The complete (total) influence coefficient matrices (C^p) were calculated using:

$$C^p = [(I - B^p)^{-1} - I]$$

where:

$$I = 21 \times 21 \text{ identity matrix}$$

Step 9: Obtain the Grey Responsibility and Influence Coefficients

The grey responsibility coefficient (driving power) of the i^{th} enabler is:

$$y_i^p = \frac{\sum_{j=1}^{21} c_{ij}^p}{\sum_{i=1}^{21} \sum_{j=1}^{21} c_{ij}^p}$$

The grey influence coefficient (dependence) of the j^{th} enabler is:

$$z_j^p = \frac{\sum_{i=1}^{21} c_{ij}^p}{\sum_{i=1}^{21} \sum_{j=1}^{21} c_{ij}^p}$$

Step 10: Obtain the Grey Importance Coefficient

The grey importance coefficient for each model was derived as:

$$t_i^p = y_i^p + z_i^p$$

Step 11: Identification of Most Influential Enablers and Analysis

The overall (aggregate) importance coefficient was calculated as the weighted mean of the three models:

$$t_i = \frac{t_i^1 + (4 \times t_i^2) + t_i^3}{l}$$

where:

l

is a weighting factor used to produce the final ranking.

The Pareto principle (top ~20%) was applied to identify the most influential enablers. Net influence values (responsibility minus dependence) were used to classify enablers into “cause” (driver) and “effect” (receiver) groups.

This rigorous, multi-model GINA approach enables a more accurate and comprehensive understanding of causal relationships while fully preserving the richness of the 35 expert responses. It is therefore highly suitable for analyzing complex systems such as maritime logistics.

All matrix operations (normalization, inversion, and coefficient calculations) were performed in MATLAB following the exact computational layout demonstrated in the GINA methodology.

3.3 Data analysis tools

The analysis of the data in the research occurs with the program of MATLAB that is famous in regard to its capabilities in the sphere of matrices calculations and numerical procedures. As the GINA method is rather complex, a number of matrix operations (normalization, inversion, and aggregation) are required to carry out it, MATLAB is going to be an efficient and effective platform to implement it. Being able to use MATLAB, one can be sure of calculating the direct and complete influence matrix appropriately, calculate responsibility, influence and importance coefficient. It is also easy to manipulate large amounts of data and offers precision in performing mathematical operations. The application of new and advanced analytical tools improves the quality of the research and gives a high degree of reliability and reprise ability of the results.

4. Results and analysis

4.1 Descriptive analysis of respondents

The study is based on 35 expert respondents from academic and industry backgrounds. The demographic and professional profile of respondents is presented in [Table 1](#).

4.2 GINA-based analytical framework

Grey Influence Analysis (GINA) was applied to model causal relationships among the 21 enablers while preserving the full variability of expert judgments. A five-point Likert scale was converted into grey numbers using the scale: 1 → (0.3), 2 → (2.5), 3 → (4.7), 4 → (6.9), and 5 → (8.10). Diagonal elements of the direct-relation matrix were forced as Critical = 35 ($1 \times n$), Ideal = 105 ($3 \times n$), and Typical = 70 ($(LB + UB)/2$), where $n = 35$ experts. Three whitenization models (Critical, Ideal, Typical) were constructed, and an Aggregate model was derived for final ranking and interpretation.

The direct-relation matrices were normalized, and the total influence matrix $T = X(I - X)^{-1}$ (where X is the normalized direct matrix) was computed for each model using MATLAB. Responsibility coefficients (r_i ; row sums) represent driving power, influence coefficients (c_i ; column sums) represent dependence, and combined importance is $t_i = r_i + c_i$. This approach avoids information loss during aggregation, addressing the limitations of conventional ISM and DEMATEL methods.

Table 1. Respondent profile

Characteristic	Category	Frequency (n)	Percentage (%)
<i>Current position</i>			
	Directors/Senior Managers (Ports)	15	42.9
	Executives (Shipping Companies)	11	31.4
	Managers (Logistics Service Providers)	6	17.1
	Academics/Researchers	3	8.6
<i>Highest qualification</i>			
	Postgraduate (MBA, MSc, or PhD)	24	68.6
	Bachelor's Degree	9	25.7
	Diploma/Other	2	5.7
<i>Years of professional experience</i>			
	Less than 10 years	5	14.3
	10–19 years	13	37.1
	20–29 years	11	31.4
	30 years and above	6	17.1

Source(s): Author's own compilation, based on primary survey data (n = 35)

4.3 Direct influence matrix

The normalized direct influence coefficient matrices for the Critical, Ideal, and Typical whitenization models are presented in [Table 3](#). These matrices capture the average grey influence of each enabler on every other enabler after normalization.

The matrices show strong direct influences among core technological enablers (e.g. Blockchain on most others) and operational-sustainability linkages (e.g. Optimizing Logistics on Green Port and Circular Economy). IoT and 5G exert notable influence on real-time monitoring clusters.

4.4 Total influence matrix (critical, ideal and typical)

The complete influence matrix is obtained using the relation:

$$B = (I - A)^{-1} - I$$

This matrix captures both direct as well as the indirect relationships among enablers.

The results indicate that IoT and AI have strong indirect influence across the system, reinforcing their importance in enabling integrated smart logistics.

4.5 Responsibility and influence coefficients

[Figure 1](#) presents the comparative analysis of grey influence coefficients, grey responsibility coefficients, and their combined importance values across Critical, Ideal, Typical, and Aggregate whitenization models. The 3D plot illustrates high consistency across models, with Critical values slightly elevated and minimal variation in driver-receiver balance, confirming the robustness of GINA.

The results demonstrate that Blockchain (B3), Optimizing Logistics (O12), and Green Port Operations (G13) exhibit the highest combined importance.

4.6 Importance ranking of enablers

Enablers are ranked by decreasing aggregate importance (t_i) derived from the Aggregate model.

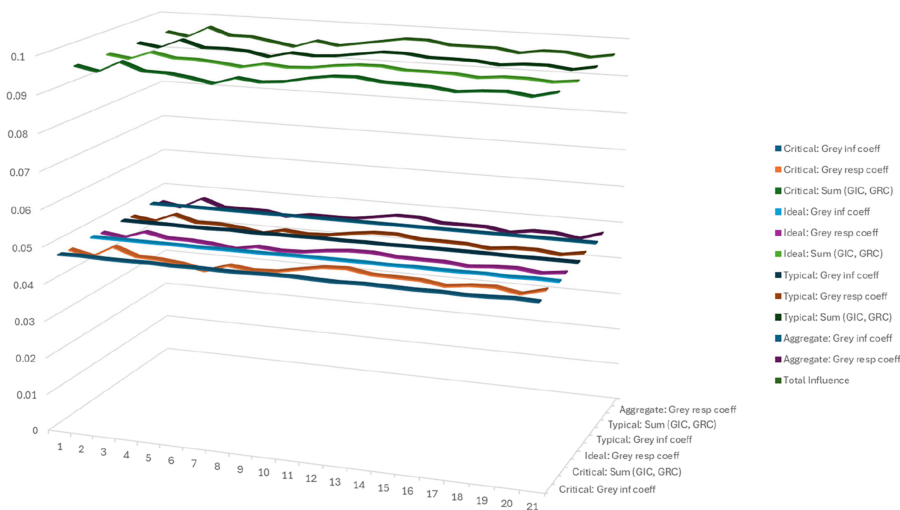


Figure 1. Comparative analysis of GINA whitening models and influence coefficients. Source: Authors’ own compilation, based on GINA analysis output

4.7 Interpretation of results

The GINA results reveal a balanced yet operationally anchored ecosystem. Blockchain (B3), Optimizing Logistics (O12), and Green Port Operations (G13) emerge as the strongest overall drivers ($t_i = 0.097$), highlighting that data integrity, process efficiency, and green infrastructure are the primary forces propelling smart-technology adoption. These enablers exert both high responsibility (driving power) and substantial system-wide influence. Technological enablers such as IoT, Digital Twins, and AI&ML, while foundational, show comparatively moderate net influence, suggesting they function best when supported by strong operational and regulatory foundations. Non-technological factors (Circular Economy, Waste Disposal, Stakeholder Collaboration, Consumer Pressure) form a tight high-importance cluster, confirming the socio-ecological nature of maritime digital transformation. The consistency across Critical, Ideal, and Typical models (Figure 1) and the sunburst visualizations (Figure 2) underscore the robustness of these findings.

4.8 Identification of most and least influential enablers

Most influential (Cause group – highest t_i): Blockchain, Optimizing Logistics, Green Port Operations, Pollution Control, and Green Procurement. These act as primary drivers.

