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Container terminal efficiency under external shocks: A hybrid DEA-Regression analysis of Dar es Salaam port (2019–2023)

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Abstract: *Purpose*. This paper evaluates the technical Efficiency of Dar es Salaam Port's container terminal operations over the period 2019–2023, explicitly accounting for the influence of macroeconomic conditions and the COVID-19 pandemic on performance metrics. The study addresses a critical gap in port efficiency research by disentangling internal operational capability from external contextual factors in a developing-economy maritime gateway serving landlocked East and Central African countries. *Methodology*. A two-stage hybrid analytical framework integrates input-oriented Data Envelopment Analysis (DEA) with Contextual Value Added (CVA) regression. DEA efficiency scores are computed using a three-year rolling window approach with inputs (quay length, gantry cranes, terminal area) and outputs (container throughput, vessel calls). Second-stage ordinary least squares regression isolates the effects of GDP, trade volume, and pandemic disruption on measured efficiency. Quantitative findings are triangulated with qualitative stakeholder surveys (n=45) and semi-structured interviews to capture operational perceptions and institutional constraints. *Results*. DEA analysis reveals temporal efficiency variation ranging from 0.838 (2019) to 0.966 (2021), with post-pandemic decline to 0.890 (2023). CVA regression identifies a statistically significant negative relationship between trade volume and efficiency ($\beta = -1.76\times10^{-5}$, $p = 0.03$), indicating binding infrastructure constraints. The COVID-19 dummy exhibits a paradoxical positive coefficient ($\beta = +0.090$, $p = 0.02$), reflecting efficiency gains under suppressed demand rather than genuine productivity enhancement. *Theoretical contribution*. This study advances port efficiency assessment by demonstrating that unadjusted frontier methods can mask capacity deficits when external demand fluctuates. The hybrid DEA-CVA framework

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enables evidence-based attribution of efficiency sources, enhancing policy relevance. *Practical implications*. Findings underscore the urgent need for infrastructure expansion and procedural digitalization to accommodate regional trade growth under the African Continental Free Trade Area.

Keywords: container terminal efficiency, data envelopment analysis, contextual regression, port performance measurement, COVID-19 maritime disruption, East African ports, infrastructure capacity constraints

Sustainable Development Goals (SDGs): SDG 8: Decent Work and Economic Growth; **SDG 9:** Industry, Innovation, and Infrastructure

1. Introduction

1.1. Background and context

Seaport operational efficiency constitutes a critical determinant of international trade competitiveness, particularly for developing economies reliant on maritime gateways to facilitate the movement of goods across global supply chains (Munim & Schramm, 2018). Container terminals serve as pivotal nodes within these supply chains, functioning as interfaces between maritime and terrestrial transport networks where cargo is transferred, stored, and distributed to hinterland destinations (Bichou & Gray, 2005). The efficient operation of these facilities directly influences transaction costs, delivery times, and the overall attractiveness of trade corridors, thereby shaping regional economic development trajectories (Cong et al., 2020).

In sub-Saharan Africa, port performance has emerged as a subject of increasing scholarly and policy attention, given the region's persistent infrastructure deficits and their constraining effects on trade facilitation (Raballand et al., 2012). Dar es Salaam Port, Tanzania's principal maritime gateway, exemplifies these dynamics. The facility handles in excess of 95 per cent of the nation's international seaborne trade and serves as a critical transit corridor for landlocked neighbouring economies, including Zambia, Malawi, the Democratic Republic of Congo, Rwanda, Burundi, and Uganda (Juma & Zhihong, 2020). Consequently, operational inefficiencies at this port generate ripple effects across the broader East and Central African regional economy, elevating logistics costs and undermining industrial competitiveness (Sun & Kauzen, 2023).

Recent years have witnessed a substantial transformation in global maritime logistics, driven by the confluence of vessel upsizing, supply chain digitalization, and intensified competition among port operators (Alamoush et al., 2020). These developments have been further complicated by exogenous disruptions, most notably the COVID-19 pandemic, which exposed systemic vulnerabilities in port operations while simultaneously catalysing innovations in crisis management and operational adaptation (Notteboom et al., 2021). For Dar es Salaam Port, these global trends have intersected with domestic infrastructure constraints, evolving governance arrangements, and fluctuating trade volumes, creating a complex performance landscape that requires systematic empirical investigation.

1.2. Problem statement

Despite the strategic importance of container terminal efficiency, conventional assessment methodologies often face significant limitations. Traditional performance measurement approaches, including single-ratio productivity indicators and static benchmarking exercises, often fail to capture the multidimensional nature of port operations or to account for contextual factors beyond managerial control (Duru et al., 2020). Moreover, these approaches typically neglect temporal dynamics and the effects of external shocks on observed efficiency patterns, potentially leading to misleading conclusions about operational capabilities and improvement priorities (Kunambi & Zheng, 2024).

