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RELATION ANALYSIS OF PORT PERFORMANCE WITH INTEGRATED SMART ENABLERS IN MARITIME SUPPLY CHAIN

David Rahadian[1]

[1]Subject Matter Expert, Kazian School of Management, Dahisar East, Mumbai-400068, India

david.krakatau@gmail.com

Abstract

This study investigates the impact of Smart Supply Chain Technology (SSCT) on Port Performance (PP) with Maritime Supply Chain Integration (MSCI) as a mediating factor, focusing on Indonesia's Banten Port. Using a mixed research approach combining explorative and descriptive methods, data were collected from 73 respondents representing port authorities, shipping companies, freight forwarders, and logistics operators. Structural Equation Modeling (PLS-SEM) was employed to examine direct and indirect relationships among SSCT, MSCI, and PP. The results reveal that SSCT has a significant positive effect on both MSCI and PP. Additionally, MSCI positively influences PP and mediates the relationship between SSCT and PP. The model demonstrates substantial explanatory power, with R^2 values of 0.661 for MSCI and 0.63 for PP, and high predictive relevance. The findings highlight the importance of digital transformation and integrated smart enablers in enhancing port efficiency, competitiveness, and operational sustainability. This study provides empirical evidence supporting smart port development strategies in emerging economies and suggests managerial implications for achieving higher logistics performance.

Keywords – Supply Chain, Port Performance, SEM, Industry 4.0, Smart Port

1. INTRODUCTION

Port performance in the knowledge management era requires support for port service business processes, including planning, service provision, monitoring, and operations as shown in Figure 1. Ports are crucial for maritime trade, accounting for 90% of international trade[1]. Digitalization, resulting from the Industrial Revolution, including big data, IoT, and cloud computing, has led to regulatory changes and a role for digital transformation in port performance. This transformation is expected to enhance logistics and maritime supply chains. Indonesia's maritime supply chain efficiency is crucial for local economy growth. Despite having the highest logistics costs among ASEAN nations, Indonesia's logistics performance index (LPI) for 2023 is falling 17 ranks to 61, down from 46 in 2018. Despite this, Indonesia must overcome obstacles to improve its maritime transportation system[2]. Port managers must consider key elements when planning digitalization capacity support for port activities. Indonesia's primary component in maritime logistics operations should adopt digitalization or digital transformation. This research aims to explore the influence of smart enablers generated in Industry 4.0 on improving port performance and maritime supply chain, evaluating the effect of Port Digitalization and whether it is genuinely beneficial.

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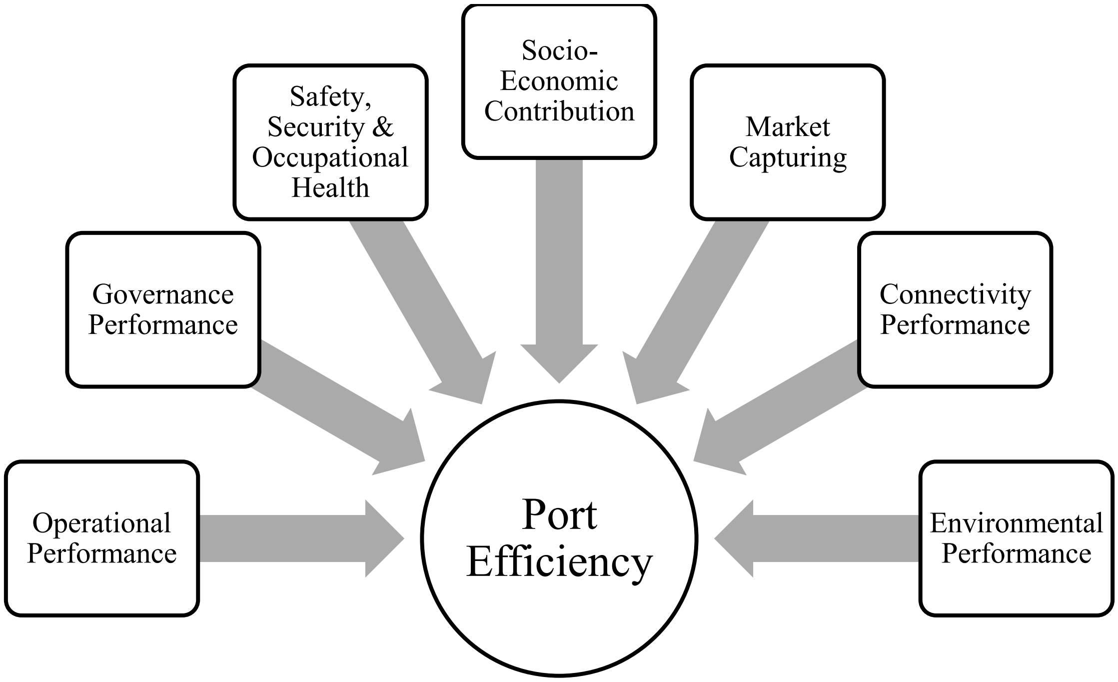