Least influential (Effect group – lowest t_i): Digital Twins, IoT, Reverse Logistics, and ISO Standards. These are more dependent on other enablers.

The updated analysis shifts emphasis toward integrated operational-sustainability enablers while retaining the systemic importance of core technologies. These insights are derived directly from the expert-driven grey matrices and are visually corroborated by the provided 3D and ring charts.

5. Discussion

5.1 Interpretation of key findings

Before interpreting the findings in detail, it is useful to revisit how the results address the three research objectives and three research questions set out in the Introduction. Objective 1 (identifying key enablers) is met through the 21 enablers categorized in Table 2 and Research

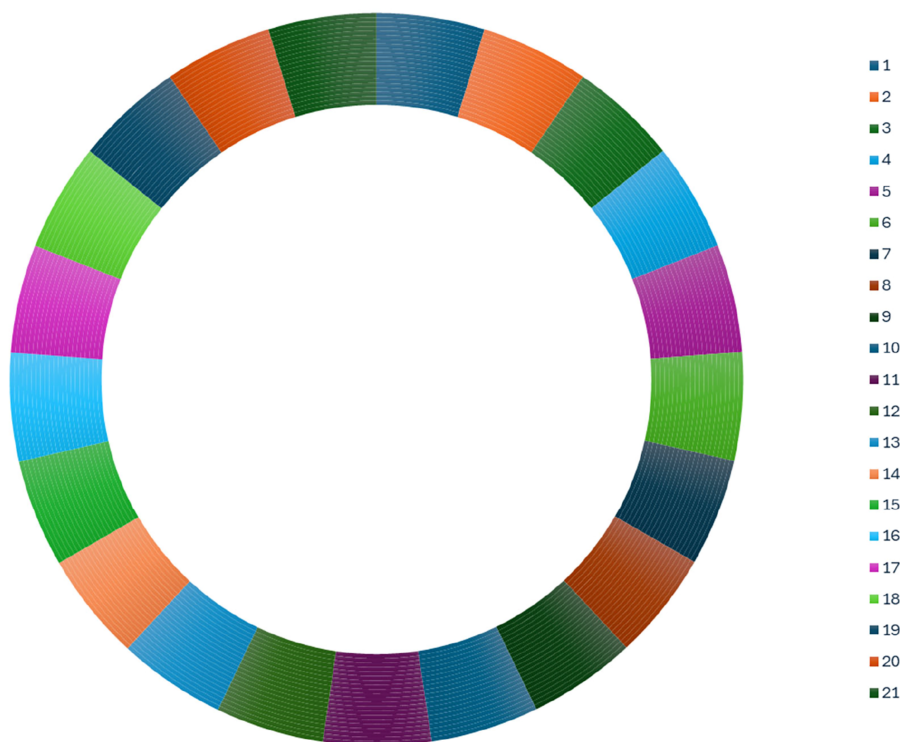


Figure 2. Sunburst charts of enabler influence strength. Source: Authors' own compilation, based on GINA analysis output

Question 1; Objective 2 (analyzing causal relationships) is addressed through the direct and total influence matrices (Tables 3 and 4) and Research Question 2; and Objective 3 (ranking the most influential enablers) is addressed through the responsibility, influence and importance rankings (Tables 5–7) and Research Question 3. The following subsections discuss these results in greater depth.

The Grey Influence Analysis (GINA) delivers a robust, multi-model picture of cause-effect relationships among the 21 enablers of smart technologies in maritime and shipping logistics. Unlike earlier assumptions that placed IoT, AI, and Digital Twins at the absolute top, the updated results (Aggregate model) identify *Blockchain for Secure Data Sharing (B3)*, *Optimizing Logistics for Cost and Efficiency (O12)*, and *Green Port Operations (G13)* as the three most influential enablers, each with a combined importance coefficient $t_i = 0.097$. These are followed closely by a cluster of sustainability-oriented factors—Pollution Control (P11), Green Procurement (G14), Circular Economy Practices (C15), Waste Disposal (P16), Resource Scarcity Management (M18), Consumer Pressure (R19), and Stakeholder Collaborations (S21)—all registering $t_i = 0.096$.

Responsibility coefficients (r_i) reveal that Blockchain, Optimizing Logistics, and Green Port Operations act as strong net drivers ($r_i \geq 0.049$), exerting substantial influence on the entire system while being only moderately dependent on other enablers. In contrast, technological enablers such as IoT ($t_i = 0.094$), Digital Twins ($t_i = 0.093$), and even AI and ML ($t_i = 0.095$) fall into the moderate-to-supporting tier. This shift indicates that while core technologies remain essential, their impact is amplified only when embedded within strong operational processes and green infrastructure. The consistency across Critical, Ideal, and

Table 2. List of identified enablers

Factor	Sub factor	Reference	Description
Technological	AI and ML for Automation and Prediction	Samad et al. (2023) , Liu et al. (2023) , Bandara and Buics (2024)	AI/ML algorithms enable predictive planning, demand forecasting, and optimization of logistics operations. They reduce human error, improve decision-making, and enhance operational efficiency across ports and shipping
	IoT and IIoT Real-Time Monitoring	Samad et al. (2023) , Liu et al. (2023) , Bandara and Buics (2024) , Nayak et al. (2023)	IoT sensors provide real-time visibility of cargo, fleet, and port operations. They improve traceability, reduce losses, and strengthen communication among stakeholders
	Blockchain for Secure Data Sharing	Bandara and Buics (2024) , Nayak et al. (2023)	Blockchain ensures secure, immutable, and transparent data management. It fosters trust among supply chain partners and supports automation through smart contracts
	Cloud Computing for Sustainability	Surucu-Balci et al. (2024)	Cloud solutions provide scalable infrastructure for real-time collaboration and storage. They reduce costs, improve interoperability, and support integration of diverse smart technologies
	5G and Advanced Connectivity	Surucu-Balci et al. (2024)	High-speed connectivity enables seamless communication between systems. 5G reduces latency, improves data transfer, and allows large-scale deployment of IoT and AI applications
	Reverse Logistics for Strategies	Nayak et al. (2023) , Shoaib et al. (2023)	Reverse logistics enables recycling and reuse, closing the supply chain loop. It supports sustainability goals and strengthens corporate responsibility
	Digital Twins	Bandara and Buics (2024)	Digital twins replicate logistics systems in a virtual environment. They allow predictive maintenance, testing of new processes, and proactive risk management
	Big Data Analytics	Bandara and Buics (2024)	Big data analytics involves collecting, processing, and analyzing vast amounts of structured and unstructured data from various sources in the supply chain to uncover valuable insights

(continued)

Table 2. Continued

Factor	Sub factor	Reference	Description
Environmental	Adoption of ISO 14000/14001 Standards	Shoaib et al. (2023)	ISO certification encourages environmentally responsible operations. However, it functions more as a regulatory requirement than a direct enabler of transformation
	Use of Green Vehicles to Cut Emissions	Nayak et al. (2023) , Shoaib et al. (2023)	Adoption of electric or alternative-fuel vehicles, along with emission-reduction systems, reduces the environmental footprint of maritime logistics
	Pollution Control in Logistics Operations	Liu et al. (2023) , Shoaib et al. (2023)	Applying emission-reducing technologies in port and logistics operations involves using digitalization, automation, electrification, and renewable energy to minimize fuel consumption and lower carbon emissions from machinery, vehicles, and buildings
Economic	Optimizing Logistics for Cost and Efficiency	Liu et al. (2023) , Shoaib et al. (2023)	Streamlining processes to lower costs and improve efficiency includes optimizing cargo handling, reducing waiting times through automated access and real-time data monitoring, and enhancing asset utilization
	Green port operations to Cut Impact and Costs	Nayak et al. (2023) , Shoaib et al. (2023)	Sustainable warehouses and eco-friendly procurement reduce operational costs and environmental impacts. They improve efficiency and create a competitive advantage in international trade
	Green Procurement for Sustainable Sourcing	Samad et al. (2023) , Shoaib et al. (2023)	Green procurement for sustainable sourcing involves prioritizing the purchase of goods and services that minimize environmental impact throughout their lifecycle, including energy efficiency, recyclability, and ethical practices
	Circular Economy Practices	Nayak et al. (2023) , Shoaib et al. (2023)	Recycling, reuse, and resource efficiency improve sustainability and reduce waste. These practices also support compliance with environmental regulations and enhance long-term resilience

(continued)