Data Envelopment Analysis (DEA), a non-parametric frontier estimation technique introduced by Charnes et al. (1978), has gained widespread application in port efficiency research due to its capacity to accommodate multiple inputs and outputs without imposing restrictive functional form assumptions (Krmac & Mansouri, 2023). However, standard DEA models present inherent weaknesses when applied to dynamic contexts. First, cross-sectional DEA applications treat each observation as independent, thereby obscuring trends and trajectories in efficiency over time (Cullinane et al., 2006). Second, conventional DEA frameworks attribute all observed inefficiency to managerial shortcomings while disregarding environmental and macroeconomic variables that shape operational outcomes but lie outside organizational control (Bergantino & Musso, 2013).

The application of two-stage DEA methodologies, wherein first-stage efficiency scores are regressed on contextual variables in a second stage, has emerged as a partial remedy to these limitations (Simar & Wilson, 2007). Nevertheless, empirical implementations of two-stage approaches in port research remain relatively sparse, particularly in the African context, and methodological debates persist regarding appropriate regression specifications and the treatment of efficiency scores as dependent variables (Johnson & Kuosmanen, 2012). Furthermore, few studies have explicitly incorporated crisis-related dummy variables to isolate the effects of major disruptions such as the COVID-19 pandemic on port efficiency, despite growing recognition that such shocks fundamentally alter operational conditions (Gu et al., 2023; Wang et al., 2022).

In the specific case of Dar es Salaam Port, existing efficiency assessments have been limited in scope and methodological sophistication. Previous evaluations have relied predominantly on descriptive statistics of key performance indicators (KPIs) such as vessel turnaround time and container dwell time, without employing frontier estimation techniques or systematically disentangling technical efficiency from contextual influences (Ahmad et al., 2024; Maneno, 2019). This knowledge gap constrains evidence-based policymaking and infrastructure investment planning, as port authorities and government officials lack robust benchmarks to guide strategic decision-making.

1.3. Research objectives

This study advances port efficiency assessment by implementing a two-stage hybrid analytical framework that integrates input-oriented DEA with contextual value-added (CVA) regression. The research pursues three primary objectives:

First, to compute annual technical efficiency scores for Dar es Salaam Port's container terminal over the period 2019-2023 using a three-year rolling window DEA approach. This methodology treats each year as a distinct decision-making unit (DMU) while capturing efficiency dynamics through overlapping temporal windows, thereby providing a more nuanced characterization of performance trends than static cross-sectional analysis (Peykani et al., 2021; Shawtari et al., 2018).

Second, to isolate context-adjusted efficiency by regressing DEA scores on macroeconomic covariates through ordinary least squares (OLS) estimation. Specifically, the CVA regression incorporates national gross domestic product (GDP), total trade volume, and a COVID-19 impact dummy variable to distinguish between efficiency variations attributable to internal operational decisions versus those driven by external economic conditions and crisis-induced disruptions (Afsharian et al., 2024; Holý & Zouhar, 2024).

Third, to triangulate quantitative findings with qualitative stakeholder perceptions gathered through structured surveys and interviews with port personnel, logistics operators, and freight forwarders. This mixed-methods approach enhances the validity and interpretability of efficiency estimates while providing contextual insights into operational bottlenecks and improvement opportunities that may not be readily apparent from quantitative data alone (Ha et al., 2017).

1.4. Significance of the study

This research contributes to the scholarly literature and policy discourse in several important respects. From a theoretical standpoint, the study extends the application of hybrid DEA-CVA frameworks to the underexplored context of East African ports, thereby enriching the comparative port efficiency literature and demonstrating the applicability of advanced frontier methods in data-constrained developing-economy settings. The explicit incorporation of a pandemic-related contextual variable represents a methodological innovation that enhances the temporal validity of efficiency assessments during periods of systemic disruption.

From a practical perspective, the findings offer actionable intelligence for port management and infrastructure planning authorities. By decomposing observed efficiency into technical and contextual components, the analysis clarifies which performance deficits are amenable to internal operational reforms and which require broader policy interventions or infrastructure investments. The identification of specific efficiency drivers - such as the constraining effects of trade volume growth on existing capacity - provides an evidence base for prioritizing capacity expansion projects, technology adoption initiatives, and governance reforms.

