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Optimization of Loading and Unloading Service Performance and Facility Requirements at Sofifi Sea Port toward 2030

Merry Mardianti*
Universitas Pancasila, Indonesia

I Nyoman Teguh Prasidha
Universitas Pancasila, Indonesia

Wahyu Dewanto
Universitas Pancasila, Indonesia

***Corresponding author:**
Merry Mardianti,
Universitas Pancasila, Indonesia.
✉merryril99@gmail.com

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Abstract

Background: Sofifi Port is an important logistics distribution hub for the capital of North Maluku Province, but its service performance has not fully kept pace with increasing vessel traffic and cargo volumes.
Objective: This study evaluates the optimization of cargo-handling services at Sofifi Port and formulates a phased development strategy through 2030.
Methods: A convergent parallel mixed-methods design was employed, integrating operational performance analysis for 2024–2025, multiple linear regression analysis involving 195 port users, field observations, and interviews with five groups of informants. Operational indicators included berth time (BT), effective time (ET), the ET/BT ratio, waiting time (WT), cargo-handling productivity, and berth occupancy ratio (BOR).
Results: BT decreased from 53.9 to 28.7 hours, ET decreased from 18.7 to 10.8 hours, and the ET/BT ratio increased from 34.7% to 37.5%. WT remained relatively stable at 18.2–18.5 minutes. However, cargo-handling productivity declined from 12.6 to 5.3 tons per hour, while BOR increased from 74% to 77%. The regression model was statistically significant, $F(2, 192) = 88.720$, $p < 0.001$, with $R^2 = 0.480$ and adjusted $R^2 = 0.475$. Physical infrastructure ($\beta = 0.546$) showed a stronger association with service performance than system administration ($\beta = 0.411$).
Conclusion: Services at Sofifi Port cannot yet be considered optimal. Optimization efforts should prioritize short-term operational improvements, medium-term facility upgrades through 2030, and longer-term regional logistics integration based on a phased smart port concept.

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INTRODUCTION

North Maluku Province is an archipelago with substantial natural resource potential, particularly in spices and agricultural commodities such as nutmeg, cloves, and copra, as well as mining products such as nickel. Data from the Central Statistics Agency indicate that North Maluku's export value from January to September 2025 exceeded US$10.5 billion, representing an increase of approximately 38.60% compared with the same period in the previous year (Utara, 2022). This economic growth increases the need for a reliable and integrated maritime logistics distribution system, considering that sea transportation is the backbone of goods distribution in archipelagic regions such as North Maluku, where ports serve as primary nodes connecting the flow of goods between regions. Globally, port efficiency and the performance of secondary and feeder ports have become central to maritime logistics competitiveness. Systematic reviews of port performance and smart-port development emphasize a shift from single-indicator

assessments toward integrated evaluations of operational performance, infrastructure, and digital capabilities (Belmoukari et al., 2023; Kishore et al., 2024; Paraskevas et al., 2024). Meanwhile, comparative benchmarking of container ports in lower-middle-income countries indicates that infrastructure adequacy and operational conditions, rather than geographic position alone, contribute to differences in efficiency (Danladi et al., 2024; Yenilmez, 2025). These global patterns position Sofifi Sea Port as a locally specific example of the broader challenges faced by secondary ports in archipelagic and developing regions.

Under existing conditions, North Maluku's logistics distribution system remains dominated by the Port of Ternate, which recorded approximately 662,900 tons of unloading activity in 2022. Much of the cargo originating from the Sofifi area and its surroundings must still pass through Ternate before reaching its final destination, thereby increasing distribution time and costs, reinforcing structural dependence on Ternate, and potentially weakening Sofifi's role as the provincial capital within the regional logistics distribution network. This situation highlights a gap between the region's economic potential and the available service capacity of Sofifi Sea Port's infrastructure.

Academically, the research gap addressed by this study lies in the limited number of studies on secondary ports in eastern Indonesia that integrate operational performance indicators, service-user perceptions, qualitative explanations of performance constraints, and projections of facility requirements within a single analytical framework. Previous studies have generally focused on major ports or container terminals and have examined only one or a limited group of indicators. Examples include productivity and facility utilization at Bitung Port (Damongilala et al., 2022), stevedoring performance and berth occupancy ratio (BOR) at the Jamrud International Terminal (Soimun et al., 2025), the relationship between waiting time and productivity at Saketa-Halmahera Port (Berliana et al., 2025), dock capacity based on the container occupancy ratio (COR) at Palaran Terminal in Samarinda (Azizah, 2021; Putri & Rahmawati, 2022), and crane-based container productivity at Tanjung Emas Port in Semarang (Prakoso et al., 2025). These studies provide an important foundation but do not integrate service-time indicators, productivity, BOR, service-user perceptions, qualitative findings, and facility projections through 2030 for non-containerized secondary ports such as Sofifi Sea Port. The scientific and methodological novelty of this study therefore lies in the development of a single, replicable analytical framework that integrates objective operational indicators, perception-based regression analysis, qualitative triangulation, and scenario-based facility projections within one analytical workflow. This framework can be applied to other secondary and feeder ports facing comparable data limitations, offering transferable insights into evidence-based prioritization rather than assuming that adding facilities alone will improve service performance.

The theoretical framework of this study comprises four complementary theories. Central Place Theory Christaller (1966) and Erber et al. (2022) explains how areas with more comprehensive service facilities develop into service centers for their surrounding hinterlands, making it relevant to assessing Sofifi's position as a regional service node. Growth Pole Theory Perroux (1955) and Parrique (2026) posits that economic growth centers require adequate infrastructure to generate spillover effects in surrounding areas. This perspective aligns with the findings of Notteboom & Rodrigue (2005) and Souza et al. (2023), who emphasize the influence of hinterland connectivity and distribution network integration on modern port development. Transport Network Theory explains the effectiveness of nodes and flows within transportation networks and is operationalized in this study through System Administration (X1), Physical Infrastructure (X2), and operational performance indicators, including berth time (BT), the effective-time-to-berth-time ratio (ET/BT), waiting time (WT), berth occupancy ratio (BOR), and loading and unloading productivity. Intermodal Logistics Theory Christopher (2016), Bichou & Gray (2004) , Han (2018) and Jahroni et al. (2025) emphasizes that logistics efficiency requires the coordination of administrative processes, physical facilities, transportation, and distribution within an integrated system.

Each of these four theories has limitations when applied individually. Central Place Theory and Growth Pole Theory primarily explain regional functions and economic development without directly measuring loading and unloading efficiency. Meanwhile, Transport Network Theory and Intermodal Logistics Theory describe the conditions required for effective integration but do not guarantee that these conditions are achieved at secondary ports. Therefore, this study develops a

conceptual framework based on a systems-engineering approach that connects operational phenomena, system boundaries, measurable variables, performance evaluation, bottleneck identification, and development decisions. System pressures, including growth in ship traffic, changes in cargo flows, dependence on Ternate, and infrastructure limitations, are assessed using BT, ET, ET/BT, WT, BOR, productivity, and cargo-volume indicators. The relationships between System Administration (X1), Physical Infrastructure (X2), and Service and Performance (Y) are examined using multiple linear regression, with the t-test, F-test, coefficient of determination (R^2), and adjusted coefficient of determination (adjusted R^2) used to evaluate the model and its predictors. The quantitative findings are then triangulated with observations and interviews to identify context-specific operational bottlenecks. Accordingly, decisions concerning the level of service optimization, the relative explanatory contributions of the predictors, and projected facility requirements through 2030 are based on integrated performance evidence rather than the assumption that additional facilities automatically improve service performance.