Figure 1. Determinants of Port Efficiency and Performance

The concept of smart ports has gained significant academic and industrial attention as maritime logistics moves toward digitalization and sustainability.Smart ports integrate advanced technologies such as IoT, automation, and data-driven analytics to improve efficiency, sustainability, and stakeholder collaboration[3,4]. Digital twin applications have emerged as critical enablers for situational awareness and predictive decision-making in port management[5]. In parallel, supply chain integration is increasingly recognized as a driver of port competitiveness, emphasizing the importance of effective information sharing and collaboration among logistics actors[6,7].

Technological integration under the Industry 4.0 paradigm is transforming port operations. Studies indicate that implementing smart solutions enhances operational efficiency and environmental performance[8,9] while also mitigating port congestion through better coordination strategies. Advanced technologies such as blockchain are being adopted to ensure secure and transparent information flows within maritime supply chains[10] and metaverse-based logistics solutions are being introduced to improve port safety and productivity[11]. Furthermore, reconceptualize ports as smart service systems, enabling enhanced service delivery and value co-creation among supply chain stakeholders[12].

The evolution of smart ports has been extensively studied through bibliometric approaches, which outline key research domains such as digital technologies, environmental sustainability, and stakeholder collaboration[13]. These studies also identify how emerging technologies like Supply Chain 4.0 solutions and blockchain contribute to traceability, transparency, and improved operational resilience[14,15]. Digital twin modeling for energy optimization and shore connection planning also represents a growing area of interest for sustainable port development[16].

Despite these advancements, challenges remain, including the need for clear success factors for digital transformation[17] and the integration of artificial intelligence (AI) into decision-making frameworks to enhance operational reliability and resilience[18]. Moreover, barrier identification and prioritization remain essential for facilitating smart port transitions, especially in developing economies[19]. Collectively, the literature indicates a strong positive relationship between technology adoption, supply chain integration, and overall port performance, supporting the conceptual model tested in this study.

Table 1: Constructs, Definitions, and References for Port Efficiency Assessment

Abbr	Construct	Definitions
PPR	Port Productivity	Output and productivity of the port, including unloading rate, waiting time, berth occupancy ratio, berth throughput.
PRB	Port Reliability	The health, safety, and security of the port.
PCE	Port Cost Efficiency	Price competitiveness, value-for-money.
PVA	Value Added Service	VAS such as ease of clearance, warehouse, logistics support, bonded area/custom facility, digitalization, eco/green port.
PCU	Port User Convenience	Customer intimacy service, personal services such as lounge, easy reach and order, payment services, gimmicks.
IIN	Internal Integration	Collaboration and integration of inter-port units through information sharing and automatic sequential action and control enabled by effective systems and IT (ERP and other IS).
IPN	Partner Integration	Collaboration and IS integration between the port and its partners (stevedoring companies, heavy equipment providers, piloting services, tally, surveyors, banking, etc.) using tools such as TOS (with handheld), API, etc.
IGS	Government Integration	Collaboration and IS integration between port operators and government agencies (Port Authority, Customs, Quarantine, Immigration) using national platforms such as Inaportnet, SITOLaut, and CIESA.
ICS	Customer Integration	Using the port's or public platform, collaboration and IS integration between port operators and their customers (Shipping Lines, Shipping Agents, Freight Forwarders, Cargo Owners, Container MLOs).
TIF	Information Management	Technology to manage service orders, resource allocation, operation monitoring, service delivery settlement, billing, and payment (ERP-

		link-TOS, Terminal Operating System, Port Control System, Cloud Computing).
TTC	Tracking and Tracing	Technology to track and trace cargo movement from origin to destination using GPS/GNSS, RFID, QR Code, Barcode, Radio Wave, Cellular Triangulation, IoT, etc.
TPA	Process Automation	Mechanization or automation of operations, including autonomous equipment, remotely operated equipment, smart equipment replacing conventional operation (autonomous cars, automatic stacking cranes, semi-automatic unloaders, IoT, OCR, Auto Truck Guidance System).
TDA	Advanced Analytics	Utilization of data analytics to optimize operation and management using big data analytics and related technologies such as Artificial Intelligence, Machine Learning, SCADA, Business Intelligence.
TIN	Integration Platform	Platform to integrate information systems among partners using API (Application Programming Interface) or Electronic Data Interchange (EDI) for sharing or communicating information or orders.