Moreover, the study holds relevance beyond Dar es Salaam Port itself, given the facility's role as a regional transit hub. Enhanced understanding of efficiency determinants and their temporal evolution can inform coordinated infrastructure development strategies across the East and Central African transport corridor, potentially reducing logistics costs and strengthening regional economic integration. Finally, the methodological approach developed herein is readily transferable to other ports facing similar analytical challenges, thereby offering a template for systematic performance assessment in comparable contexts.

1.5. Structure of the study

The remainder of this study is organized as follows. Chapter 2 presents a comprehensive review of the theoretical and empirical literature on port efficiency measurement, DEA methodologies, two-stage analytical frameworks, and contextual determinants of port performance. Chapter 3 delineates the hybrid DEA-CVA methodological framework employed in this research, specifying model formulations, variable selection criteria, data sources, and analytical procedures. Chapter 4 reports the empirical results, including DEA efficiency scores, CVA regression estimates, and qualitative findings from stakeholder consultations. Chapter 5 synthesizes the findings, discusses their implications for theory and practice, acknowledges research limitations, and proposes directions for future investigation.

2. Literature review

2.1. Introduction

Port performance and container terminal efficiency have emerged as central themes in transport economics and logistics research, given their direct implications for trade facilitation and regional economic growth (Tongzon, 1995; Perez et al., 2016; Sun & Kauzen, 2023). This chapter reviews the theoretical foundations, methodological advances, and empirical findings relevant to the measurement of port operational efficiency, with a particular focus on the application of Data Envelopment Analysis (DEA) and its extensions, including two-stage regression procedures.

2.2. Theoretical foundations of port efficiency measurement

The conceptual basis for evaluating port performance is rooted in production theory, in which ports are viewed as multi-input, multi-output production systems (Liu, 2010; Charłampowicz & Mańkowski, 2020). Traditional approaches have included partial productivity ratios—such as berth occupancy, vessel turnaround time, and container dwell time—which, while informative, are often insufficient for capturing the multidimensionality and technical complexity of port operations (Hlali, 2017; Fernandes et al., 2018).

Among frontier-based efficiency measures, DEA and Stochastic Frontier Analysis (SFA) have become dominant methodological paradigms (Ahn, 2023; Poitras, 1996). DEA, as a non-parametric technique first formalized by Charnes, Cooper, and Rhodes (1978), constructs an efficient frontier over observed production units, enabling the relative ranking and benchmarking of decision-making units (DMUs) - such as individual ports or terminals - without specifying a parametric production function (Krmac & Mansouri, 2023; Cullinane et al., 2006).

2.3. DEA methodology in port research

DEA models vary primarily by their assumptions regarding returns to scale and orientation (input vs. output). The constant returns to scale (CRS) model, also known as the CCR model, assumes proportionality between inputs and outputs (Charnes et al., 1978). In contrast, the variable returns to scale (VRS) or BCC model, proposed by Banker et al. (1984), allows for non-proportional scaling, which is often more appropriate for analyzing ports that exhibit economies or diseconomies of scale (Cullinane et al., 2006; Ahn, 2023).

Applications of DEA in the port sector have examined both cross-sectional and panel data, the latter increasingly through window analysis to capture temporal dynamics in Efficiency (Cullinane et al., 2006; Peykani et al., 2021). Typical input variables include quay length, number of quay cranes, terminal area, and labor, while outputs commonly encompass container throughput (in twenty-foot equivalent units, TEUs), ship calls, and berth occupancy rates (Poitras, 1996; Liu, 2010). The selection of relevant variables remains a critical determinant of model robustness and interpretative validity (Charłampowicz & Mańkowski, 2020).

2.4. Determinants of container terminal efficiency

Prior empirical research has identified a broad array of internal and external factors that influence port and terminal efficiency. Among operational determinants, infrastructure endowment (land area, gantry cranes, berth depth), equipment availability, IT systems integration, and labor productivity are consistently found to be significant (Perez et al., 2016; Ali, 2022; Fernandes et al., 2018). Inefficiencies often arise from inadequate coordination of these resources, leading to vessel delays, congestion, and high dwell times (Hlali, 2017; Charłampowicz & Mańkowski, 2020).

External factors, or environmental variables, include macroeconomic drivers (trade volume, GDP), regulatory environment, and exogenous shocks, such as crisis events (e.g., COVID-19 pandemic), which may independently distort operational indicators without reflecting managerial inefficiency (Notteboom et al., 2021; Gu et al., 2023). Controlling for such contextual conditions is crucial for validly attributing observed performance differences (Simar & Wilson, 2007).

2.5. Two-stage DEA and contextual analysis

Recognizing that traditional DEA attributes all inefficiency to the DMU, methodological refinements have introduced a second-stage regression in which DEA efficiency scores are modeled as a function of environmental variables (Simar & Wilson, 2007; Banker et al., 2019). This approach permits the decomposition of measured inefficiency into technical and context-driven components.