Based on the research background and identified gaps, this study addresses five research questions: (1) What are the existing conditions of cargo loading and unloading services at Sofifi Sea Port? (2) How does the port's operational performance compare across cargo volume, BT, ET/BT, WT, BOR, and loading and unloading productivity, and which indicators exhibit the largest and smallest performance gaps based on changes between 2024 and 2025 and available benchmarks? (3) What are the main factors contributing to suboptimal service performance in terms of infrastructure, operational processes, technology, human resources, policies, and service-user perceptions? (4) To what extent can loading and unloading services be optimized, as assessed through operational performance indicators and comparisons with applicable port operational standards or benchmarks? (5) What service optimization strategies and facility development requirements are needed to improve port performance through 2030?

In line with these research questions, the objectives of this study are to: (1) analyze the existing conditions of loading and unloading services, including port facilities, cargo flow patterns, and ship service patterns; (2) measure operational performance using BT, ET, ET/BT, WT, BOR, cargo volume, and productivity indicators, and identify the indicators with the largest and smallest performance gaps; (3) identify the dominant factors contributing to suboptimal performance in terms of infrastructure, operational processes, technology, human resources, policies, and service-user perceptions; (4) evaluate the level of optimization of loading and unloading services against applicable port operational standards and benchmarks; and (5) formulate service optimization strategies and identify facility development requirements through 2030 to strengthen the role of Sofifi Sea Port as a secondary port and regional logistics node.

The multiple linear regression model in this study is limited to two independent variables: System Administration (X1) and Physical Infrastructure (X2), with Service and Performance (Y) as the dependent variable. Human resources, operational processes, technology, weather, policy, and cargo characteristics are treated as contextual factors and analyzed through observations and interviews to triangulate the quantitative findings rather than being included as additional predictors in the regression model. The performance gap analysis compares relative changes between periods and numerical benchmarks where available. Because BT, ET, WT, BOR, productivity, and cargo volume have different units of measurement and interpretive directions, this study does not combine them into a single composite index. Instead, each indicator is interpreted according to its operational characteristics, and the findings are subsequently integrated during the discussion.

METHOD

This study employed a mixed-methods approach with a convergent parallel design, in which quantitative and qualitative data were collected during the same period and the results were integrated during the analysis and conclusion-drawing stages. This design was selected because port operational performance encompasses two complementary dimensions: measurable performance, reflected in operational data and user perceptions, and contextual factors that require direct observation and interviews. Integration was conducted at the interpretation stage through the comparison, confirmation, and explanation of findings, rather than to establish causality that had not been tested experimentally or longitudinally, given the

cross-sectional survey design.

The research was conducted at Sofifi Class III Port, located in Sofifi Village, North Oba District, Tidore Islands City, North Maluku Province. This location was selected because of its strategic role in handling the flow of goods and passengers and supporting logistics connectivity across the archipelago, as well as its location within the provincial capital area. The primary operational data covered the 2024–2025 period and were obtained from the Sofifi Class III Port Operator Unit (*Unit Penyelenggara Pelabuhan*, UPP). Facility requirements were projected through 2030 using a scenario-based approach.

The study population comprised users of Sofifi Sea Port services. According to data from the Sofifi Class III UPP, the number of sea transportation users recorded in 2024 was 19,102 people annually, with an average weekly user population of 334 people. The weekly population was used as the sampling frame because it more closely represented the accessible population during the field data collection period, whereas the annual figure described the overall scale of port service activity. Methodologically, the weekly sampling frame of 334 users was considered appropriate because it represented the realistically accessible population during the field data collection period and avoided implying a level of sampling precision based on the entire annual population of 19,102 users. Because port users may use the services repeatedly within a given week, the weekly frame was intended to capture the effective sampling universe for measuring user perceptions. The resulting minimum sample size of 182 respondents, with 195 respondents ultimately obtained, was considered sufficient for estimating a two-predictor regression model. However, the adequacy of statistical power also depends on the expected effect sizes, significance level, and other model assumptions.

The sample size was determined using Slovin's formula with a 5% margin of error: $n = N / (1 + N \cdot e^2)$. With N = 334 and e = 0.05, the calculation was $n = 334 / (1 + 334 \times 0.0025) = 334 / 1.835 \approx 182$ respondents. In practice, 195 responses were obtained through an online questionnaire administered using Google Forms, exceeding the minimum required sample size. The additional responses provided a margin for potential data exclusions and increased the available degrees of freedom for estimating the model with two independent variables. Purposive sampling was employed to select respondents with direct experience of Sofifi Port services who could meaningfully assess administrative procedures, physical infrastructure, and port service performance. Accordingly, the survey findings represent users who met the study's selection criteria rather than a probability-based estimate of the entire annual user population.

Primary data were obtained through direct field observations of loading and unloading activities, interviews with informants selected purposively to represent five functional groups involved in port services, and an online questionnaire administered to 195 port users to measure System Administration (X1), Physical Infrastructure (X2), and Service and Performance (Y). Secondary data were obtained from documents and archives maintained by the Sofifi Class III UPP, including cargo-flow data, vessel calls, vessel service times, facilities and infrastructure, loading and unloading equipment, labor, productivity, waiting times, operational standards, and service performance records for 2024–2025. These data sources were subsequently integrated through quantitative analysis, qualitative analysis, and triangulation in accordance with the convergent parallel mixed-methods design.

Table 1
Research Interview Informant

Code	Informants	Quantity	Information Focus
I1	Manager/UPP	1 person	Administration, ship schedules, service data, and document bottlenecks
I2	Dock operational officer	1 person	Docking arrangements, waiting time, berth time, and dock coordination
I3	TKBM/loading and unloading operator	2 people	Tool availability, productivity, idle time, and field constraints
I4	Service	2 people	Quality of service, access to information,

Code	Informants	Quantity	Information Focus
	user/expedition/merchant		cost, and user satisfaction
I5	Agencies related to logistics development	1 person	Policy direction, connectivity, and facility needs until 2030

Source: primary data, processed (2026).

The research variables were clearly distinguished among statistical constructs, operational performance indicators, and contextual factors to prevent the conflation of regression results, port performance indicators, and observational and interview findings into an untested causal relationship. System Administration (X1) was defined as an independent variable measuring user perceptions of procedural clarity, administrative efficiency, digitalization, coordination, access to information, data accuracy, and service transparency. Physical Infrastructure (X2) was defined as an independent variable measuring user perceptions of the adequacy of berths, loading and unloading areas, warehouses and storage yards, vehicle access, lighting, utilities, security, and supporting facilities. Service and Performance (Y) was defined as the dependent variable, reflecting user perceptions of service speed, safety, reliability, and efficiency. In the inferential model, only X1 and X2 were included as predictors of Y. Cargo volume and port capacity were used in the operational analysis and facility projections rather than as predictors in the main regression model. Human resources, operational conditions, technology, weather, policy, and cargo characteristics were treated as contextual factors for triangulation.

In addition to the Y construct, operational performance was assessed using key indicators, including Berth Time (BT), Effective Time (ET), the ET/BT ratio, Waiting Time (WT), loading and unloading productivity, Berth Occupancy Ratio (BOR), and cargo volume. These indicators provided objective evidence for examining whether perceptions of X1, X2, and Y were consistent with actual operating conditions; they were not included as additional predictors in the regression equation. The statistical relationships examined were X1 → Y and X2 → Y, both individually and jointly. The results were subsequently triangulated with operational indicators and qualitative findings to establish priorities for optimization.

Table 2
Operational Definition of Research Variables (Table layout standardized to the journal template: consistent font size and column spacing applied for readability.)