Table 2. Continued

Factor	Sub factor	Reference	Description
Ecological	Proper Waste Disposal to Reduce Pollution	Nayak <i>et al.</i> (2023)	Proper waste disposal to reduce pollution involves systematically managing and disposing of waste to prevent environmental contamination, using recycling, safe treatment methods, and compliance with regulations. This minimizes harmful emissions and protects ecosystems while promoting sustainable operational practices
	Adoption of Eco-Friendly Materials	Nayak <i>et al.</i> (2023)	Adoption of eco-friendly materials means using biodegradable, recyclable, or sustainable alternatives in packaging and logistics processes to reduce environmental impact. These materials help lower landfill waste and decrease pollution, contributing to circular economy goals
	Managing Resource Scarcity through Sustainability	Bandara and Buics (2024)	Managing resource scarcity through sustainability focuses on optimizing resource use, recycling, and adopting renewable energy to conserve finite materials and ensure long-term supply chain resilience. This supports environmental stewardship and cost-efficiency
Social	Responding to Consumer Pressure for Green Products	Shoaib <i>et al.</i> (2023)	Growing demand for green logistics practices compels firms to adopt sustainable solutions. This external pressure accelerates the adoption of smart technologies aligned with environmental goals
	Commitment to Corporate Social Responsibility (CSR)	Nayak <i>et al.</i> (2023)	Commitment to Corporate Social Responsibility (CSR) in logistics involves integrating ethical, social, and environmental concerns into business operations to minimize negative impacts while enhancing community well-being and sustainability. This fosters trust, strengthens brand reputation, and aligns business practices with broader societal values
	Stakeholder Collaborations	Shoaib <i>et al.</i> (2023)	Stakeholder collaborations entail working jointly with suppliers, customers, regulators, and communities to promote transparency, innovation, and sustainability across the supply chain. Such partnerships enable shared responsibilities, improved compliance, and collective progress towards efficient and responsible logistics

Source(s): Author’s own compilation, based on an extensive literature review and expert validation

Table 3. Direct influence coefficient matrix

Critical	A1	I2	B3	C4	G5	R6	D7	B8	I9	G10	P11	O12	G13	G14	C15	P16	E17	M18	R19	C20	S21
A1	0.009	0.053	0.053	0.055	0.05	0.05	0.05	0.051	0.049	0.05	0.05	0.051	0.047	0.048	0.046	0.049	0.048	0.045	0.046	0.047	0.048
I2	0.048	0.009	0.05	0.052	0.051	0.046	0.051	0.05	0.047	0.049	0.048	0.044	0.049	0.045	0.046	0.049	0.044	0.046	0.049	0.044	0.049
B3	0.054	0.051	0.009	0.052	0.055	0.054	0.053	0.055	0.048	0.052	0.049	0.052	0.052	0.047	0.05	0.048	0.051	0.05	0.052	0.052	0.051
C4	0.052	0.051	0.05	0.009	0.051	0.048	0.049	0.05	0.05	0.046	0.048	0.051	0.049	0.049	0.049	0.05	0.046	0.047	0.048	0.049	0.048
G5	0.05	0.053	0.053	0.052	0.009	0.054	0.052	0.047	0.044	0.049	0.047	0.049	0.047	0.046	0.047	0.047	0.049	0.051	0.048	0.046	0.047
R6	0.051	0.049	0.052	0.049	0.049	0.009	0.051	0.046	0.048	0.046	0.046	0.05	0.044	0.049	0.047	0.047	0.049	0.049	0.048	0.048	0.048
D7	0.049	0.051	0.05	0.05	0.048	0.048	0.009	0.049	0.045	0.043	0.047	0.043	0.044	0.044	0.048	0.046	0.045	0.048	0.046	0.049	0.046
B8	0.053	0.051	0.05	0.05	0.054	0.052	0.052	0.009	0.047	0.046	0.048	0.05	0.049	0.046	0.045	0.045	0.05	0.048	0.05	0.046	0.049
I9	0.048	0.047	0.046	0.044	0.047	0.05	0.047	0.046	0.009	0.05	0.049	0.047	0.049	0.051	0.049	0.053	0.05	0.051	0.048	0.047	0.048
G10	0.046	0.046	0.041	0.044	0.045	0.048	0.046	0.046	0.052	0.009	0.053	0.054	0.053	0.054	0.05	0.046	0.047	0.049	0.05	0.053	0.049
P11	0.047	0.051	0.047	0.047	0.048	0.048	0.046	0.05	0.051	0.053	0.009	0.05	0.051	0.055	0.048	0.052	0.052	0.048	0.053	0.053	0.049
O12	0.054	0.051	0.052	0.052	0.054	0.051	0.05	0.055	0.051	0.052	0.05	0.009	0.052	0.05	0.049	0.05	0.052	0.05	0.048	0.05	0.051
G13	0.049	0.051	0.052	0.054	0.052	0.049	0.051	0.048	0.049	0.054	0.053	0.051	0.009	0.053	0.051	0.052	0.052	0.048	0.051	0.055	0.054
G14	0.048	0.05	0.051	0.05	0.048	0.049	0.05	0.051	0.052	0.052	0.05	0.049	0.053	0.009	0.053	0.051	0.051	0.05	0.049	0.051	0.049
C15	0.053	0.051	0.052	0.051	0.049	0.05	0.047	0.049	0.051	0.047	0.049	0.05	0.048	0.052	0.009	0.052	0.052	0.053	0.05	0.051	0.048
P16	0.048	0.05	0.047	0.048	0.048	0.046	0.047	0.048	0.052	0.052	0.052	0.049	0.05	0.049	0.055	0.009	0.052	0.055	0.052	0.052	0.051
E17	0.049	0.045	0.049	0.045	0.045	0.05	0.049	0.048	0.052	0.051	0.05	0.05	0.049	0.053	0.053	0.049	0.009	0.047	0.05	0.05	0.049
M18	0.049	0.046	0.05	0.046	0.051	0.049	0.05	0.049	0.047	0.049	0.051	0.049	0.05	0.051	0.051	0.055	0.05	0.009	0.052	0.053	0.053
R19	0.046	0.048	0.05	0.05	0.05	0.048	0.046	0.052	0.052	0.052	0.05	0.053	0.052	0.052	0.051	0.05	0.051	0.009	0.049	0.051	0.051
C20	0.046	0.048	0.044	0.048	0.047	0.049	0.049	0.047	0.05	0.05	0.052	0.051	0.047	0.049	0.051	0.048	0.052	0.052	0.049	0.009	0.052
S21	0.052	0.052	0.052	0.051	0.051	0.05	0.054	0.052	0.052	0.05	0.051	0.05	0.053	0.05	0.051	0.049	0.051	0.049	0.049	0.049	0.009

Ideal	A1	I2	B3	C4	G5	R6	D7	B8	I9	G10	P11	O12	G13	G14	C15	P16	E17	M18	R19	C20	S21
A1	0.018	0.051	0.051	0.052	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.049	0.048	0.048	0.047	0.049	0.048	0.047	0.047	0.047	0.048
I2	0.048	0.018	0.049	0.05	0.049	0.047	0.05	0.05	0.048	0.048	0.048	0.046	0.049	0.046	0.047	0.048	0.046	0.047	0.048	0.046	0.049
B3	0.051	0.05	0.018	0.051	0.052	0.052	0.051	0.052	0.048	0.051	0.049	0.05	0.051	0.048	0.049	0.048	0.05	0.05	0.05	0.051	0.05
C4	0.051	0.05	0.05	0.018	0.05	0.048	0.049	0.05	0.049	0.047	0.048	0.05	0.049	0.049	0.049	0.049	0.047	0.048	0.048	0.049	0.048
G5	0.049	0.051	0.051	0.051	0.018	0.052	0.051	0.048	0.046	0.049	0.048	0.049	0.048	0.047	0.048	0.048	0.049	0.05	0.048	0.047	0.048
R6	0.05	0.049	0.051	0.049	0.049	0.018	0.05	0.047	0.048	0.047	0.047	0.05	0.046	0.049	0.048	0.048	0.047	0.049	0.049	0.048	0.048
D7	0.049	0.05	0.049	0.05	0.048	0.048	0.018	0.049	0.046	0.046	0.047	0.045	0.046	0.046	0.048	0.047	0.046	0.048	0.047	0.049	0.047

(continued)