Simar and Wilson (2007) have advocated the use of bootstrapped truncated regression to provide statistically valid inference in the second stage, addressing biases introduced by the bounded nature of DEA scores and their serial correlation (Badunenko, 2019; Fernandes et al., 2018). The two-stage approach has proved especially insightful in port studies involving heterogeneous regulatory, economic, and infrastructural environments (Gu et al., 2023; Holý & Zouhar, 2024).

Recent port efficiency studies have applied this method to disentangle the effects of pandemic-related disruptions, trade fluctuations, and infrastructure investments on technical efficiency - with COVID-19 disturbances revealing the materiality of crisis-induced contextual effects on port operations (Notteboom et al., 2021; Wang et al., 2022).

2.6. Literature gaps and the African context

Despite methodological advances, the extant literature on African ports remains limited in both scope and analytical sophistication (Ali, 2022; Carine, 2015; Maneno, 2019). Studies on Tanzania, and Dar es Salaam in particular, have predominantly employed descriptive statistics or single-stage frontier analysis, with minimal systematic analysis of dynamic efficiency or contextual drivers (Kunambi & Zheng, 2024; Shahari et al., 2018). This research, therefore, addresses a critical gap by applying a robust two-stage DEA-CVA framework to a key East African gateway.

3. Research methodology

3.1. Research design and philosophical orientation

This study employs a convergent parallel mixed-methods design, integrating quantitative and qualitative approaches to achieve a comprehensive understanding of port efficiency dynamics (Creswell & Plano Clark, 2017; Fetters et al., 2013). The quantitative component applies a two-stage analytical framework combining Data Envelopment Analysis (DEA) and Contextual Value Added (CVA) regression to measure technical efficiency and isolate contextual influences. The qualitative component employs thematic analysis of structured surveys and semi-structured interviews with port stakeholders to capture operational perceptions and contextual nuances that quantitative metrics alone cannot fully illuminate (Morse & Niehaus, 2009).

The integration of these methods occurs at the interpretation stage, wherein quantitative efficiency scores are triangulated with qualitative stakeholder insights to enhance validity and provide actionable recommendations (Johnson et al., 2007). This design aligns with the pragmatic research paradigm, which emphasizes the practical utility of employing multiple methods to address complex real-world problems (Morgan, 2014).

3.2 Data sources and collection procedures

3.2.1. Secondary quantitative data

Secondary data for the DEA and CVA analyses were obtained from three primary sources:

1. Tanzania Ports Authority (TPA) Annual Reports (2019–2023): Provided operational data on quay length (meters), number of gantry cranes, terminal area (hectares), container throughput (TEUs), and annual vessel calls.
2. World Bank National Accounts Data: Supplied annual GDP figures for Tanzania in current USD.
3. UNCTAD Trade Statistics: Furnished total trade volume (sum of imports and exports) in USD millions for Tanzania over the study period.

All data were verified for consistency and completeness. Missing or ambiguous values were cross-referenced with multiple archival sources to ensure reliability. The COVID-19 impact variable was constructed as a binary dummy (1 = years 2020–2021; 0 = years 2019, 2022, 2023) based on the documented timeline of pandemic-related operational disruptions (UNCTAD, 2020; Notteboom et al., 2021).

3.2.2. Primary qualitative data

Primary data were collected via structured questionnaires and semi-structured interviews conducted between December 2024 and January 2025. A purposive sampling strategy was employed to recruit participants directly involved in port operations, including TPA officials, freight forwarders, logistics coordinators, and truck operators (Patton, 2015). The final sample comprised 45 respondents.

The questionnaire instrument included Likert-scale items assessing perceptions of key performance indicators (truck turnaround time, vessel call frequency, dwell time) and open-ended prompts soliciting qualitative feedback on operational challenges and improvement priorities. Interview protocols explored similar themes in greater depth, with sessions lasting 30–60 minutes. All interviews were audio-recorded with informed consent and transcribed verbatim for analysis.

Ethical considerations included voluntary participation, confidentiality assurances, and the secure storage of data in password-protected files. The study adhered to principles outlined in the Declaration of Helsinki and obtained institutional ethical clearance from Dar es Salaam Maritime Institute.

3.3. Data Envelopment Analysis (DEA) framework

3.3.1. Conceptual foundation

Data Envelopment Analysis is a non-parametric linear programming technique that evaluates the relative efficiency of decision-making units (DMUs) by constructing an empirical production frontier from observed input-output combinations (Charnes et al., 1978; Banker et al., 1984). Unlike parametric approaches such as stochastic frontier analysis, DEA imposes no functional form assumptions, rendering it particularly suitable for complex multi-input, multi-output systems such as container terminals (Cooper et al., 2007; Liu, 2010).