Variables/Indicators	Operational Definition	Formula/Size	Units
X1 System Administration	User perception of procedures, coordination, digitization, and clarity of service information	Average questionnaire indicator score X1	Likert Scale 1–5
X2 Physical Infrastructure	User perception of the adequacy of docks, warehouses, tools, stacking areas, access, and supporting facilities	Average questionnaire indicator score X2	Likert Scale 1–5
Y Service and Performance	User assessment of the speed, security, reliability, and efficiency of port services	Average score of the questionnaire indicator Y	Likert Scale 1–5
Berth Time (BT)	The total time the ship is at the dock	Last line time – first line	Clock/ship
Effective Time (ET)	Effective time of loading and unloading activities	Completion time – activity start time	Clock/ship
ET/BT	Proportion of mooring time used productive	(ET/BT) × 100%	Presses

Variables/Indicators	Operational Definition	Formula/Size	Units
Waiting Time (WT)	Waiting time for the ship before docking	Time of entry assignment − time of arrival	Minutes/ship
Berth Occupancy Ratio	Wharf-utilization rate	(Σ mooring time/available time) × 100%	Presses
Loading and Unloading Productivity	Ability to handle goods per unit of time	Loading and unloading volume/working time	Tons/hour
Volume of Goods	Number of items unloaded/loaded	Item tonnage recapitulation	Tons/year

Note: X2 is a composite construct formed by eight infrastructure items. Standardized beta X2 can be compared to X1 to assess dominance at the construct level, but does not state one particular infrastructure item as the most influential predictor; physical priorities are determined through triangulation between regression results, operational indicators, observations, and interviews. Source: primary data, processed (2026).

The aggregation of items into the X1 and X2 constructs was theoretically grounded. The System Administration items operationalized the administrative and coordination dimensions emphasized by Transport Network Theory and Intermodal Logistics Theory, whereas the Physical Infrastructure items operationalized the facility adequacy dimension emphasized by Central Place Theory and Growth Pole Theory. The unidimensionality and internal consistency of each construct were assessed empirically using Pearson item-total correlations for validity testing and Cronbach's alpha for reliability testing, with the results reported in Table 7.

Data were collected using three techniques: direct observation of loading and unloading operations, facility use, and physical constraints in the field; online questionnaires measuring service users' perceptions of X1, X2, and Y; and visual and administrative documentation recording facility conditions, activity-area layouts, and field conditions during the study.

Quantitative analysis employed descriptive and comparative statistics. Operational data were calculated by vessel and/or reporting period and summarized using totals, means, percentages, ratios, and growth rates. The results were compared between 2024 and 2025 and against relevant operational standards or benchmarks. The calculations were conducted as follows: BT = time of last line cast off − time of first line ashore; ET = effective time spent on loading and/or unloading activities; ET/BT ratio = (ET/BT) × 100%; WT = time of berthing − arrival time at the port waiting area; productivity = cargo volume handled / effective working time (tons/hour); BOR = (total vessel berth-occupancy time / total available berth time) × 100%; and cargo volume was analyzed by total loading and unloading volume, commodity type, and year-over-year growth.

The performance gap was assessed in two ways. First, the relative change between periods was calculated using Δ% = [(2025 value − 2024 value) / 2024 value] × 100%. The direction of improvement differed across indicators: lower BT and WT values were considered favorable when accompanied by adequate service output; higher ET/BT ratios and productivity values were considered favorable; and BOR was assessed against the reference benchmark of 70%. Absolute ET was not ranked directly because its duration depends on the volume and characteristics of the work performed on each vessel. Second, where a numerical benchmark was available, the gap was calculated as the difference between the observed value and the benchmark. Because the indicators use different units, the largest and smallest gaps were not identified by comparing raw numerical differences across units. Instead, relative changes (Δ%) were used to compare changes over time. The decline in productivity was identified as the largest operational concern, whereas WT exhibited the smallest relative change. BOR was discussed separately as a berth-capacity indicator in relation to the 70% reference benchmark.

Qualitative analysis was conducted to identify and explain contextual factors associated with the quantitative findings through observations, interviews, and documentation. These factors included weather conditions, facility limitations, equipment conditions, workforce availability and capability, activity coordination, administrative conditions, and other operational constraints. Interview data were analyzed through data reduction, thematic grouping into infrastructure, equipment, human resources, administration, weather, and policy categories, matrix-based presentation, and interpretation. The qualitative findings were then used to contextualize the decline in productivity, the increase in BOR, and the relatively stronger statistical association between Physical Infrastructure (X2) and Service and Performance (Y), without interpreting these relationships as evidence of causation.

The questionnaire was developed using a five-point Likert scale (Very Good = 5; Good = 4; Adequate = 3; Poor = 2; Very Poor = 1). Instrument validity was assessed using Pearson item-total correlations between each item's score and the corresponding variable's total score. An item was considered valid if the calculated correlation coefficient (r_count) exceeded the critical correlation coefficient (r_critical) at the 5% significance level and the corresponding p-value was less than 0.05. Instrument reliability was assessed using Cronbach's alpha, with a coefficient of at least 0.70 considered indicative of acceptable internal consistency. Reliability was evaluated separately for X1, X2, and Y.

Multiple linear regression was used to examine the statistical associations of System Administration (X1) and Physical Infrastructure (X2) with Port Service and Performance (Y), using the equation $Y = a + b_1X_1 + b_2X_2 + e$. The individual regression coefficients were tested using t-tests to evaluate H1 and H2. A predictor was considered statistically significant if its p-value was less than 0.05, and the direction of the association was determined by the sign of its regression coefficient. The joint statistical significance of the two predictors was evaluated using the F-test to test H3. X1 and X2 were considered jointly statistically significant predictors of Y when the F-test p-value was less than 0.05. The coefficient of determination (R^2) and adjusted R^2 were used to indicate the proportion of variation in Y explained by the model, while standardized beta coefficients and semipartial (part) correlations were used to assess the relative contributions of the individual predictors. Before interpreting the regression results, model assumptions were examined through tests of residual normality, heteroscedasticity, and multicollinearity. Throughout this article, the terms “effect” and “influence,” when used in the regression context, refer to statistically significant associations or predictive relationships rather than experimentally established causal effects, consistent with the cross-sectional survey design.

The R^2 value was treated as an empirical result rather than a target to be artificially increased. Variables were not added solely to obtain a higher R^2 without an adequate theoretical basis, appropriate measurement instruments, and supporting data. Given the two predictors established through theoretical considerations and the study's scope, model evaluation was further conducted using adjusted R^2, standardized beta coefficients, semipartial correlations, classical regression assumption tests, and triangulation. Model development incorporating additional variables, such as human resources, coordination, weather, policy, cargo characteristics, and hinterland integration, was reserved for future research requiring additional data collection and model reestimation.

Facility requirements were projected through 2030, taking into account cargo-flow growth and the limitations of the short 2024–2025 historical data series. Because the historical series was relatively short, projections were interpreted through three scenarios: a conservative scenario, characterized by low cargo-flow growth and no significant diversion of cargo flows from Ternate; a moderate scenario, based on the 2024–2025 trend and the potential development of Sofifi's logistics sector, which served as the principal basis for projections through 2030; and an optimistic scenario, characterized by improved connectivity, increased facility capacity, and the diversion of some regional cargo flows to Sofifi. The projections were intended to provide indicative estimates of facility requirements rather than absolute predictions. To avoid overstating the precision of projections derived from the short 2024–2025 series, the assumed 10% exponential annual growth rate for non-fuel cargo and the assumed linear trend for fuel cargo were treated as the central moderate scenario, bounded by the conservative and optimistic scenarios described above. A sensitivity range of approximately ±5 percentage points around the

assumed growth rate was also considered, meaning that the projected figures should be interpreted as indicative planning estimates rather than deterministic point forecasts.