2. MATERIAL AND METHODS

2.1 Mixed Research Approach with Banten Port as the Case Study

This study adopts a mixed research approach, including both discovery and descriptive methods. The purpose of the Discovery Research component is to develop literature-based constructions and identify relevant factors in a structured way, which makes the basis for the hypothesis development. Investigation -based methods are then used to examine the relationship between the identified variables, which allow the hypothesis for testing and theoretical verification. These relationships are evaluated for positive or negative effects, which support the ideological structure of the study. Subsequently, a descriptive research design is used to check the current conditions in the Indonesian ports' sector, which focuses on real -time and technical preparedness performance. This phase represents the initial stage of scientific examination, and emphasizes the collection of data characterized by existing events and operating realities of ports.

The study centers on a bulk port located in Banten Province, Indonesia, which, as a major public terminal, handles more than one million tons of cargo annually. Due to this threshold, the number of eligible terminals in the region is limited, providing a manageable scope for empirical observation. Respondents in the survey include key stakeholders from the maritime supply chain, such as port and terminal authorities, shipping companies, shipping agencies, cargo owners, freight-forwarding and logistics companies, stevedoring firms, and multimodal transport operators[12]. Respondents are permitted to submit one response per terminal they manage; however, individuals overseeing multiple terminals, such as shipping line managers, may provide separate

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responses for each location. This strategy is expected to enhance data reliability and accuracy, as it allows respondents to perform comparative evaluations across different terminals.

2.2 Sample Size Determination and Measurement Model

A critical methodological consideration in this research is the determination of sample size for the Partial Least Squares Structural Equation Modeling (PLS-SEM). PLS-SEM is widely recognized for its flexibility in handling smaller sample sizes and its robustness in exploratory and predictive research compared to covariance-based SEM[11,13]. Minimum sample size is influenced by the f^2 effect size[15], with large effects requiring as few as 30 samples to achieve a statistical power level of 0.80. It is supported that, sample size determination using the gamma-exponential and inverse square root methods[17], where the latter suggests a minimum of 51 observations when path coefficients are ≥0.35. Similarly, it is recommended a minimum of 69 samples to achieve 80% statistical power at a 5% significance level for path coefficients[12] ranging between 0.21 and 0.30.

For this study, an optimum sample size of 50 was adopted, as it provides a power of 0.81 and an effect size (f^2) ranging[13] between 0.437 and 0.506. This meets the threshold of influencing the model outcome by at least 0.8% statistical power[11] when the effect size is 0.15 and the path coefficient is 0.20 (Tijan et al., 2024) The measurement model, also known as the outer model, evaluates the reliability and validity of the relationships between reflective indicators and latent constructs. Three primary testing - Perceptions are performed using reliability, internal stability and convergence/discriminatory validity - confirmation factor analysis. Indicators with more than 0.35 factor load are considered valid. Subsequently, the structural model (internal model) is evaluated to investigate the cause relationship between the latent variables. The endogenous latent variables are evaluated on the basis of their variance (R^2), while statistical significance is determined by the use of the tea men obtained through bootstrapping[12]. Figure 1 depicts the structural model path diagram developed for this research using the PLS estimation method.

2.3 Structural Model Specification

Structural models employs Partial least squares Structural Modeling (PLS-Sem) to establish a ratio of three important constructions: Smart Supply Chain Technology (SSCT), Maritime Supply Chain Integration (MSCI) and performance of port (PP). The evaluation of the model begins with the evaluation of the coefficient of determination (R OFF) for the endogenous latent variables, which reflects the ratio of the variance explained by the outflow variables. The value of 0.67 or higher is considered sufficient, 0.333 as moderate, and 0.19 are considered weak (Klar et al., 2022). Previous research has accepted lower R^2 values for less understood phenomena, such as 0.258 and 0.267. The track coefficient is investigated to determine the strength and importance of the relationship planned between the latent variables[17]. In addition, the model examines the modeling effects, where a third variable affects the relationship between an independent and dependent variable. In this case, MSCI (moderator, M) is hypothesized to moderate the relationship between SSCT (independent variable, X) and PP (dependent variable, Y). Figure 2 illustrates this moderating effect, highlighting the interaction pathway from MSCI to the SSCT–PP relationship.