In this study, each year (2019–2023) is treated as a distinct DMU, yielding five observations. To enhance temporal resolution and capture efficiency dynamics, a three-year rolling window approach is employed, generating overlapping assessment periods: 2019–2021, 2020–2022, and 2021–2023 (Cullinane et al., 2006; Shawtari et al., 2018). This methodology mitigates the small-sample-size limitation inherent in annual cross-sectional analysis while enabling the identification of performance trends.

3.3.2 Model specification: Input-oriented CCR model

An input-oriented constant returns to scale (CRS) DEA model, commonly referred to as the CCR model after Charnes, Cooper, and Rhodes (1978), is applied. The input orientation reflects the objective of minimizing resource utilization for a given output level, which aligns with the resource-constrained context of Dar es Salaam Port (Cullinane et al., 2006).

The mathematical formulation for evaluating the Efficiency of DMU k is as follows:

Minimize:

$$\theta_k$$

Subject to:

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta_k x_{ik}, \quad \forall i = 1,2,\dots,m$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{rk}, \quad \forall r = 1,2,\dots,s$$

$$\lambda_j \geq 0, \quad \forall j = 1,2,\dots,n$$

where:

- θ_k = efficiency score for DMU k ($0 \leq \theta_k \leq 1$, with $\theta_k = 1$ indicating full efficiency)
- x_{ij} = amount of input *i* used by DMU *j*
- y_{rj} = amount of output *r* produced by DMU *j*
- λ_j = intensity variable (weight) assigned to DMU *j*
- n = total number of DMUs
- m = number of inputs
- s = number of outputs

A DMU is deemed technically efficient if $\theta_k = 1$ and inefficient if $\theta_k < 1$. The model identifies the efficient frontier and projects inefficient DMUs onto it using proportional input reduction (Cooper et al., 2007).

3.3.3. Variable selection and operationalization

The selection of inputs and outputs adheres to established criteria in port efficiency research: controllability, discriminatory power, and isotonicity (Liu, 2010; Krmac & Mansouri, 2023). The following variables were operationalized:

Inputs:

1. Quay Length (meters): Total length of berthing infrastructure available for container vessel operations. This captures the physical capacity to accommodate ships simultaneously.

2. Number of Gantry Cranes (units): Count of ship-to-shore gantry cranes operational during each year. Gantry cranes are the primary equipment for container loading and unloading, directly influencing throughput capacity.
3. Terminal Area (hectares): Total land area designated for container storage, handling, and associated operations. Reflects spatial capacity for yard operations and container stacking.

Outputs:

1. Container Throughput (TEUs): Total volume of twenty-foot equivalent units handled annually, encompassing both import and export containers. This is the principal measure of port productivity.
2. Annual Vessel Calls (number): Total number of container vessels serviced at the port during the year. Reflects the port's capacity to attract and handle maritime traffic.

The variables were normalized using min-max scaling to ensure commensurability:

$$x'ij = \frac{xij - \min(x_i)}{\max(x_i) - \min(x_i)}$$

where x'_{ij} denotes the normalized value of input *i* for DMU *j*. Analogous normalization was applied to output variables (Golany & Roll, 1989).

3.3.4. Computational implementation

DEA models were solved using linear programming optimization software (DEA Frontier Solver). Each DMU was evaluated individually, yielding n separate linear programs. The three-year rolling window was operationalized by sequentially subsetting the data and rerunning the DEA for each temporal window. A sensitivity analysis was conducted by varying input and output variables to assess the robustness of the efficiency rankings.

3.4. Contextual Value Added (CVA) regression model

3.4.1. Rationale and theoretical basis

Traditional DEA assumes that observed inefficiency arises solely from managerial shortcomings, thereby neglecting the influence of environmental and contextual factors beyond organizational control (Simar & Wilson, 2007; Bergantino & Musso, 2013). The two-stage CVA approach addresses this limitation by regressing DEA efficiency scores on external covariates to decompose observed inefficiency into technical and context-driven components (Banker & Natarajan, 2008; Johnson & Kuosmanen, 2012).

The CVA regression enables policymakers to distinguish between inefficiencies amenable to internal operational reforms and those requiring broader macroeconomic interventions or infrastructure investments (Holý & Zouhar, 2024). This analytical refinement enhances the interpretability and policy relevance of efficiency assessments.