RESULTS AND DISCUSSION

Results

Existing Conditions of Sofifi Port

Sofifi Port serves various types of vessels on routes connecting Sofifi with Ternate, Gita, Manado, and Sanana. Vessel traffic is dominated by multipurpose vessels that transport both passengers and goods, alongside general cargo vessels, landing craft tanks (LCTs) used to transport heavy equipment and bulk cargo, and self-propelled oil barges (SPOBs) used for fuel distribution. Based on a sample of operational data for 2024–2025, KM Cantika Lestari 7F (GT 1,083) served the Gita–Manado route, with an unloading volume of 12,500 tons/m^3, while KM Venecian (GT 712) served the Sofifi–Ternate–Sanana route, with an unloading volume of 36,850 tons/m^3 and a loading volume of 35,320 tons/m^3. These figures indicate considerable variation in cargo-handling activity across vessels and suggest that Sofifi functions not only as a receiving point but also as a distribution point within the inter-island logistics network.

The cargo handled is dominated by vegetables and mixed goods (general cargo), reflecting the community's basic needs and a recurring demand for essential commodities rather than industrial commodities or large-scale containerized cargo. In terms of facilities, loading and unloading activities are still performed conventionally, relying on loading and unloading labor (*Tenaga Kerja Bongkar Muat,* or TKBM) without adequate support from mechanical handling equipment. The available berths primarily serve small- to medium-sized vessels, and the port does not yet have a permanent storage warehouse. These conditions indicate that Sofifi Port functions as a feeder port supporting the distribution of essential goods, with a radial distribution pattern that remains dependent on Ternate as the principal connecting node. This pattern is consistent with Central Place Theory and underscores the need to strengthen service capacity so that the port's role is supported by adequate operational performance.

Operational Performance of Loading and Unloading Services 2024–2025

Operational performance was assessed using six key indicators: berth time (BT), effective time (ET), the ET/BT ratio, waiting time (WT), cargo-handling productivity, and berth occupancy ratio (BOR). In 2024, the average BT was 53.9 hours per vessel, representing a total of 468,767 minutes across 145 vessel calls. The highest monthly average BT was 113.0 hours in April, while the lowest was 24.5 hours in February. In 2025, the average BT decreased to 28.7 hours per vessel, representing a total of 487,328 minutes across 283 vessel calls, although the number of vessel calls nearly doubled. Average ET decreased from 18.7 hours in 2024 to 10.8 hours in 2025, while the ET/BT ratio improved from 34.7% to 37.5%. The highest monthly ET/BT ratio was recorded in February 2025 (48.4%), and the lowest was recorded in December 2024 (25.3%).

The decreases in BT and ET indicate shorter recorded service durations per vessel call, while the increase in the ET/BT ratio indicates a modest improvement in the proportion of berth time classified as effective time. However, neither ET nor BT alone provides sufficient evidence of improved efficiency because cargo volumes and load characteristics may also have changed between visits. The defensible conclusion is that recorded service durations per visit decreased and the proportion of effective time increased slightly, rather than that overall cargo-handling efficiency improved. A more comprehensive assessment requires the time-based indicators to be interpreted alongside productivity, BOR, cargo volumes, and qualitative findings, as summarized in Table 3.

Waiting time (WT) was the most stable indicator among those measured. Average WT changed only slightly, from 18.2 minutes in 2024 to 18.5 minutes in 2025, despite a 95.2% increase in vessel calls (from 145 to 283). The highest WT was recorded in September 2024 (20.8 minutes), while the lowest was recorded in March 2024 (15.3 minutes). The stability of WT suggests that vessel-arrival coordination remained relatively consistent. However, WT alone cannot establish that port capacity was sufficient or underutilized, because low waiting times can coexist with high BOR when congestion or service pressure occurs after vessels berth.

In contrast, cargo-handling productivity declined sharply, from an average of 12.6 tons/hour in 2024 to 5.3 tons/hour in 2025—a decrease of approximately 57.9%, representing

the largest operational gap among the performance indicators measured. The highest productivity in 2024 was recorded in February (70.2 tons/hour), and the lowest was recorded in April (3.1 tons/hour). In 2025, the range was narrower, at 3.4–8.0 tons/hour, indicating a more consistent but substantially lower productivity level. BOR increased from 74% in 2024 to 77% in 2025. Both annual averages exceeded the 70% reference benchmark adopted in this study, with the 2025 average standing 7 percentage points above the benchmark. On a monthly basis, BOR exceeded 100% in several instances, including January 2024 (153%), October 2025 (112%), and November 2025 (133%). These values indicate potential berth-capacity pressure and warrant verification of the number of effective berths and the consistency of the time-recording data used in the calculations.

Table 3
Summary of Test Results of Sofifi Port Operational Performance Indicators 2024–2025

Indicator	2024	2025	Change (Δ%)	Interpretation
Berth Time (BT)	53.9 hours	28.7 hours	−46.8%	Shorter mooring duration; not enough to prove efficiency without output and BOR
Effective Time (ET)	18.7 hours	10.8 hours	−42.2%	Decreases with changes in volume/load characteristics per visit
ET/BT Ratio	34.7%	37.5%	+2.8 points	The proportion of effective time is improving; NOT/idle time still needs to be reduced
Waiting Time (WT)	18.2 minutes	18.5 minutes	+1.65%	Smallest relative change; WT stable despite increased ship traffic
Loading and Unloading Productivity	12.6 tons/hour	5.3 tons/hour	−57.9%	Largest operational gap; productivity recovery priorities
Berth Occupancy Ratio (BOR)	74%	77%	+7 points from 70% reference	Most critical capacity gaps; dock utilization pressure
Number of Ship Visits	145 ships	283 ships	+95.2%	Traffic increased, but not followed by a comparable increase in productivity

Source: Sofifi Class III UPP Office, processed (2026).

In terms of relative change, cargo-handling productivity represents the largest operational gap (−57.9%), whereas WT exhibits the smallest change (+1.65%). The 2025 BOR also indicates a capacity concern, standing 7 percentage points above the 70% reference benchmark. These findings suggest that the principal issue at Sofifi Port does not lie primarily in vessel queuing before berthing but in the capacity to handle cargo after vessels berth and the resulting pressure on berth utilization. To avoid redundancy with Table 3, the following discussion emphasizes the direction and magnitude of change rather than repeating every tabulated value.

Volume and Composition of Cargo

The volume of unloaded cargo in the general cargo, liquid bulk, and heavy equipment categories increased from 28,108 tons in 2024 to 33,879 tons in 2025, while loaded volumes decreased sharply from 5,556 tons to 1,170 tons over the same period. This pattern indicates that

Sofifi Port functions predominantly as a receiving port rather than as a port for outbound cargo. When all commodity categories, including fuel, are considered, total unloading volume increased from 27,302 tons in 2024 to 35,051.8 tons in 2025, an increase of approximately 28.4%. Fuel was the dominant commodity in both years, increasing from 20,120 tons in 2024 to 27,786.9 tons in 2025. On the loading side, total activity decreased from 5,494 tons in 2024 to 1,169.7 tons in 2025. Loading activity was dominated by vehicles, reported as 3,390 units in 2024, and fuel, totaling 592 tons in 2025.

Table 4
Volume and Type of Goods per Year (T/M^3)

Categories	Activities	2024	2025
General Charge	Unload/Load/Total	7.040 / 4.751 / 11.791	7.781 / 210 / 7.991
Liquid Bulk	Unload/Load/Total	20.780 / 417 / 21.197	25.732 / 450 / 26.182
Heavy Equipment	Unload/Load/Total	288 / 388 / 676	366 / 510 / 876
Quantity	Unload/Load/Total	28.108 / 5.556 / 33.664	33.879 / 1.170 / 35.049

Source: Sofifi Class III UPP Office, processed (2026).