Table 3. Continued

Ideal	A1	I2	B3	C4	G5	R6	D7	B8	I9	G10	P11	O12	G13	G14	C15	P16	E17	M18	R19	C20	S21
B8	0.051	0.05	0.049	0.049	0.051	0.05	0.05	0.018	0.048	0.047	0.049	0.05	0.049	0.047	0.047	0.047	0.05	0.048	0.049	0.047	0.049
I9	0.048	0.047	0.047	0.046	0.047	0.049	0.048	0.047	0.018	0.05	0.049	0.048	0.049	0.05	0.049	0.051	0.049	0.05	0.048	0.047	0.048
G10	0.047	0.047	0.044	0.046	0.047	0.048	0.047	0.047	0.051	0.018	0.051	0.051	0.051	0.052	0.049	0.047	0.047	0.049	0.049	0.051	0.049
P11	0.048	0.05	0.048	0.048	0.048	0.049	0.047	0.049	0.05	0.051	0.018	0.05	0.05	0.052	0.049	0.051	0.05	0.049	0.051	0.051	0.049
O12	0.052	0.05	0.051	0.051	0.051	0.05	0.049	0.052	0.05	0.051	0.05	0.018	0.051	0.049	0.049	0.049	0.05	0.05	0.048	0.05	0.05
G13	0.049	0.05	0.051	0.051	0.051	0.049	0.05	0.048	0.049	0.051	0.051	0.05	0.018	0.051	0.05	0.051	0.05	0.049	0.051	0.052	0.051
G14	0.048	0.049	0.05	0.049	0.049	0.049	0.05	0.05	0.051	0.051	0.049	0.049	0.051	0.018	0.051	0.05	0.05	0.049	0.049	0.05	0.049
C15	0.051	0.05	0.05	0.05	0.049	0.049	0.048	0.049	0.05	0.048	0.049	0.049	0.048	0.05	0.018	0.051	0.051	0.051	0.049	0.05	0.048
P16	0.048	0.049	0.048	0.048	0.048	0.047	0.048	0.048	0.05	0.05	0.051	0.049	0.05	0.049	0.052	0.018	0.051	0.052	0.051	0.051	0.05
E17	0.049	0.047	0.049	0.047	0.046	0.05	0.048	0.048	0.05	0.05	0.049	0.05	0.049	0.051	0.051	0.049	0.018	0.048	0.049	0.049	0.049
M18	0.049	0.047	0.049	0.047	0.05	0.048	0.05	0.049	0.048	0.049	0.05	0.049	0.05	0.05	0.05	0.052	0.049	0.018	0.051	0.051	0.051
R19	0.047	0.048	0.049	0.049	0.049	0.048	0.047	0.051	0.051	0.051	0.05	0.05	0.051	0.05	0.051	0.051	0.05	0.05	0.018	0.049	0.05
C20	0.047	0.048	0.046	0.048	0.048	0.049	0.049	0.048	0.05	0.049	0.05	0.05	0.047	0.049	0.05	0.049	0.051	0.051	0.049	0.018	0.05
S21	0.05	0.05	0.05	0.05	0.05	0.049	0.051	0.05	0.05	0.049	0.05	0.05	0.051	0.049	0.05	0.048	0.05	0.049	0.049	0.049	0.018

Typical	A1	I2	B3	C4	G5	R6	D7	B8	I9	G10	P11	O12	G13	G14	C15	P16	E17	M18	R19	C20	S21
A1	0.014	0.051	0.052	0.053	0.049	0.05	0.05	0.05	0.049	0.049	0.049	0.05	0.048	0.048	0.047	0.049	0.048	0.046	0.047	0.047	0.048
I2	0.048	0.014	0.049	0.051	0.05	0.046	0.05	0.05	0.048	0.048	0.048	0.045	0.049	0.046	0.047	0.049	0.045	0.047	0.049	0.045	0.049
B3	0.052	0.05	0.014	0.052	0.053	0.053	0.052	0.053	0.048	0.051	0.049	0.051	0.051	0.048	0.05	0.048	0.051	0.05	0.051	0.051	0.051
C4	0.051	0.05	0.05	0.014	0.05	0.048	0.049	0.05	0.049	0.047	0.048	0.05	0.049	0.049	0.049	0.049	0.047	0.047	0.048	0.049	0.048
G5	0.049	0.051	0.052	0.051	0.014	0.053	0.051	0.048	0.046	0.049	0.047	0.049	0.048	0.047	0.048	0.048	0.049	0.05	0.048	0.047	0.048
R6	0.051	0.049	0.051	0.049	0.049	0.014	0.051	0.047	0.048	0.047	0.047	0.05	0.045	0.049	0.047	0.048	0.047	0.049	0.049	0.048	0.048
D7	0.049	0.05	0.049	0.05	0.048	0.048	0.014	0.049	0.046	0.045	0.047	0.045	0.045	0.045	0.048	0.047	0.046	0.048	0.046	0.049	0.047
B8	0.052	0.05	0.049	0.049	0.052	0.051	0.051	0.014	0.048	0.047	0.048	0.05	0.049	0.047	0.046	0.046	0.05	0.048	0.05	0.046	0.049
I9	0.048	0.047	0.047	0.045	0.047	0.05	0.047	0.046	0.014	0.05	0.049	0.048	0.049	0.05	0.049	0.052	0.05	0.05	0.048	0.047	0.048
G10	0.047	0.047	0.043	0.045	0.046	0.048	0.047	0.047	0.051	0.014	0.051	0.052	0.052	0.053	0.049	0.047	0.047	0.049	0.05	0.052	0.049
P11	0.048	0.05	0.047	0.047	0.048	0.049	0.046	0.05	0.05	0.052	0.014	0.05	0.051	0.053	0.049	0.051	0.051	0.049	0.052	0.052	0.049
O12	0.052	0.051	0.051	0.052	0.052	0.05	0.05	0.053	0.051	0.051	0.05	0.014	0.051	0.049	0.049	0.05	0.051	0.05	0.048	0.05	0.051
G13	0.049	0.05	0.051	0.052	0.051	0.049	0.05	0.048	0.049	0.052	0.052	0.05	0.014	0.052	0.051	0.051	0.051	0.049	0.051	0.053	0.052
G14	0.048	0.049	0.05	0.05	0.049	0.049	0.05	0.051	0.051	0.051	0.049	0.049	0.051	0.014	0.052	0.051	0.05	0.049	0.049	0.05	0.049

(continued)

Table 3. Continued

Typical	A1	I2	B3	C4	G5	R6	D7	B8	I9	G10	P11	O12	G13	G14	C15	P16	E17	M18	R19	C20	S21
C15	0.052	0.05	0.051	0.05	0.049	0.05	0.047	0.049	0.05	0.048	0.049	0.05	0.048	0.051	0.014	0.051	0.051	0.052	0.05	0.05	0.048
P16	0.048	0.05	0.048	0.048	0.048	0.047	0.047	0.048	0.051	0.051	0.051	0.049	0.05	0.049	0.053	0.014	0.051	0.053	0.051	0.051	0.05
E17	0.049	0.046	0.049	0.046	0.046	0.05	0.048	0.048	0.051	0.05	0.049	0.05	0.049	0.052	0.052	0.049	0.014	0.048	0.049	0.049	0.049
M18	0.049	0.047	0.05	0.047	0.05	0.049	0.05	0.049	0.047	0.049	0.05	0.049	0.05	0.05	0.05	0.053	0.05	0.014	0.051	0.052	0.052
R19	0.047	0.048	0.05	0.049	0.049	0.048	0.047	0.051	0.051	0.051	0.051	0.05	0.052	0.051	0.051	0.051	0.05	0.051	0.014	0.049	0.05
C20	0.046	0.048	0.045	0.048	0.048	0.049	0.049	0.048	0.05	0.05	0.051	0.051	0.047	0.049	0.05	0.049	0.052	0.052	0.049	0.014	0.051
S21	0.051	0.051	0.051	0.05	0.05	0.05	0.052	0.051	0.051	0.049	0.05	0.05	0.052	0.05	0.051	0.049	0.05	0.049	0.049	0.049	0.014

Source(s): Author's own computation, using the GINA methodology (MATLAB output)