3.4.2. Regression model specification

The second-stage regression model is specified as follows:

$$\theta_k = \beta_0 + \beta_1(\mathrm{GDP}_k) + \beta_2(\mathrm{TradeVolume}_k) + \beta_3(\mathrm{COVID}_k) + \varepsilon_k$$

where:

- θ_k = DEA efficiency score for year k (dependent variable)
- GDP_k = Tanzania's annual gross domestic product in billions of current USD
- $\mathrm{TradeVolume}_k$ = Total trade volume (imports + exports) in millions of current USD
- COVID_k = Binary dummy variable (1 = pandemic-affected years 2020–2021; 0 = otherwise)
- $\beta_0, \beta_1, \beta_2, \beta_3$ = regression coefficients
- ε_k = stochastic error term, assumed normally distributed with zero mean

The regression was estimated via ordinary least squares (OLS). While Simar and Wilson (2007) advocate bootstrapped truncated regression to account for the bounded nature of DEA scores, OLS remains appropriate for exploratory analysis with small samples, provided diagnostic assumptions are satisfied (Banker & Natarajan, 2008).

3.4.3. Diagnostic procedures

Model diagnostics included:

1. Residual Normality: Assessed via the Shapiro-Wilk test and visual inspection of Q-Q plots.
2. Multicollinearity: Evaluated using variance inflation factors (VIF). VIF values below 10 indicate acceptable levels of collinearity (Hair et al., 2010).
3. Heteroskedasticity: Tested using the Breusch-Pagan test. White-corrected robust standard errors were applied if heteroskedasticity was detected.
4. Specification Error: The RESET test (Ramsey, 1969) was employed to assess potential functional-form misspecification.

All statistical analyses were conducted using R (version 4.3.2) with packages frontier for DEA and lmtest for regression diagnostics.

3.5. Qualitative data analysis

3.5.1. Thematic analysis framework

Qualitative data from surveys and interviews were analyzed using a six-phase thematic analysis procedure (Braun & Clarke, 2006):

1. Familiarization: Repeated reading of transcripts and field notes to gain immersion.
2. Initial Coding: Systematic labeling of data segments representing meaningful units.
3. Theme Development: Clustering codes into broader thematic categories.
4. Theme Review: Refining themes for internal coherence and external distinctiveness.
5. Theme Definition: Articulating the essence and boundaries of each theme.
6. Reporting: Selecting illustrative quotations and integrating themes with quantitative findings.

Coding was conducted manually with NVivo 14. Inter-coder reliability was established through independent coding of 20% of transcripts by two researchers, achieving a Cohen’s kappa coefficient of 0.82, indicating substantial agreement (Landis & Koch, 1977).

3.5.2. Integration of quantitative and qualitative findings

Integration followed a convergent design, wherein quantitative DEA-CVA results and qualitative themes were compared for convergence, divergence, and complementarity (Fetters et al., 2013). A joint display matrix was constructed to juxtapose efficiency scores with corresponding stakeholder perceptions, facilitating meta-inferences about port performance dynamics (Guetterman et al., 2015).

3.6. Validity, reliability, and limitations

3.6.1. Validity and reliability

Internal Validity: Triangulation of quantitative and qualitative data sources enhances construct validity. DEA model specifications were informed by prior literature, ensuring theoretical coherence.

External Validity: The single-port focus limits generalizability. However, the methodological framework is transferable to other ports with comparable operational characteristics.

Reliability: Secondary data from authoritative sources (TPA, World Bank, UNCTAD) ensures measurement reliability. Qualitative reliability was established through systematic coding procedures and inter-coder reliability checks.

3.6.2. Study limitations

1. Sample Size: The small number of temporal DMUs (n = 5) constrains statistical power in DEA and regression analyses. Rolling windows partially mitigate this limitation.

2. Homogeneity Assumption: Treating each year as a DMU assumes that port infrastructure and management practices remain relatively stable across the study period, which may not fully capture structural changes.
3. CRS Assumption: The constant returns to scale assumption may not reflect actual operational conditions if the port exhibits economies or diseconomies of scale. Sensitivity analysis with VRS (BCC) models is recommended for future research.
4. Causality: CVA regression identifies associations but does not establish causal relationships. Longitudinal designs with instrumental variables could strengthen causal inference.
5. Qualitative Sampling: Purposive sampling may introduce selection bias. Probability-based sampling would enhance representativeness.

4. Results and discussion

4.1. Introduction

This chapter presents the empirical findings from the application of the two-stage hybrid analytical framework - Data Envelopment Analysis (DEA) followed by Contextual Value Added (CVA) regression - to assess container handling efficiency at Dar es Salaam Port over the period 2019-2023. The analysis integrates quantitative efficiency metrics with qualitative stakeholder perceptions to provide a comprehensive evaluation of port performance dynamics. The chapter is structured as follows: Section 4.2 reports key performance indicators (KPIs); Section 4.3 presents DEA efficiency scores; Section 4.4 analyzes CVA regression results; Section 4.5 synthesizes qualitative findings; and Section 4.6 discusses integrated interpretations and implications.