The dominance of fuel unloading underscores Sofifi Port's strategic role as a regional energy distribution center, given that fuel supplies remain dependent on shipments from the Ternate and Wayame fuel terminals using small tankers and SPOBs. Meanwhile, the substantial cement-unloading volume reported for 2024 (2,500 tons) indicates relatively active infrastructure development. The increase in the bulk cargo category (BC+) from 392 tons to 3,342.9 tons also suggests an expansion in the distribution of bulk and mixed goods. The much smaller and more variable loading volumes compared with unloading volumes—including months with no recorded loading activity in 2025—further confirm that Sofifi functions primarily as a port for distributing regional supplies rather than as a port for exporting goods outside the region.

Projected Facility Needs until 2030

The projection of fuel-unloading volume uses a linear trend under a moderate-growth scenario. Fuel volume increased from 20,120 tons in 2024 to 27,787 tons in 2025, an annual increase of approximately 7,667 tons. On this basis, the projection equation is Y = 20,120 + 7,667X. Using 2024 as the base year X = 0, projected fuel-unloading volume reaches 66,122 tons in 2030. For nonfuel cargo, the reported actual data indicate a relatively small increase, from 7,182 tons in 2024 to approximately 7,265 tons in 2025. The projection nevertheless adopts a moderate exponential growth scenario of 10% per year, expressed as $Y = 7{,}182(1.10)^n$, yielding a projected volume of approximately 12,724 tons in 2030 (Table 5).

Table 5
Projected Volume of Fuel and Non-Fuel Unloading until 2030 (Moderate Scenario)

Year	Fuel Projection (Tons)	Fuel Growth	Non-Fuel Projections (Tons)	Non-Fuel Growth
2024	20.120	—	7.182	—
2025	27.787	38.1%	7.900	10%
2026	35.454	27.6%	8.690	10%
2027	43.121	21.6%	9.559	10%
2028	50.788	17.8%	10.515	10%
2029	58.455	15.1%	11.567	10%
2030	66.122	13.1%	12.724	10%

Source: data processing results of UPP Class III Sofifi (2026), moderate scenario.

Based on these projections, the supporting facility requirements through 2030 include a logistics warehouse with an area of approximately 1,000–1,500 m^2, calculated using an assumed storage capacity of 3–5 tons/m^2 and adjusted to account for the direct-transit and distribution function, which is estimated to handle 30–40% of the theoretical storage requirement. An additional open stacking area of 1,500–2,000 m^2 is proposed for vehicles, heavy equipment, and construction materials. The plan also proposes adding two to three fuel storage tanks, each with a capacity of 500–1,000 kL, because the existing storage capacity, including gas station storage tanks of 45–100 kL and operational tanks at diesel power plants (PLTDs), is estimated to be insufficient for the projected fuel-unloading volume of 66,122 tons in 2030. Additional cargo-handling equipment is proposed, as presented in Table 6.

For transparency, each facility estimate is linked explicitly to the projected 2030 volumes rather than being assumed a priori. The warehouse area is estimated by dividing the projected throughput requiring storage by an assumed storage capacity of 3–5 tons/m^2 and then adjusting for the 30–40% transit-distribution factor. The stacking area is scaled to the projected flows of vehicles, heavy equipment, and construction materials. The number of fuel tanks is estimated in relation to the projected 2030 fuel volume of 66,122 tons and an assumed working capacity of 500–1,000 kL per tank, taking tank turnover into account. Heavy-equipment requirements are scaled to the projected cargo-handling workload. These figures remain preliminary capacity-planning estimates based on the limited 2024–2025 baseline data; they should not be treated as definitive investment specifications.

Table 6
Heavy Equipment Needs Analysis until 2030

Types of Heavy Equipment	Current Conditions	Projections 2030
Forklift	0–1 unit (non-fixed)	2–3 units
Mobile Crane	0 units	1–2 units
Excavator	0–1 unit	2 units
Wheel Loader	0 units	1–2 units
Trailer/Truck	1–2 units	4–6 units
Reach Stacker	0 units	1 unit (optional)

Source: results of heavy equipment needs analysis, processed (2026).

The current reliance on vessel-mounted equipment or third-party rental equipment confirms the urgent need to expand the availability of cargo-handling equipment. This recommendation is consistent with the observed 57.9% decline in productivity, although the extent to which equipment limitations account for that decline must be established through further operational analysis.

Test Results of Multiple Linear Regression Instruments and Models

A validity test using Pearson's correlation coefficients for 195 respondents showed that all items measuring X1 (eight items), X2 (eight items), and Y (ten items) had calculated correlation coefficients ranging from 0.803 to 0.906, substantially exceeding the critical correlation coefficient of 0.140 at the 5% significance level. All items were statistically significant at ($p < 0.001$) and were therefore considered valid. Reliability testing using Cronbach's alpha indicated excellent internal consistency for all three variables (Table 7), with coefficients well above the minimum criterion of 0.70.

Table 7
Summary of Instrument Validity and Reliability Tests

Variable	Number of Items	Range r Calculate	r Table	Cronbach's Alpha	Remarks
X1 – Digitization & System Administration	8	0.858–0.895	0.140	0.956	Valid & Reliable
X2 – Facilities & Physical Infrastructure	8	0.879–0.906	0.140	0.962	Valid & Reliable
Y – Quality of Service & Performance	10	0.803–0.834	0.140	0.945	Valid & Reliable

Source: SPSS 27 processed results of 195 respondents (2026).

Before the regression results were interpreted, the model was assessed using three classical assumption tests (Table 8). Residual normality tests using the Kolmogorov–Smirnov test (statistic = 0.040; significance = 0.200) and the Shapiro–Wilk test (statistic = 0.996; significance = 0.911) did not indicate a significant departure from normality, as both significance values exceeded 0.05. Heteroscedasticity testing using the Glejser test yielded significance values of 0.219 for X1 and 0.733 for X2, providing no statistically significant evidence of heteroscedasticity at the 5% significance level. The multicollinearity test produced a tolerance value of 0.999 and a variance inflation factor (VIF) of 1.001 for each independent variable, indicating no evidence of problematic multicollinearity. Taken together, these results support the use of the regression model for further analysis, subject to the usual assumptions and limitations of the tests employed.

Table 8
Summary of the Classical Assumption Test

Test	Results	Criteria	Conclusion
Normality (Kolmogorov-Smirnov)	Stats 0.040; Sig. 0.200	Sig. > 0.05	Normally distributed data
Normality (Shapiro-Wilk)	Stat. 0.996; Sig. 0.911	Sig. > 0.05	Normally distributed data
Heteroskedasticity – X1 (Glejser)	B = 0.038; t = 1.232; sig. 0.219	Sig. > 0.05	Heteroscedasticity does not occur
Heteroskedasticity – X2 (Glejser)	B = −0.010; t = −0.341; sig. 0.733	Sig. > 0.05	Heteroscedasticity does not occur
Multicollinearities – X1	Tolerance 0.999; LIFE 1.001	Tolerance>0.10; VIF<10	Multicollinearity does not occur
Multicollinearity – X2	Tolerance 0.999; LIFE 1.001	Tolerance>0.10; VIF<10	Multicollinearity does not occur

Source: processed products SPSS 27 (2026).

The results of multiple linear regression showed a coefficient of determination R = 0.693; R^2 = 0.480; Adjusted R^2 = 0.475; standard error 2.964; and Durbin-Watson 1.958, which means that 48.0% of Y variations can be explained by X1 and X2 in the study sample, while 52.0% are related to factors outside the model and random variations. The R^2 value is treated as an empirical result and is not artificially inflated or post hoc; the deepening of the model is done through Adjusted R^2, standardized beta, and part correlation, not by adding predictors without theoretical basis.