Table 4. Total influence matrix

Critical	A1	I2	B3	C4	G5	R6	D7	B8	I9	G10	P11
A1	308.986	309.933	308.731	308.449	309.322	308.144	308.44	308.145	308.145	309.338	309.924
I2	300.393	301.235	300.106	299.832	300.683	299.533	299.826	299.538	299.537	300.697	301.266
B3	321.552	322.491	321.2	320.946	321.861	320.635	320.942	320.636	320.632	321.875	322.482
C4	307.63	308.529	307.332	307.01	307.923	306.748	307.044	306.75	306.752	307.935	308.52
G5	306.619	307.519	306.326	306.044	306.873	305.747	306.04	305.741	305.74	306.927	307.507
R6	302.508	303.392	302.218	301.938	302.796	301.604	301.935	301.641	301.644	302.809	303.383
D7	294.957	295.823	294.675	294.404	295.239	294.114	294.36	294.116	294.114	295.249	295.813
B8	307.523	308.422	307.225	306.943	307.819	306.645	306.94	306.604	306.643	307.827	308.412
I9	303.483	304.37	303.189	302.909	303.773	302.618	302.907	302.615	302.582	303.791	304.366
G10	305.069	305.963	304.771	304.494	305.361	304.2	304.491	304.199	304.207	305.342	305.963
P11	313.047	313.968	312.746	312.459	313.348	312.155	312.453	312.157	312.16	313.369	313.921
O12	320.419	321.354	320.109	319.815	320.726	319.501	319.808	319.506	319.504	320.74	321.346
G13	321.979	322.923	321.672	321.378	322.29	321.06	321.371	321.059	321.063	322.308	322.918
G14	315.408	316.333	315.107	314.817	315.71	314.509	314.812	314.511	314.514	315.73	316.326
C15	314.835	315.755	314.532	314.242	315.133	313.934	314.233	313.934	313.937	315.148	315.746
P16	314.265	315.187	313.962	313.674	314.566	313.366	313.669	313.369	313.375	314.586	315.182
E17	308.295	309.194	307.998	307.711	308.586	307.415	307.71	307.414	307.42	308.608	309.191
M18	313.722	314.638	313.421	313.129	314.024	312.826	313.128	312.827	312.827	314.039	314.635
R19	314.929	315.853	314.629	314.34	315.234	314.032	314.332	314.036	314.038	315.252	315.849
C20	307.623	308.525	307.325	307.046	307.918	306.747	307.043	306.746	306.751	307.937	308.522
S21	318.611	319.544	318.305	318.011	318.915	317.7	318.009	317.702	317.704	318.931	319.536

Critical	O12	G13	G14	C15	P16	E17	M18	R19	C20	S21
A1	308.443	308.143	309.329	308.727	308.137	308.732	307.541	307.844	309.621	308.433
I2	299.822	299.539	300.686	300.104	299.53	300.106	298.952	299.249	300.97	299.82
B3	320.943	320.635	321.863	321.242	320.623	321.247	320.009	320.325	322.172	320.935

(continued)

Table 4. Continued

Critical	O12	G13	G14	C15	P16	E17	M18	R19	C20	S21
C4	307.048	306.751	307.93	307.334	306.744	307.334	306.152	306.454	308.222	307.038
G5	306.038	305.743	306.917	306.323	305.735	306.329	305.151	305.448	307.208	306.03
R6	301.936	301.641	302.805	302.216	301.635	302.219	301.058	301.353	303.09	301.927
D7	294.395	294.113	295.244	294.675	294.107	294.676	293.544	293.831	295.528	294.391
B8	306.94	306.645	307.82	307.223	306.632	307.231	306.046	306.349	308.112	306.932
I9	302.909	302.62	303.785	303.194	302.615	303.199	302.032	302.326	304.069	302.903
G10	304.501	304.208	305.378	304.782	304.193	304.783	303.611	303.911	305.666	304.489
P11	312.459	312.16	313.364	312.75	312.152	312.757	311.549	311.86	313.658	312.451
O12	319.771	319.505	320.731	320.109	319.494	320.115	318.881	319.192	321.035	319.804
G13	321.372	321.024	322.3	321.674	321.056	321.678	320.436	320.754	322.607	321.368
G14	314.813	314.515	315.682	315.112	314.504	315.114	313.9	314.207	316.021	314.806
C15	314.238	313.935	315.145	314.493	313.93	314.538	313.328	313.633	315.442	314.229
P16	313.672	313.373	314.576	313.972	313.325	313.973	312.767	313.071	314.877	313.667
E17	307.713	307.417	308.603	308.004	307.409	307.966	306.816	307.121	308.892	307.705
M18	313.129	312.83	314.033	313.425	312.826	313.427	312.181	312.529	314.332	313.126
R19	314.337	314.039	315.245	314.634	314.028	314.636	313.425	313.693	315.541	314.331
C20	307.046	306.748	307.929	307.334	306.741	307.338	306.155	306.453	308.182	307.04
S21	318.007	317.705	318.924	318.306	317.693	318.31	317.083	317.394	319.225	317.961

Ideal	A1	I2	B3	C4	G5	R6	D7	B8	I9	G10	P11
A1	-122.761	-122.848	-122.727	-122.728	-122.612	-122.492	-122.73	-122.612	-122.732	-122.97	-122.971
I2	-120.813	-120.959	-120.81	-120.81	-120.695	-120.578	-120.81	-120.694	-120.814	-121.049	-121.049
B3	-126.203	-126.326	-126.233	-126.202	-126.08	-125.956	-126.202	-126.08	-126.207	-126.449	-126.452
C4	-123.1	-123.221	-123.1	-123.132	-122.982	-122.864	-123.102	-122.982	-123.104	-123.344	-123.344
G5	-123.086	-123.203	-123.082	-123.084	-122.997	-122.843	-123.083	-122.967	-123.09	-123.326	-123.328

(continued)

Table 4. Continued

Ideal	A1	I2	B3	C4	G5	R6	D7	B8	I9	G10	P11
R6	−122.019	−122.138	−122.016	−122.02	−121.902	−121.813	−122.018	−121.904	−122.022	−122.26	−122.261
D7	−119.843	−119.958	−119.841	−119.841	−119.728	−119.61	−119.872	−119.727	−119.847	−120.08	−120.079
B8	−122.97	−123.09	−122.97	−122.971	−122.851	−122.732	−122.97	−122.883	−122.974	−123.214	−123.213
I9	−121.791	−121.91	−121.79	−121.793	−121.674	−121.553	−121.79	−121.674	−121.822	−122.027	−122.029
G10	−122.162	−122.28	−122.163	−122.163	−122.044	−121.923	−122.161	−122.044	−122.16	−122.429	−122.397
P11	−124.552	−124.671	−124.551	−124.552	−124.432	−124.309	−124.553	−124.431	−124.552	−124.793	−124.825
O12	−126.092	−126.217	−126.092	−126.093	−125.971	−125.849	−126.094	−125.97	−126.096	−126.339	−126.341
G13	−126.346	−126.468	−126.342	−126.344	−126.222	−126.1	−126.344	−126.224	−126.347	−126.591	−126.591
G14	−124.901	−125.021	−124.897	−124.9	−124.779	−124.657	−124.898	−124.778	−124.9	−125.142	−125.145
C15	−124.539	−124.66	−124.538	−124.539	−124.42	−124.298	−124.541	−124.42	−124.541	−124.785	−124.784
P16	−124.556	−124.676	−124.555	−124.556	−124.436	−124.315	−124.556	−124.436	−124.556	−124.798	−124.797
E17	−123.115	−123.237	−123.114	−123.117	−122.999	−122.875	−123.115	−122.997	−123.116	−123.355	−123.356
M18	−124.439	−124.561	−124.437	−124.44	−124.317	−124.197	−124.437	−124.318	−124.441	−124.682	−124.681
R19	−124.803	−124.923	−124.8	−124.801	−124.68	−124.559	−124.802	−124.678	−124.801	−125.043	−125.045
C20	−123.101	−123.22	−123.101	−123.1	−122.981	−122.86	−123.099	−122.981	−123.1	−123.34	−123.34
S21	−125.015	−125.137	−125.014	−125.015	−124.895	−124.773	−125.014	−124.894	−125.017	−125.261	−125.26

Ideal	O12	G13	G14	C15	P16	E17	M18	R19	C20	S21
A1	−122.969	−122.971	−122.734	−122.972	−122.852	−122.614	−122.972	−122.496	−122.974	−122.614
I2	−121.049	−121.047	−120.817	−121.049	−120.932	−120.699	−121.049	−120.58	−121.052	−120.696
B3	−126.449	−126.449	−126.208	−126.45	−126.33	−126.083	−126.45	−125.961	−126.451	−126.083
C4	−123.34	−123.342	−123.105	−123.342	−123.224	−122.986	−123.343	−122.866	−123.344	−122.985
G5	−123.325	−123.327	−123.09	−123.326	−123.208	−122.968	−123.325	−122.85	−123.33	−122.969
R6	−122.256	−122.261	−122.022	−122.258	−122.141	−121.905	−122.258	−121.785	−122.261	−121.904
D7	−120.079	−120.079	−119.848	−120.077	−119.963	−119.731	−120.078	−119.614	−120.079	−119.73

(continued)