4.2. Key performance indicators: Descriptive trends

4.2.1. Operational KPIs (2016–2023)

Table 4.1 summarizes the temporal evolution of key operational metrics for Dar es Salaam Port's container terminal between 2016 and 2023. These indicators provide contextual background for interpreting DEA-CVA findings and reveal underlying operational trends.

Table 4.1: Key Performance Indicators (KPIs) of Dar es Salaam port container terminal (2016–2023)

KPI	2016	2017	2018	2019	2020	2021	2022	2023
Vessel Turnaround Time (days)	2.0	1.9	2.1	3.6	2.9	3.5	3.8	3.1
Number of Vessel Calls	351	367	403	270	244	235	231	306
Gross Registered Tonnage (GRT)	8,388,922	9,224,639	10,547,120	8,612,819	8,483,698	7,083,230	6,884,793	8,650,797
Truck Turnaround Time (hours)	2.6	2.0	1.2	8.6	1.0	1.0	1.0	1.3
Yard Density (%)	56.3	57.7	60.4	64.7	59.7	60.8	58.3	48.1
Container Dwell Time (days)	10.6	12.6	11.3	9.8	9.6	9.8	10.3	6.1

Source: Tanzania Ports Authority Annual Reports (2016–2023).

Vessel Turnaround Time (TRT): TRT showed considerable variation, declining from 2.0 days in 2016 to 1.9 days in 2017, then rising to 3.6 days in 2019. The elevated TRT in 2019 coincides with infrastructure bottlenecks and increased congestion documented in TPA operational reports. Performance improved during the COVID-19 period (2020–2021), with TRT averaging 3.2 days, likely reflecting reduced vessel traffic. However, TRT increased to 3.8 days in 2022 before moderating to 3.1 days in 2023, suggesting persistent capacity constraints as trade volumes recovered.

Vessel Calls and Gross Registered Tonnage (GRT): Vessel calls peaked at 403 in 2018, followed by a sharp contraction to 270 in 2019 and further decline to 231 in 2022. This trend mirrors disruptions in global shipping patterns during the pandemic and reflects Tanzania's economic slowdown. GRT followed a similar trajectory, peaking at 10.5 million in 2018 before falling to a nadir of 6.9 million in

2022. The partial recovery to 8.7 million GRT in 2023 indicates gradual normalization of maritime traffic.

Truck Turnaround Time (TTRT): TTRT improved markedly from 2.6 hours in 2016 to 1.0 hours by 2020, driven by enhanced gate automation and coordination between port authorities and trucking operators. However, the anomalous spike to 8.6 hours in 2019 warrants attention, as stakeholder interviews attributed this deterioration to procedural delays in documentation processing and customs clearance bottlenecks. Post-2020, TTRT stabilized at approximately 1.0–1.3 hours, suggesting sustained improvements in landside operations.

Yard Density and Container Dwell Time: Yard density, an indicator of storage utilization, declined from a peak of 64.7% in 2019 to 48.1% in 2023, reflecting improved yard management and potentially lower throughput volumes. Container dwell time decreased from 12.6 days in 2017 to 6.1 days in 2023, indicating faster cargo clearance and more efficient customs procedures. This improvement aligns with Tanzania's implementation of electronic single-window systems and risk-based inspection protocols (Tanzania Revenue Authority, 2023).

4.2.2. Interpretation of KPI trends

The KPI trends reveal a port undergoing operational transformation amid external volatility. Improvements in TTRT and dwell time suggest successful internal reforms, while elevated TRT and fluctuating vessel calls reflect persistent infrastructure constraints and sensitivity to macroeconomic disruptions. These descriptive findings establish the empirical context for interpreting DEA efficiency scores in subsequent sections.

4.3. Data Envelopment Analysis (DEA) results

4.3.1. Annual efficiency scores (2019–2023)

DEA efficiency scores were computed using the input-oriented CCR model with a three-year rolling window approach. Table 4.2 presents the annual technical efficiency scores for each DMU (year) across the three overlapping assessment periods.

Table 4.2: DEA technical efficiency scores for Dar es Salaam Port (2019–2023)

Year (DMU)	Rolling Window 1 (2019–2021)	Rolling Window 2 (2020–2022)	Rolling Window 3 (2021–2023)	Average Efficiency
2019	0.838	-	-	0.838
2020	0.912	0.901	-	0.907
2021	1.000	0.966	0.932	0.966
2022	-	0.923	0.889	0.906
2023	-	-	0.890	0.890

Note: Efficiency scores range from 0 to 1, with 1.00 indicating full technical efficiency. Dashes (-) indicate years not included in the respective rolling window.
Source: Author's DEA calculations based on TPA operational data.