The F test showed a significant model simultaneously, F(2.192) = 88.720; p<0.001, so H3 was supported. The t-test showed that System Administration (X1) had a positive and significant effect on Y (B=0.405; β=0.411; t=7.905; p<0.001), so H1 was supported; Physical Infrastructure

(X2) also had a positive and significant effect on Y (B=0.505; β=0.546; t=10.487; p<0.001), so H2 was supported. The regression equation obtained is $\hat{Y}$ = 10.229 + 0.405X1 + 0.505X2, with a constant of 10.229 (t=5.095; p<0.001) as the predictive value of Y when X1 and X2 are zeroed on the model scale, while the two positive coefficients show an increase in the prediction of Y for each increase of one predictor unit of predictor with another constant (Table 9).

Table 9
Results of Determination Coefficient, F Test, and t Test

Components	Value	Remarks
R	0.693	—
R^2	0.480	48.0% variation Y explained model
Adjusted R^2	0.475	—
Std. Error / Durbin-Watson	2.964 / 1.958	—
F test (simultaneous)	F(2,192) = 88,720; p<0.001	Significant model; H3 supported
Constant (a)	B = 10.229; t = 5.095; p<0.001	Significant
System Administration (X1)	B = 0.405; β=0.411; t=7.905; p<0.001	Significant positive; H1 supported
Physical Infrastructure (X2)	B=0.505; β=0.546; t=10.487; p<0.001	Significant positive; H2 supported

Source: SPSS 27 (2026) processing. Equation: $\hat{Y}$ = 10.229 + 0.405X1 + 0.505X2.

At the construct level, Physical Infrastructure (X2) is relatively more dominant than System Administration (X1) because βX2 = 0.546 > βX1 = 0.411. Based on the partial correlation, X2's unique contribution to Y variation is about 29.8% (0.546^2) and X1 is about 16.9% (0.411^2); the difference includes intersecting parts of the predictors as well as factors outside the model. This dominance is construct dominance, not evidence that a particular infrastructure item (e.g. dock alone, or warehouse alone) is statistically most statistically significant to Y, since the regression model only estimates the influence of X2 as a composite construct formed by eight questionnaire items together.

Table 10
Summary of Hypothesis Testing Results

Hypothesis	Test Results	Verdict
H1: X1 → Y	β = 0.411; t(192) = 7.905; p<0.001	Supported — X1 has a significant positive effect on Y
H2: X2 → Y	β = 0.546; t(192) = 10.487; p<0.001	Supported — X2 has a significant positive effect on Y
H3: X1 & X2 → Y (simultaneous)	F(2.192) = 88.720; p<0.001; R^2=0.480	Supported — X1 and X2 simultaneously have a significant effect on Y

Source: processed products SPSS 27 (2026).

Qualitative Findings: Factors Causing Not Optimal Service

The findings from observations and interviews with five groups of informants (Table 1) reinforce the interpretation of the quantitative results. Regarding infrastructure, informants reported that the berths were becoming congested and that permanent warehouses and stacking areas remained limited. These observations are consistent with the reported BOR of 74%–77%,

which exceeds the study's 70% reference benchmark. Regarding equipment, cargo-handling equipment remained limited, and some activities depended on vessel-mounted equipment or third-party equipment. This finding is consistent with the decline in productivity from 12.6 to 5.3 tons/hour. Regarding human resources, informants considered the skills of the cargo-handling workforce reasonably adequate for routine operations but identified a need for additional training and more structured work scheduling, particularly as vessel activity increased. Regarding administration, the recording of schedules, documents, and service data was not yet fully digitized or available in real time, consistent with the statistically significant association between System Administration (X1) and Y in the regression model. Weather conditions, including rain, waves, and wind, could also disrupt cargo-handling schedules and create unproductive periods. Finally, regarding policy, the development of Sofifi Port as a secondary port had not yet been fully guided by a phased facility-development roadmap and clearly defined performance indicators (Table 11).

Table 11
Summary of Interview Findings by Theme

Theme	Key Findings	Relevance to Quantitative Outcomes	Strategy Implications
Infrastructure	The docks are starting to get crowded; permanent warehouses and stacking areas are still limited	BOR 74%–77%, exceeding ideal mold ~70%	Arrangement of loading and unloading zones, development of warehouses, expansion of stacking areas
Equipment	Fixed loading and unloading tools are still limited; some depend on ship/third-party tools	Productivity decreased from 12.6 to 5.3 tons/hour	Addition of forklifts, mobile cranes, and auxiliary equipment according to 2030 projections
HR	Workforce skills are quite helpful, but they require training and work scheduling	Productivity has not stabilized as ship activity increases	Training of TKBM, tool operators, and administrative officers
Administration	Recording of schedules, documents, and data is not yet fully digital/real-time	System Administration Variable (X1) has a significant effect on Y	Digitization of documents, ship queue systems, and performance dashboards
Weather	Rain, waves, and wind still disrupt loading and unloading schedules	Causing unproductive time in a certain period	SOP for weather mitigation and adjustment of operational schedules
Policy	The development of secondary ports is not yet fully roadmap based	The need for facilities until 2030 needs to be set in stages	Short, medium, and long-term development plans

Source: results of observations and interviews, processed (2026).

The six themes are consolidated in a matrix of factors inhibiting service performance (Table 12), which explicitly links field findings to their operational impacts and the corresponding optimization measures.

Table 12
Matrix of Factors Inhibiting Sofifi Port Loading and Unloading Services

Inhibiting Aspects	Key Findings	Impact on Performance	Optimization Implications
Infrastructure	The dock is starting to get crowded; the warehouse/stacking area is limited; the loading and unloading equipment is inadequate	BOR exceeds 70% and productivity drops	Addition of tools, expansion of areas, warehouses, and arrangement of loading and unloading zones
Operational	Coordination of ship schedules, labor, and freight flows is not yet fully integrated	Idle time occurs; ET/BT utilization is not optimal	SOP scheduling, idle time reduction, service time supervision
Technology	Record-keeping and administration are not yet fully digital and integrated	service data is not real-time; slow coordination	Digitization of documents, performance dashboards, ship queuing systems
HR	Operational skills and adaptation of digital systems still need to be improved	Productivity and speed of service have not been stable	Training of TKBM, tool operators, and administrative officers
Policy	No phased development priorities for Sofifi secondary port yet	Facility development is not entirely based on projected needs	Development plan until 2030 based on performance indicators and regional logistics needs

Source: results of observation, interviews, and analysis of operational data, processed (2026).

Loading and Unloading Service Optimization Strategy

The optimization strategy is structured in stages to ensure that recommendations are directly linked to the performance analysis, regression results, and projected facility requirements. It comprises three interdependent stages: restoring short-term operational efficiency without waiting for major investment; strengthening medium-term capacity in response to productivity gaps and berth-utilization pressure; and pursuing long-term regional logistics integration once operational processes, data management, and essential facilities are stable (Table 13).

Table 13
Sofifi Port Loading and Unloading Service Optimization Strategy Matrix

Stage of Time	Priority Focus	Priority Programs	Success Indicators
Short Term (0–1 year)	Priority I — restoring the efficiency of existing operations without waiting for a large investment	SOPs and ship scheduling slots; standardization of BT, ET, WT, NOT, and productivity record-keeping; reduction of idle time; zoning of loading and unloading areas; readiness of equipment/TKBM; simple performance dashboard	WT remains under control, ET/BT increases, causes of idle time documented, productivity begins to recover
Medium Term	Priority II — capacity	Addition/determination of fixed loading and unloading equipment	Productivity recovers at comparable loads,

Stage of Time	Priority Focus	Priority Programs	Success Indicators
(2026–2030)	strengthening confirmed by productivity gaps, BOR pressures, and projected needs until 2030	(forklift/mobile crane); maintenance program; development of warehouses and stacking areas; improvement of vehicle access; fuel/non-fuel facilities; evaluation of mooring capacity based on validated BOR data	BOR moves towards benchmarks, space conflicts reduce, facility capacity follows 2030 projections
Long-Term Direction (post-2030)	Priority III — regional logistics integration once the operational foundation, data, and key facilities are stable	Goods terminal development; Sofifi–Ternate–Halmahera data integration; Port information system; hinterland connectivity; gradual implementation of Smart Ports based on process readiness, human resources, and infrastructure	Sofifi is evolving as a more autonomous, integrated, scalable, and data-driven regional logistics node

Source: results of integration of quantitative and qualitative analysis, processed (2026).