Table 4. Continued

Ideal	O12	G13	G14	C15	P16	E17	M18	R19	C20	S21
B8	−123.21	−123.212	−122.976	−123.213	−123.095	−122.853	−123.213	−122.735	−123.216	−122.854
I9	−122.028	−122.028	−121.791	−122.027	−121.908	−121.673	−122.027	−121.556	−122.032	−121.675
G10	−122.395	−122.396	−122.159	−122.398	−122.282	−122.045	−122.398	−121.925	−122.399	−122.043
P11	−124.792	−124.793	−124.551	−124.794	−124.672	−124.431	−124.794	−124.31	−124.794	−124.432
O12	−126.37	−126.339	−126.097	−126.341	−126.22	−125.973	−126.34	−125.853	−126.342	−125.974
G13	−126.59	−126.622	−126.346	−126.591	−126.469	−126.224	−126.592	−126.101	−126.592	−126.223
G14	−125.143	−125.142	−124.932	−125.141	−125.022	−124.779	−125.144	−124.659	−125.145	−124.781
C15	−124.782	−124.784	−124.542	−124.813	−124.662	−124.419	−124.782	−124.301	−124.785	−124.422
P16	−124.797	−124.797	−124.558	−124.795	−124.708	−124.434	−124.796	−124.314	−124.798	−124.435
E17	−123.353	−123.355	−123.116	−123.353	−123.237	−123.027	−123.356	−122.878	−123.357	−122.997
M18	−124.68	−124.68	−124.44	−124.68	−124.559	−124.319	−124.712	−124.197	−124.682	−124.318
R19	−125.043	−125.043	−124.802	−125.042	−124.922	−124.681	−125.044	−124.591	−125.047	−124.681
C20	−123.338	−123.341	−123.102	−123.338	−123.221	−122.979	−123.338	−122.862	−123.372	−122.981
S21	−125.258	−125.258	−125.019	−125.259	−125.141	−124.896	−125.26	−124.776	−125.262	−124.927

Typical	A1	I2	B3	C4	G5	R6	D7	B8	I9	G10	P11
A1	−5680.42	−5674.85	−5674.86	−5669.36	−5669.36	−5685.82	−5669.35	−5680.36	−5675.02	−5685.92	−5674.95
I2	−5564.62	−5559.22	−5559.2	−5553.81	−5553.81	−5569.94	−5553.8	−5564.58	−5559.36	−5570.04	−5559.29
B3	−5873.45	−5867.72	−5867.77	−5862.05	−5862.05	−5879.07	−5862.03	−5873.42	−5867.9	−5879.17	−5867.83
C4	−5664.65	−5659.13	−5659.14	−5653.69	−5653.66	−5670.07	−5653.65	−5664.62	−5659.3	−5670.18	−5659.23
G5	−5674.8	−5669.26	−5669.28	−5663.78	−5663.81	−5680.22	−5663.77	−5674.77	−5669.44	−5680.33	−5669.37
R6	−5619.94	−5614.46	−5614.47	−5609.03	−5609.03	−5625.35	−5609.02	−5619.91	−5614.63	−5625.42	−5614.56
D7	−5497.63	−5492.26	−5492.28	−5486.95	−5486.95	−5502.89	−5486.98	−5497.6	−5492.43	−5502.99	−5492.37
B8	−5669.17	−5663.65	−5663.66	−5658.17	−5658.17	−5674.6	−5658.16	−5669.18	−5663.82	−5674.7	−5663.75
I9	−5610.04	−5604.56	−5604.58	−5599.15	−5599.14	−5615.4	−5599.13	−5610.01	−5604.77	−5615.5	−5604.66

(continued)

Table 4. Continued

Typical	A1	I2	B3	C4	G5	R6	D7	B8	I9	G10	P11
G10	−5638.32	−5632.82	−5632.84	−5627.37	−5627.37	−5643.71	−5627.36	−5638.29	−5632.99	−5643.84	−5632.92
P11	−5759.27	−5753.65	−5753.67	−5748.09	−5748.09	−5764.77	−5748.08	−5759.23	−5753.82	−5764.87	−5753.79
O12	−5857.18	−5851.47	−5851.48	−5845.81	−5845.81	−5862.78	−5845.8	−5857.15	−5851.64	−5862.88	−5851.57
G13	−5863.86	−5858.14	−5858.15	−5852.47	−5852.47	−5869.46	−5852.46	−5863.83	−5858.31	−5869.57	−5858.24
G14	−5775.03	−5769.4	−5769.41	−5763.82	−5763.82	−5780.55	−5763.81	−5775	−5769.57	−5780.66	−5769.5
C15	−5770.05	−5764.42	−5764.44	−5758.84	−5758.85	−5775.57	−5758.84	−5770.02	−5764.59	−5775.67	−5764.53
P16	−5759.34	−5753.72	−5753.74	−5748.16	−5748.16	−5764.85	−5748.15	−5759.31	−5753.9	−5764.95	−5753.83
E17	−5676.69	−5671.16	−5671.17	−5665.67	−5665.67	−5682.12	−5665.66	−5676.66	−5671.32	−5682.22	−5671.26
M18	−5759.79	−5754.17	−5754.18	−5748.6	−5748.6	−5765.29	−5748.59	−5759.75	−5754.34	−5765.4	−5754.27
R19	−5776.62	−5770.99	−5771	−5765.4	−5765.4	−5782.14	−5765.4	−5776.59	−5771.16	−5782.25	−5771.09
C20	−5692.18	−5686.63	−5686.65	−5681.13	−5681.13	−5697.62	−5681.12	−5692.15	−5686.8	−5697.72	−5686.73
S21	−5818.83	−5813.15	−5813.17	−5807.53	−5807.53	−5824.39	−5807.52	−5818.8	−5813.33	−5824.5	−5813.26
Sum	−120002	−119885	−119885	−119769	−119769	−120117	−119769	−120001	−119888	−120119	−119887

Typical	O12	G13	G14	C15	P16	E17	M18	R19	C20	S21
A1	−5691.41	−5680.41	−5691.44	−5691.43	−5691.37	−5685.95	−5680.45	−5674.93	−5680.45	−5680.41
I2	−5575.42	−5564.64	−5575.45	−5575.43	−5575.38	−5570.06	−5564.68	−5559.27	−5564.68	−5564.63
B3	−5884.85	−5873.48	−5884.88	−5884.87	−5884.81	−5879.19	−5873.51	−5867.81	−5873.51	−5873.47
C4	−5675.64	−5664.68	−5675.68	−5675.67	−5675.61	−5670.2	−5664.72	−5659.21	−5664.72	−5664.67
G5	−5685.81	−5674.82	−5685.84	−5685.83	−5685.77	−5680.35	−5674.86	−5669.34	−5674.86	−5674.82
R6	−5630.84	−5619.97	−5630.88	−5630.87	−5630.81	−5625.44	−5620	−5614.54	−5620	−5619.96
D7	−5508.3	−5497.65	−5508.33	−5508.32	−5508.26	−5503.01	−5497.69	−5492.35	−5497.69	−5497.65
B8	−5680.17	−5669.2	−5680.21	−5680.2	−5680.14	−5674.72	−5669.24	−5663.73	−5669.24	−5669.19
I9	−5620.92	−5610.06	−5620.95	−5620.94	−5620.88	−5615.52	−5610.09	−5604.64	−5610.1	−5610.05
G10	−5649.25	−5638.34	−5649.29	−5649.28	−5649.22	−5643.83	−5638.38	−5632.9	−5638.37	−5638.33

(continued)

Table 4. Continued

Typical	O12	G13	G14	C15	P16	E17	M18	R19	C20	S21
P11	−5770.44	−5759.29	−5770.47	−5770.46	−5770.4	−5764.9	−5759.33	−5753.73	−5759.32	−5759.28
O12	−5868.58	−5857.2	−5868.58	−5868.57	−5868.51	−5862.91	−5857.24	−5851.55	−5857.24	−5857.2
G13	−5875.23	−5863.91	−5875.26	−5875.25	−5875.19	−5869.59	−5863.92	−5858.22	−5863.92	−5863.87
G14	−5786.24	−5775.05	−5786.3	−5786.26	−5786.2	−5780.68	−5775.09	−5769.48	−5775.09	−5775.05
C15	−5781.24	−5770.07	−5781.28	−5781.3	−5781.21	−5775.69	−5770.11	−5764.5	−5770.11	−5770.07
P16	−5770.52	−5759.36	−5770.55	−5770.53	−5770.51	−5764.97	−5759.4	−5753.8	−5759.4	−5759.36
E17	−5687.7	−5676.71	−5687.73	−5687.72	−5687.67	−5682.28	−5676.75	−5671.23	−5676.75	−5676.71
M18	−5770.96	−5759.81	−5770.99	−5770.98	−5770.92	−5765.42	−5759.88	−5754.25	−5759.84	−5759.8
R19	−5787.83	−5776.64	−5787.86	−5787.85	−5787.79	−5782.27	−5776.68	−5771.1	−5776.68	−5776.64
C20	−5703.22	−5692.2	−5703.26	−5703.24	−5703.19	−5697.74	−5692.24	−5686.71	−5692.27	−5692.19
S21	−5830.12	−5818.85	−5830.15	−5830.14	−5830.08	−5824.52	−5818.89	−5813.24	−5818.89	−5818.88
Sum	−120235	−120002	−120235	−120235	−120234	−120119	−120003	−119887	−120003	−120002