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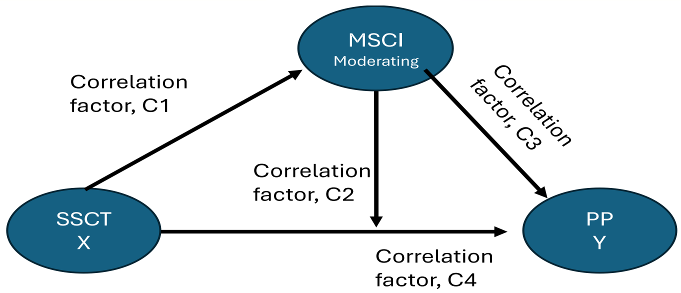

Figure 2. Relationship between variables

Table 2 presents the formulated hypotheses that examine the direct and indirect relationships among Smart Supply Chain Technology (SSCT), Maritime Supply Chain Integration (MSCI), and Port Performance (PP). The hypotheses cover both null and alternative statements to test the significance of these relationships, including mediation effects through MSCI.

Table 2: Research Hypotheses on Smart Supply Chain Technology, Maritime Supply Chain Integration, and Port Performance

Hypothesis Code	Hypothesis Statement
H0	Maritime supply chain integration (MSCI) is **not significantly impacted** by smart supply chain technology (SSCT).
H1	Maritime supply chain integration (MSCI) is **significantly impacted** by smart supply chain technology (SSCT).
H2	Port performance (PP) is **not significantly impacted** by smart supply chain technology (SSCT).
H3	Port performance (PP) is **significantly impacted** by smart supply chain technology (SSCT).
H4	Maritime supply chain integration (MSCI) has **no discernible impact** on port performance (PP).
H5	Maritime supply chain integration (MSCI) has a **discernible impact** on port performance (PP).
H6	Through maritime supply chain integration (MSCI), smart supply chain technology (SSCT) has **no appreciable impact** on ports.
H7	Through maritime supply chain integration (MSCI), smart supply chain technology (SSCT) has an **appreciable impact** on ports.

3. RESULTS AND DISCUSSION

3.1. Questionnaire Test and Profile of Respondents

A total of 73 participants were gathered from Banten and Jakarta Bulk Terminal. Most respondents are 41-50 years old (32.9%), followed by 31-40 years old. Most respondent companies are Port Companies (32.9%), followed by freight forwarding and sea transport/NVOCC (26.1%). Most participating positions are managers/assistant managers (34.2%). Out of the 37 respondents who participated in this survey, 37 have undergraduate degrees (61.9%). Based on the result, all 15 question items show a high validity coefficient, which is not less than 0.907, above the critical value of 0.325, showing it is very beneficial. In all three constructs, Cronbach's alpha is not less than 0.83, above 0.7 critical value, showing high reliability.

Table 3: Respondent Demographics and Measurement Reliability

Category	Details	Percentage (%)
Total Participants	Banten and Jakarta Bulk Terminal	73
Age Group	41–50 years	32.9
	31–40 years	(Next highest)
Company Type	Port Companies	32.9
	Freight Forwarding & Sea Transport/NVOCC	26.1
Position	Managers / Assistant Managers	34.2
Education	Undergraduate Degree Holders (out of 37 responses)	61.9
Validity (15 items)	Minimum validity coefficient	0.907 (≥ 0.325)
Reliability (Cronbach's α)	Three constructs minimum value	0.83 (≥ 0.70)

3.2. Measurement Model Analysis

Convergent validity is the extent to which the indicators of one latent variable measure the same construct. The average variance extracted (AVE) is typically used to assess convergent validity (Sim et al., 2024). The Construct should have an AVE value of at least 0.50. Table 4 shows that all variable's AVE values are higher than the critical point[16] (0.5), thus indicating it is valid. The measurement model's dependability has been determined by looking at The Composite Reliability and Cronbach's Alpha. The measurement model is verified to be very trustworthy as all of the Composite Reliability and Cronbach's Alpha values are close to or exceed the suggested standards of 0.7, respectively, as shown in Table 4.