The three priorities are interdependent. In the short term, the focus is on restoring operational discipline and improving data quality. In the medium term, through 2030, investment should target equipment, warehouses and stacking areas, access infrastructure, fuel and nonfuel handling facilities, and berth capacity in response to identified gaps and projected requirements. The post-2030 direction concerns regional logistics integration and should be understood as a proposed policy direction rather than a result derived directly from the quantitative projections in this study. Smart-port development is deliberately placed at the final stage, after basic processes, data quality, human resources, and infrastructure have become sufficiently stable, to avoid merely transferring inefficient processes into electronic systems.

Discussion

The results show that the performance of Sofifi Port cannot be assessed using a single indicator in isolation. Shorter BT and stable WT are positive signals regarding vessel service, but both must be interpreted alongside the volume of cargo handled. According to the available records, productivity declined by 57.9%, while cargo volume per vessel call also tended to be lower. Therefore, the shorter service duration per vessel was insufficient to demonstrate that cargo-handling services had become optimal. The ET/BT ratio increased from 34.7% to 37.5%, but this improvement occurred alongside a decline in productivity from 12.6 to 5.3 tons/hour and an increase in BOR from 74% to 77%. Considered together, these findings—productivity as the largest operational gap, WT as the most stable indicator, and BOR as a measure of berth-utilization pressure relative to the 70% benchmark—provide the basis for prioritizing interventions: first, restore cargo-handling capability; second, manage berth-utilization pressure; and third, improve the organization of storage space and service data flows. The following discussion proceeds from the results to their interpretation and practical implications while maintaining consistent operational terminology with the Results section.

A key interpretive question is why cargo-handling productivity declined by 57.9% even as vessel calls increased by 95.2%. This pattern is consistent with a system facing capacity constraints. The near-doubling of vessel calls coincided with an increase in average BOR from 74% to 77%, above the study's 70% benchmark, while the availability of dedicated cargo-handling equipment remained very limited. Consequently, additional vessels continued to be served largely through conventional methods that depended on manual labor and vessel-mounted or rented equipment. If the increase in vessel calls was accompanied by smaller average consignments, handling effort would have been distributed across more visits, potentially reducing average throughput per hour even as berth time per vessel shortened. This explanation links the

equipment limitations documented in Tables 11 and 12 to the observed productivity gap and illustrates how a port may record shorter service durations per call while handling cargo at a lower hourly rate. However, the proposed mechanism should be treated as an interpretation rather than a demonstrated causal relationship unless supported by disaggregated data on cargo volume per call, equipment availability, labor deployment, and handling time.

The regression results reinforce this interpretation from the perspective of service users. The overall model was statistically significant, ($F(2, 192) = 88.720$), ($p < 0.001$), with ($R^2 = 0.480$) and adjusted ($R^2 = 0.475$). These values indicate a meaningful degree of explanatory power for the cross-sectional perception data analyzed in this study. The (R^2) value is reported as observed, without post hoc inflation, while adjusted (R^2), standardized beta coefficients, and appropriate partial or semipartial correlations provide additional information for interpreting the model. Both X1 and X2 were statistically significant predictors, with Physical Infrastructure (X2; ($\beta = 0.546$)) showing a stronger standardized association with Y than System Administration (X1; ($\beta = 0.411$)). However, the stronger association of X2 does not mean that any individual infrastructure item is independently the most statistically significant predictor of Y, because the model estimates X2 as a composite construct measured by eight questionnaire items. Accordingly, physical investment priorities should be established through triangulation rather than by relying on a single regression coefficient. The limitations in cargo-handling equipment are directly relevant to the observed productivity gap; berth-utilization pressure is reflected in the BOR values above the benchmark; and the limitations in warehouses, stacking areas, and logistics access are consistent with the observations and interviews summarized in Tables 11 and 12. The recommended order of physical interventions is therefore to improve the availability and adequacy of cargo-handling equipment, manage berth capacity, and then improve the organization of warehouses, stacking areas, and logistics access.

The finding that Physical Infrastructure is more strongly associated with Y than System Administration at the construct level is broadly consistent with previous port studies emphasizing the importance of physical facilities and operational capacity. Damongilala et al. (2022) and Soimun et al. (2025), for example, highlight the relevance of productivity and facility utilization to port-service performance. However, these studies primarily examine larger ports or container terminals and generally focus on a narrower set of indicators. The present study extends this perspective by integrating service-time indicators, cargo-handling productivity, BOR, perception-based regression, qualitative evidence, and facility projections within the context of a noncontainerized secondary port. Importantly, the stronger statistical association of Physical Infrastructure (X2) should be interpreted at the construct level; it does not establish that any individual infrastructure component independently constitutes the primary cause of service performance.

From the perspectives of Central Place Theory and Growth Pole Theory, Sofifi's role as a service center and growth node requires operational capacity that can accommodate increases in vessel calls and cargo activity. The 95.2% increase in vessel calls, without a comparable improvement in cargo-handling productivity, suggests that the port's service-center function has not yet been fully supported by adequate operational capacity. Transport Network Theory and Intermodal Logistics Theory further suggest that cargo-handling equipment, berths, warehouses, vehicles, human resources, administrative procedures, and data systems should operate as an integrated system. The ET/BT ratio of 37.5% in 2025 indicates that opportunities may remain to reduce non-operational time (NOT) and idle time, although these categories should be distinguished consistently in the operational records. Productive time may increase when documentation is completed before vessel berthing, equipment and labor are ready at the start of operations, and cargo transfers to storage areas or vehicles proceed without avoidable interruption. Accordingly, the strategy presented in Table 13 does not call for simultaneous infrastructure expansion across all areas. Instead, it recommends phased interventions whose effects can be monitored using the study's operational indicators.

Practically, the findings have important policy implications for the management of secondary ports in eastern Indonesia. First, an increase in vessel calls should not be used as the sole indicator of successful port development; cargo-handling productivity must also be considered. Second, investment decisions concerning physical facilities should be based on the

triangulation of quantitative evidence, including regression results and operational indicators, with qualitative evidence from observations and interviews. This approach can help establish more targeted budget priorities, such as whether to prioritize cargo-handling equipment or warehouse expansion. Third, administrative digitization (X1) remains statistically significant even though its standardized association with Y is smaller than that of Physical Infrastructure. Low-cost, short-term measures, such as standardizing operational records and introducing simple performance dashboards, can therefore be implemented without waiting for large-scale physical investment.

This study has several methodological limitations that should be considered when interpreting its findings and recommendations. First, the main operational data cover only 2024–2025, making the projections through 2030 indicative rather than definitive. Second, the regression model uses cross-sectional, perception-based data and two principal predictors. Its results therefore demonstrate statistical associations within the study sample rather than causality, and they cannot be used to rank the separate effects of the eight X2 questionnaire items. Third, BOR is sensitive to the definitions of available berth time and the number of effective berths used in the calculation. The denominator and underlying time records must therefore be verified for consistency with the data maintained by the Sofifi Class III UPP Office before BOR is used to justify capacity investments.