Source(s): Author’s own computation, using the GINA methodology (MATLAB output)

Table 5. Responsibility and influence scores (Aggregate model)

Enabler	Responsibility (<i>r_i</i>)	Influence (<i>c_i</i>)	Total importance (<i>t_i</i>)
A1 AI and ML	0.047	0.048	0.095
I2 IoT and IIoT	0.046	0.048	0.094
B3 Blockchain	0.049	0.048	0.097
C4 Cloud Computing	0.047	0.048	0.095
G5 5G and adv. connectivity	0.047	0.048	0.095
R6 Reverse logistics	0.047	0.048	0.094
D7 Digital twins	0.046	0.048	0.093
B8 Big data analytics	0.047	0.048	0.095
I9 ISO 14000	0.047	0.048	0.094
G10 Green vehicles	0.047	0.048	0.095
P11 Pollution control	0.048	0.048	0.096
O12 Optimizing logistics	0.049	0.048	0.097
G13 Green port	0.049	0.048	0.097
G14 Green procurement	0.048	0.048	0.096
C15 Circular economy	0.048	0.048	0.096
P16 Waste disposal	0.048	0.048	0.096
E17 Eco-materials	0.047	0.048	0.095
M18 Resource scarcity	0.048	0.048	0.096
R19 Consumer pressure	0.048	0.048	0.096
C20 CSR	0.047	0.048	0.095
S21 Stakeholder collaborations	0.048	0.048	0.096

Source(s): Author’s own compilation, based on GINA analysis output (Aggregate model)

Table 6. Ranking of enablers

Rank	Enabler	Aggregate <i>t_i</i>
1	Blockchain for Secure Data Sharing	0.097
2	Optimizing Logistics for Cost and Efficiency	0.097
3	Green Port Operations	0.097
4	Pollution Control	0.096
5	Green Procurement	0.096
6	Circular Economy Practices	0.096
7	Proper Waste Disposal	0.096
8	Managing Resource Scarcity	0.096
9	Consumer Pressure for Green Products	0.096
10	Stakeholder Collaborations	0.096
11	AI and ML	0.095
12	Cloud Computing	0.095
13	5G and Advanced Connectivity	0.095
14	Big Data Analytics	0.095
15	Eco-Materials	0.095
16	CSR	0.095
17	Green Vehicles	0.095
18	IoT and IIoT	0.094
19	Reverse Logistics	0.094
20	ISO 14000	0.094
21	Digital Twins	0.093

Source(s): Author’s own compilation, based on GINA analysis output

Table 7. Categorized influence strength (Aggregate model)

Enabler	r_i (Grey resp. coeff.)	c_i (Grey inf. coeff.)	$r_i - c_i$	t_i (Aggregate)	Influence strength	Group
AI and ML for automation and prediction	0.047	0.048	-0.001	0.095	Medium	Effect (Receiver)
IoT and IIoT real-time monitoring	0.046	0.048	-0.002	0.094	Low	Effect (Receiver)
Blockchain for secure data sharing	0.049	0.048	+0.001	0.097	Very High	Cause (Driver)
Cloud computing for sustainability	0.047	0.048	-0.001	0.095	Medium	Effect (Receiver)
5G and advanced connectivity	0.047	0.048	-0.001	0.095	Medium	Effect (Receiver)
Reverse logistics for strategies	0.047	0.048	-0.001	0.095	Medium	Effect (Receiver)
Digital twins	0.046	0.048	-0.002	0.093	Very Low	Effect (Receiver)
Big data analytics	0.047	0.048	-0.001	0.095	Medium	Effect (Receiver)
Adoption of ISO 14000/14001 Standards	0.047	0.048	-0.001	0.095	Medium	Effect (Receiver)
Use of green vehicles to cut emissions	0.047	0.048	-0.001	0.095	Medium	Effect (Receiver)
Pollution control in logistics operations	0.048	0.048	0.000	0.096	High	Cause (Driver)
Optimizing logistics for cost and efficiency	0.049	0.048	+0.001	0.097	Very High	Cause (Driver)
Green port operations to cut impact and costs	0.049	0.048	+0.001	0.097	Very High	Cause (Driver)
Green procurement for sustainable sourcing	0.048	0.048	0.000	0.096	High	Cause (Driver)
Circular economy practices	0.048	0.048	0.000	0.096	High	Cause (Driver)
Proper waste disposal to reduce pollution	0.048	0.048	0.000	0.096	High	Cause (Driver)
Adoption of eco-friendly materials	0.047	0.048	-0.001	0.095	Medium	Effect (Receiver)
Managing resource scarcity through sustainability	0.048	0.048	0.000	0.096	High	Cause (Driver)
Responding to consumer pressure for green products	0.048	0.048	0.000	0.096	High	Cause (Driver)
Commitment to corporate social responsibility (CSR)	0.047	0.048	-0.001	0.095	Medium	Effect (Receiver)
Stakeholder collaborations	0.048	0.048	0.000	0.096	High	Cause (Driver)

Source(s): Author's own compilation, based on GINA analysis output (Aggregate model)

Typical whitenization models (Figure 1) and the sunburst visualizations (Figure 2) confirm the robustness of this hierarchy.

The pre-eminence of Blockchain is indicative of its role as the base layer of trust and transparency in an extremely fragmented global maritime ecosystem. The practical integrator that transforms the digital data into tangible cost-saving and efficiency-enhancing is Optimizing Logistics, and the nexus between the technological adoption and environmental compliance is the Green Port Operations. The three enablers create a strong operational-sustainability triad which is the driving force behind the rest of the variables, including the lower-ranking technological enablers. These findings thus describe smart maritime transformation as a socio-technical and ecological system, as opposed to a technology driven system.

5.2 Comparison with existing literature

The current results are compatible with as well as expand the current literature on maritime digitalization. Previous analyses (Samad *et al.*, 2023; Shoaib *et al.*, 2023; Liu *et al.*, 2023) have continuously indicated the role of blockchain in sharing data securely and green port projects in decreasing emissions and operational expenses. The latest GINA analysis confirms these observations but with a more detailed causal priority. In contrast to earlier studies that either used enablers separately or as a sum of expert opinion (ISM-DEMATEL), GINA grey-number method does not reduce the variability of the 35 expert responses and is more reliable.

It is important to note that a moderate position of IoT, AI, and Digital Twins correlates with some of the recent literature (Bandara and Buics, 2024; Hasan and Crawford, 2025) that positioned them as the major drivers. This mismatch hints at contextual specificity: in developed maritime environments, the technologies would be most effective as a supporting infrastructure once the blockchain-supported trust, optimized logistics, and green port infrastructures are in place. The integrated perspective, which is technological, economic, ecological, and social enablers interacting with each other within a single model, fills a major gap in the literature review and provides a more comprehensive causal model than atomistic technology-focused research.

5.3 Role of key enablers

The most powerful driver is blockchain (B3). It ensures the interchange of data between shippers, ports, customs authorities, and insurers is immutable, transparent, and secure and it minimizes fraud, documentation errors, and delays directly. Its large responsibility coefficient attests to the fact that it affects almost all other enablers, and thus it forms the basis of any smart maritime ecosystem.

Green Port Operations (G13) and Optimizing Logistics (O12) are the pragmatic engines of change. They transfer digital capabilities to real products, less turnaround time, less fuel, optimized cargo handling, and emission regulations. The fact that they lead the ranking confirms that the operational excellence and environmental performance are not by-products but major levers of adoption of smart-technology.

Less significant in terms of net influence, technological enablers like IoT, 5G, AI and ML, and Digital Twins are, nevertheless, unavoidable. IoT and 5G offer the real-time data streams to feed blockchain and optimization algorithms; AI and ML offer predictive analytics; and Digital Twins offer scenario simulation. Their moderate t_i values imply that they are amplifiers and not drivers of effect, they only provide maximum value when there is already the presence of the operational-sustainability triad.