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Table 4. **Validity and reliability test**

Variable	Average (AVE)	Variance	Extracted	Cronbach's Alpha	Composite Reliability
Maritime Supply Chain Integration	0.906			0.965	0.967
Port Performance	0.855			0.957	0.959
Smart Supply Chain Technology	0.856			0.958	0.958

3.3. Structural Model Analysis

The PLS-SEM analysis's findings are at the 5% significance level, as shown in Table 5. All of the P-values are not more than 0.012 < 0.05, and all the statistical T-values are not less than 2,519, which is higher than the t-t table value of 1.96. As a result, the testing hypothesis results show that while H1, H3, H5, and H7 are accepted, H0, H2, H4, and H6 are rejected.

Table 5. Path Coefficient and P Values

Variable Relation	Path Coefficient (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Smart Supply Chain Technology -> Maritime Supply Chain Integration	0.813	0.811	0.066	12.245	0.000
Smart Supply Chain Technology -> Port Performance	0.394	0.379	0.156	2.519	0.012
Maritime Supply Chain Integration -> Port Performance	0.440	0.458	0.147	2.987	0.003
Smart Supply Chain Technology -> Maritime Supply Chain Integration -> Port Performance	0.358	0.375	0.138	2.586	0.010

This indicates that SSCT significantly affects MSCI. As shown in Figure 3, the SSCT variable on MSCI has an original path coefficient of 0.813 with a positive direction, indicating that the MSCI will rise by 0.813 for every improvement in SSCT. Additionally, the SSCT variable on PP has an original sample of 0.394 with a positive direction, indicating that the higher the SSCT, the higher the PP by 0.394. The original sample of the MSCI variable on PP was 0.440, indicating a positive direction. This means that as the MSCI increases, so does the PP by 0.440. This implies that SSCT significantly affects PP via MSCI. The initial sample of this argument, generated from the SSCT variable on PP through MSCI, was 0.358 in a positive direction. This indicates that when SSCT improves, PP through MSCI will grow by 0.358.

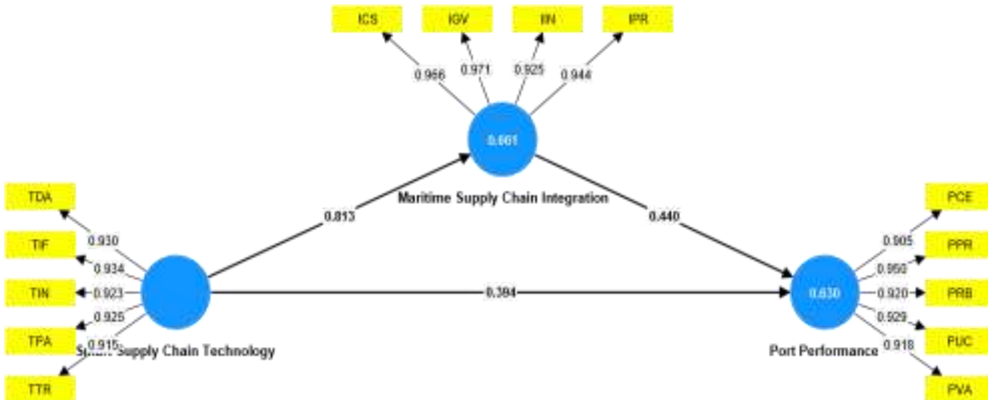

Figure 3. Path Coefficient and R^2

Even as predictive analysis, the number of samples should meet the required path analysis coefficient. Since all of the path coefficients are above 0.35, the number of samples collected 73 is above 50, which requires a statistical power of 0.8 at a significance level of 5% (Kock, 2018).

As seen in Figure 3, the blue circle shows the R^2 value. According to the coefficient of determination (R-square) value, the MSCI variable can be described by the SSCT by 66.1% regarding the validation processes of different tests. The R-square value for the MSCI variable is 0.661. In the meantime, the PP variable's R-square value of 0.63 shows that the SSCT and MSCI variables account for 63% of the PP variable's explanation. This relation can be considered substantial[19].

Cohen's F2 effect size test revealed that SSCT has the largest impact on MSCI, with an effect size value of 1.946. According to Cohen's assessment, an F2 value > 0.35 indicates that SSCT has a significant effect size on MSCI. F2 values > 0.15 indicate that SSCT and MSCI have a medium effect size on PP[19].