CONCLUSION

The findings demonstrate that cargo-handling services at Sofifi Port cannot yet be considered optimal, despite improvements in several time-based indicators during 2024–2025. BT decreased from 53.9 to 28.7 hours, ET decreased from 18.7 to 10.8 hours, the ET/BT ratio increased from 34.7% to 37.5%, and WT remained relatively stable at 18.2–18.5 minutes. However, cargo-handling productivity declined from 12.6 to 5.3 tons/hour, representing the largest operational gap at 57.9%, while BOR increased from 74% to 77%, exceeding the 70% benchmark adopted in this study. The overall regression model was statistically significant, with $R2 = 0.480$ and adjusted $R2 = 0.475$, and both System Administration (X1) and Physical Infrastructure (X2) were statistically significant predictors of Service Quality and Performance (Y). Physical Infrastructure showed the stronger standardized association at the construct level $\beta = 0.546$, compared with System Administration $\beta = 0.411$, although this result does not establish any individual infrastructure component as a causal determinant of service performance. The integrated quantitative and qualitative findings therefore identify cargo-handling equipment readiness, berth-capacity management, warehouses and stacking areas, logistics access, and continued administrative improvement as the principal priorities.

Accordingly, service optimization should be implemented progressively. Short-term priorities include strengthening SOPs and vessel scheduling, reducing idle time, improving equipment and TKBM readiness, organizing cargo-handling zones, standardizing operational data, and developing a simple monitoring dashboard. Medium-term priorities for 2026–2030 include expanding cargo-handling equipment, strengthening maintenance capacity, developing warehouses and stacking areas, improving vehicle access, upgrading fuel and nonfuel handling facilities, and managing berth capacity based on validated BOR data. The post-2030 direction emphasizes gradual regional logistics integration and smart-port connectivity. These recommendations must be interpreted within the study's limitations: the operational data cover only 2024–2025, the regression model is based on cross-sectional perception data with two predictors, and the 2030 facility projections are indicative rather than deterministic. Future research should therefore use longer-term longitudinal data, examine additional contextual predictors and individual infrastructure components, and validate projected facility requirements against subsequently observed cargo volumes and vessel calls.

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AUTHOR CONTRIBUTION STATEMENT

Merry Mardianti, I Nyoman Teguh Prasidha, and Wahyu Dewanto jointly contributed to the conceptualization of the study, development of the research methodology, data interpretation, preparation and critical review of the manuscript, and approval of the final version. All authors participated in ensuring the accuracy, consistency, and academic integrity of the manuscript and agreed to be accountable for the published work.

REFERENCES

Azizah, A. (2021). Analisis kapasitas dermaga terminal peti kemas Pelabuhan Peti Kemas Palaran Samarinda berdasarkan nilai Berth Occupancy Ratio dan Berth Throughput. *Jurnal Maritim*, *11*(2), 51–57.

Belmoukari, B., Audy, J.-F., & Forget, P. (2023). Smart port: A systematic literature review. *European Transport Research Review*, *15*(1), 4. https://doi.org/10.1186/s12544-023-00581-6

Berliana, D., Maemunah, S., Ricardianto, P., & Agusinta, L. (2025). Efektivitas dan waktu tunggu kapal sebagai bukti empiris kinerja dan produktivitas bongkar muat pada Pelabuhan Saketa-Halmahera. *Jurnal Manajemen Transportasi & Logistik*, *8*(1), 100–112. https://doi.org/10.38035/rrj.v8i1.1872

Bichou, K., & Gray, R. (2004). A logistics and supply chain management approach to port performance measurement. *Maritime Policy & Management*, *31*(1), 47–67. https://doi.org/10.1080/0308883032000174454

Christaller, W. (1966). *Central Places in Southern Germany*.

Christopher, M. (2016). *Logistics & Supply Chain Management*.

Damongilala, P., Sutrisno, A., & Mende, J. (2022). Analisis kinerja pelayanan di Pelabuhan Bitung (pengukuran kinerja operasi bongkar muat peti kemas). *Jurnal Teknik Sipil*, *8*, 5–11.

Danladi, C., Tuck, S., Tziogkidis, P., Tang, L., & Okorie, C. (2024). Efficiency analysis and benchmarking of container ports operating in lower-middle-income countries: A DEA approach. *Journal of Shipping and Trade*, *9*(1), 7. https://doi.org/10.1186/s41072-024-00163-2

Erber, W., Khan, F., Zavadska, D., Freimane, Z., Dobler, G., Böhmer, M. M., Jodar, L., & Schmitt, H. J. (2022). Effectiveness of TBE vaccination in southern Germany and Latvia. *Vaccine*, *40*(5). https://doi.org/10.1016/j.vaccine.2021.12.028

Han, C. (2018). Assessing the impacts of port supply chain integration on port performance. *The Asian Journal of Shipping and Logistics*, *34*(2), 129–135. https://doi.org/10.1016/j.ajsl.2018.06.009

Jahroni, J., Mukhsin, M., & Satyanegara, D. (2025). The Impact Of Supply Chain Integration On Supply Chain Performance. *Journal of Management : Small and Medium Enterprises (SMEs)*, *18*(3). https://doi.org/10.35508/jom.v18i3.16783

Kishore, L., Pai, Y. P., Ghosh, B. K., & Pakkan, S. (2024). Maritime shipping ports performance: A systematic literature review. *Discover Sustainability*, *5*(1), 108. https://doi.org/10.1007/s43621-024-00299-y

Notteboom, T. E., & Rodrigue, J.-P. (2005). Port regionalization: towards a new phase in port development. *Maritime Policy & Management*, *32*(3), 297–313. https://doi.org/10.1080/03088830500139885

Paraskevas, A., Madas, M., Zeimpekis, V., & Fouskas, K. (2024). Smart Ports in Industry 4.0: A Systematic Literature Review. In *Logistics* (Vol. 8, Number 1). https://doi.org/10.3390/logistics8010028

Parrique, T. (2026). *La science de la post-croissance*. Actes Sud.

Perroux, F. (1955). Note sur la notion de pôle de croissance. *Économie Appliquée*, *8*, 307–320. https://doi.org/10.3406/ecoap.1955.2522

Prakoso, B. G., Rusmiyanto, D., & Pratomo, S. A. (2025). Analisis produktivitas bongkar muat peti kemas dalam proses logistik di Pelabuhan Tanjung Emas Semarang. *Jurnal Sains Bangunan*,

2(1), 30–41. https://doi.org/10.58906/alsaba.v2i1.140

Putri, K. W., & Rahmawati, A. (2022). Analisis Kapasitas Dermaga Terminal Petikemas Makassar New Port Berdasarkan Nilai Berth Occupancy Ratio (BOR) dan Berth Throughput (BTP). *Riset Sains Dan Teknologi Kelautan*. https://doi.org/10.62012/sensistek.v5i2.24254

Soimun, A., Rupaka, A. P. G., Santi, N. M. K., & Fitri, S. N. (2025). Optimization of port terminal operations: a case study of international cargo handling at Jamrud Terminal. *Jurnal Manajemen Pelabuhan*, *6*(1), 1–14. https://doi.org/10.52920/jttl.v6i1.440

Souza, M. F. de, Tisler, T. R., Castro, G. S. A., & Oliveira, A. L. R. de. (2023). Port regionalization for agricultural commodities: Mapping exporting port hinterlands. *Journal of Transport Geography*, *106*. https://doi.org/10.1016/j.jtrangeo.2022.103506

Utara, B. P. S. P. M. (2022). *Statistik Transportasi Provinsi Maluku Utara 2022*.

Yenilmez, İ. (2025). Efficiency Analysis of Turkish Container Ports: SFA or DEA? *Verimlilik Dergisi*, (Productivity For Logistics). https://doi.org/10.51551/verimlilik.1522007