Sustainability enablers (Circular Economy, Waste Disposal, Green Procurement, Consumer Pressure, Stakeholder Collaboration) form a supportive cluster at $t_i = 0.096$. They reinforce the system by aligning economic incentives with ecological goals and ensuring stakeholder buy-in, creating a virtuous cycle that sustains long-term digital transformation.

5.4 Importance of visibility and coordination

The visibility and coordination are the key deliverables of the smart-technology ecosystem, yet the GINA findings reveal that they are most efficiently implemented with the operational-sustainability triad instead of the single technological implementation. Blockchain ensures the trusted single source of truth, and Optimizing Logistics and Green Port Operations transforms visibility into actionable coordination across vessels, ports and the hinterland networks. This visibility can be improved through real-time monitoring (IoT) and predictive capabilities (AI/Digital Twins) but their success relies on the basic trust and optimization of the processes made possible by the highest-ranking enablers. The synergistic impact is evident: the more visible it becomes, the less uncertainty about it, better coordination means fewer costs and emissions, and a combination of both enhances supply-chain resiliency.

6. Implications

This section discusses the practical implications for managers and shipping companies (Sections 6.1-6.2), the policy and political implications for regulators (Section 6.3), and the social implications for the wider maritime workforce and communities (Section 6.4).

6.1 Managerial implications

The key focus areas by port authorities should be to invest in the development of Blockchain platform to share data safely, integrated logistics optimization systems, and green port infrastructure. These three enablers have the greatest system wide impact and provide the greatest payback on digital transformation activities. IoT and 5G real-time data must be fed into blockchain-enabled dashboards and simulation platforms (Digital Twins) to facilitate dynamic berth assignment, automated cargo manipulation, and emissions. The priority list generated by GINA can be utilized by port masters to prioritize implementation: to start with, blockchain and green port frameworks should be created, and more advanced technologies can be added to the top. This strategy will minimize congestion, operational costs, and make ports leaders in sustainable maritime logistics.

6.2 Implications for shipping companies

Shipping lines are advised to combine Blockchain and logistics optimization software to obtain end-to-end visibility and predictive routing. When blockchain will guarantee reliable data transfer between charterers and ports, fuel optimization, predictive maintenance, and just-in-time arrival can be significantly improved. Businesses are also encouraged to work together in green port projects and circular-economy (e.g. joint waste-management guidelines) in order to fulfill the regulatory and customer expectations. The medium score of AI and Digital Twins implies that these tools will show the highest ROI when implemented on the top of already-optimized and blockchain-secured processes and not standalone.

6.3 Policy and political implications

The policymakers have to develop facilitating structures that will fast track the highest ranked enablers. High-impact interventions are regulatory sandboxes of blockchain-based maritime data exchanges, incentives to become a green port, and subsidies to logistics optimization technologies. Fragmentation will be minimized by international data interoperability and cybersecurity standards (in line with the ISO 14000 principles). The mandatory sustainability reporting and public-private partnership can be leveraged to use consumer pressure and stakeholder collaboration. Governments can boost maritime supply chains towards being faster, more resilient and lower-carbon by prioritizing policy on the operational-sustainability triad.

From a political perspective, the concentration of influence in Blockchain-based data-sharing infrastructure raises questions of data sovereignty, cross-border regulatory alignment, and geopolitical competition over standard-setting in maritime digital corridors. Bilateral and multilateral trade and shipping agreements will need to address interoperability and cybersecurity standards explicitly so that smaller or developing maritime economies are not disadvantaged in the transition, and so that digital-infrastructure investment does not become a source of strategic dependency between trading nations.

6.4 Social implications

The findings also carry important social implications for workforce development, community welfare, and stakeholder inclusion within maritime logistics ecosystems. As Blockchain-enabled data-sharing platforms and green port operations become central to smart-technology adoption, port authorities and shipping companies will need to invest in reskilling and upskilling programs for dockworkers, logistics staff, and small-scale operators whose roles

may be affected by automation and digitalization. Stakeholder collaboration and consumer pressure, identified among the enablers, indicate that community and civil-society engagement – including transparent communication with coastal communities affected by port expansion or emissions-reduction initiatives – is essential for the social legitimacy of smart-technology adoption. Furthermore, equitable access to digital infrastructure and training should be prioritized to prevent smaller ports, logistics operators, and developing-economy stakeholders from being left behind in the digital transition, thereby supporting inclusive and socially sustainable maritime development.

7. Theoretical contributions

The work contributes to the research in the field of maritime logistics in three significant aspects. First, it shows that the use of Grey Influence Analysis (GINA) is more practical than the traditional MCDM techniques (ISM, DEMATEL) by maintaining the variability of expert judgment in 35 responses. The three whitenization models and aggregate ranking offer a more refined causal map compared to crisp averaging methods. Second, the study provides a multi-dimensional, systemic framework that incorporates technological, economic, ecological and social enablers in a single causal theory-an approach that was largely lacking in previous fragmented research. Third, the empirical ranking (Blockchain, Optimizing Logistics, Green Port Operations as top drivers) argues against the technology-based narrative so common in the Industry 4.0 literature and highlights the importance of operational and sustainability as the basis of the foundations. The cause and effect model and categorized influence table (Table 7) provides a template which can be reused in future research in other transport or supply-chain areas.

8. Limitations of the study

Although rigorously done, the study has limitations. The 35 experts sample, although well-qualified and experienced, is relatively small to apply to grey-systems and might not be representative of global variability. The responses of experts are subjective by nature and might be biased towards individuals or regions, especially since the respondents will be concentrated in a few maritime hubs. The GINA model is based on the model of fixed expert perceptions instead of longitudinal performance data and thus the actual implementation results can be different. Lastly, enablers are considered in a linear manner; non-linear interactions or feedback loops (which could be present in real-world maritime systems) are not explicitly modeled.

9. Future research directions

Future research is to increase the size of the expert panel to 100 + respondents in various continents to enhance generalisability and be able to make cross-regional comparisons. Longitudinal field studies would prove the GINA-based priorities by monitoring the real rates of adoption and performance indicators prior and post the implementation of the top enablers. Mixed frameworks of GINA and machine-learning algorithms or live IoT data feeds would enable dynamic adaptation of causal relationships. There are also the moderating effects that researchers can investigate the effects of regulatory environments or firm size on the influence coefficients. Lastly, GINA would be subjected to comparative uses in related industries (air freight, rail logistics) to assess the generalisability of the operational-sustainability triad found here.

10. Conclusion

This study assessed the major enablers influencing the adoption of smart technologies in maritime and shipping logistics using the Grey Influence Analysis (GINA) approach. The

findings reveal that *Blockchain for Secure Data Sharing*, *Optimizing Logistics for Cost and Efficiency*, and *Green Port Operations to Cut Impact and Costs* are the most influential enablers driving smart maritime transformation. In addition, technologies such as IoT, Artificial Intelligence, 5G connectivity, and Digital Twins were identified as important supporting enablers that strengthen operational efficiency, sustainability, and real-time decision-making capabilities. The findings further indicate that sustainability-oriented and stakeholder-related factors significantly influence the successful implementation of smart technologies within maritime logistics systems.

The study also confirms that the GINA methodology provides a more comprehensive understanding of causal relationships among technological, environmental, economic, ecological, and social enablers while preserving the variability of expert judgments. The results provide important managerial and policy insights for accelerating digital transformation in maritime logistics.

These findings both extend and diverge from earlier technology-adoption research in maritime and allied supply-chain contexts. Whereas several prior studies using ISM and DEMATEL (e.g. Bongomin *et al.*, 2020; Karunarathna *et al.*, 2019) have positioned core digital technologies such as IoT, AI and Digital Twins as the primary drivers of smart-technology adoption, the present GINA-based analysis reveals that operational and sustainability-oriented enablers – Blockchain for secure data sharing, Optimizing Logistics, and Green Port Operations – exert a stronger combined influence than the technologies themselves. This is broadly consistent with recent digitalization research in adjacent agri-food and logistics sectors (Kumar *et al.*, 2015; Sharma *et al.*, 2022, 2024), which similarly finds that IT-enablement and infrastructural readiness, rather than the technology itself, are the binding constraints on successful adoption. The comparison suggests that maritime digital-transformation strategies should prioritize trust, data-integrity, and green-infrastructure investments alongside – rather than subordinate to – the deployment of AI, IoT and Digital Twin technologies.

These conclusions should be interpreted in light of the study's expert-panel-based approach and cross-sectional design (Section 8); future research that expands the panel size and adopts a longitudinal design (Section 9) would further strengthen the generalisability of these findings.

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