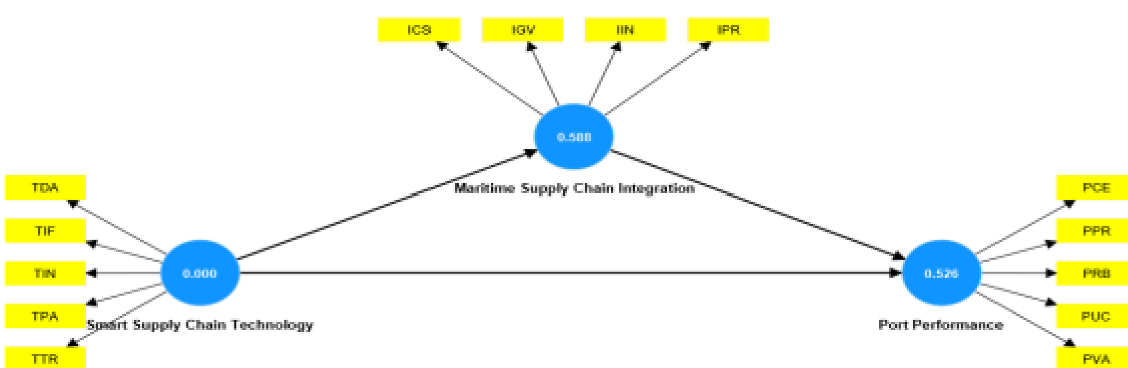

Figure 4. **Predictive Relevance Q^2**

PLS-SEM has a superior predictive capability (Hair, 2017). PLS-SEM accurately predicts the indicator data points when it demonstrates predictive significance. When an endogenous latent variable has a Q^2 value greater than zero, it suggests that the PLS path model has predictive importance for this construct. As illustrated in Figure 4, Given that the MSCI variable has a Q2 value of 0.588, it can be concluded that the SSCT variable has a high predictive relevance value to MSCI when considering predictive relevance (Q2). Despite the PP variable having a Q2 value of 0.526, SSCT and MSCI have a high predictive relevance value to PP. Therefore, the quantification above shows a substantial relationship between SSCT and PP. SSCT also has a large effect size on MSCI. It was also found that SSCT and MSCI have a large predictive relevance value to PP.

The results confirm the planned relationship, indicating that smart supply chain technologies are the most important promoters for port performance when they are effectively integrated into marine logistics networks. Strong track coefficients between SSCT and MSCI ($\beta = 0.813$, $p < 0.001$) indicate that digital technologies such as IoT, advanced analysis and process automation increase the integration of marine stakeholders. This aligns with prior findings emphasizing the role of technology-driven collaboration in port competitiveness[17,18]. Furthermore, the positive influence of MSCI on PP ($\beta = 0.440$, $p < 0.01$) supports earlier research highlighting integration as a critical success factor in achieving operational reliability and service efficiency[15]. Arbitration analysis suggests that MSCI partially conveys the ratio of SSCT and PP ($\beta = 0.358$, $p < 0.05$), suggesting that technology alone does not guarantee better portions until effective integration strategies are supplemented with strategies. It is consistent with discovery studies that it indicates that ports that use digitalisation without effort alignment often face limited performance benefits[11,12]. Additionally, the high R^2 and Q^2 values suggest that the model has strong explanatory and predictive capabilities, validating PLS-SEM as an appropriate analytical framework for port digitalization research. From a managerial perspective, the results highlight the need for port operators to prioritize technology-enabled integration platforms and collaboration with government agencies, shipping lines, and logistics providers. For policymakers, the findings emphasize the importance of supporting digital infrastructure, regulatory harmonization, and workforce training to accelerate smart port adoption.

4. CONCLUSION

This study indicates that smart supply chain technologies largely affect the integration of the sea supply chain and port performance, and play a mediation role with integration. Conclusions provide empirical support for increasing emphasis on smart inabilities in digitization strategies. By using techniques such as IoT, process automation, advanced analyzes and integration platforms, gate can achieve high efficiency, reliability and customer satisfaction. However, technology investments must be supplemented to feel strong cooperation structure and the result reforms from the management system. For emerging economies such as Indonesia, where the costs of logistics and infrastructure barriers offer challenges, smart port development represents a strategic opportunity to improve global competition. Future research can detect digital changes, cross conditions and several intermediaries such as organizational preparedness and longitudinal effects of regulatory structure. Overall, this study contributes to both academic literature and industry practice by providing data -driven structure to evaluate digital changes in marine logistics.

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