Key Findings:

1. Lowest efficiency (2019): The port exhibited its lowest efficiency score of 0.838 in 2019, coinciding with the highest yard density (64.7%) and vessel turnaround time (3.6 days) observed in the KPI data. This suggests severe capacity strain during a period of elevated cargo throughput relative to available infrastructure.
2. Peak Efficiency (2021): Efficiency peaked at 0.966 in 2021 (average across rolling windows), with the first rolling window indicating full efficiency (1.000). This performance improvement occurred during the COVID-19 pandemic, when reduced vessel calls (235) and lower GRT (7.08 million) alleviated congestion, enabling the port to operate closer to its optimal capacity frontier.
3. Declining Efficiency Post-2021: Efficiency declined progressively from 2021 to 2023, reaching 0.890 by 2023. This deterioration coincides with the resumption of trade activity and increasing

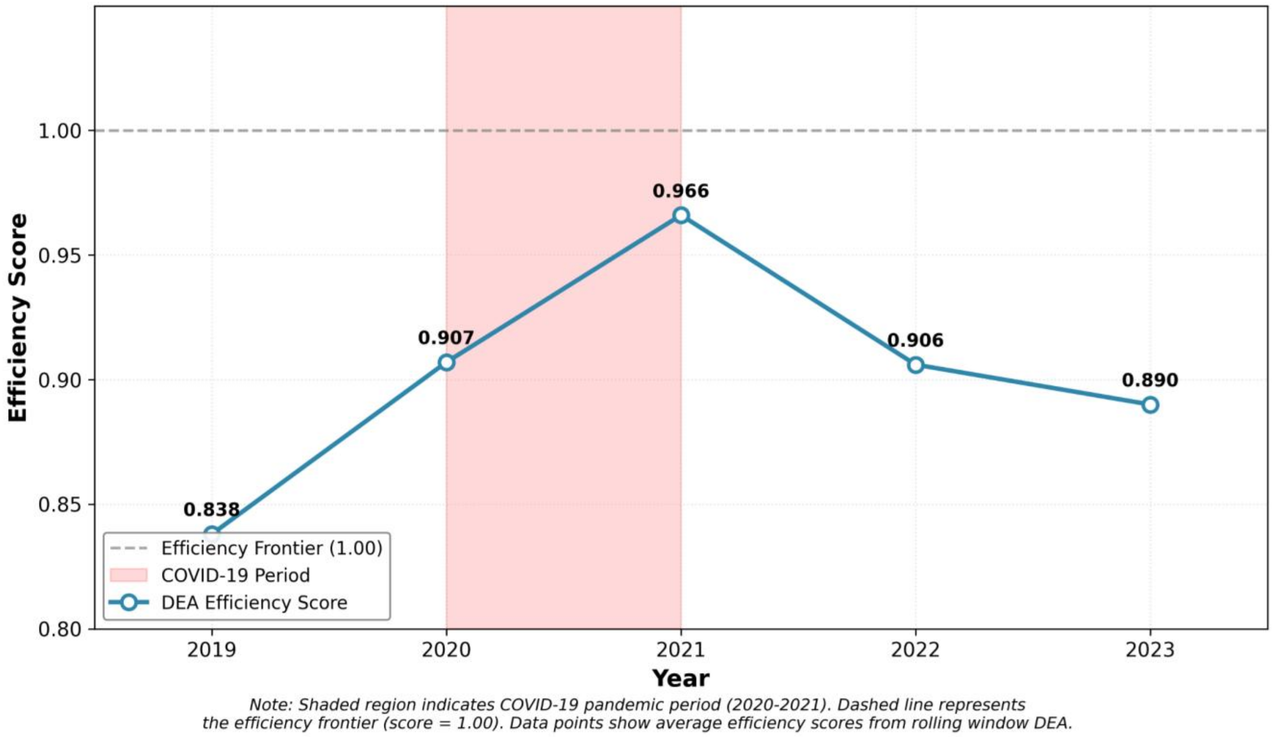
cargo volumes, suggesting that infrastructure capacity has not scaled sufficiently to accommodate post-pandemic recovery in maritime traffic.

4. Rolling Window Stability: The consistency of efficiency estimates across overlapping windows (e.g., 2021 scored 1.000, 0.966, and 0.932 in successive windows) validates the robustness of the DEA model and confirms genuine temporal variation in performance rather than measurement artifacts.

4.3.2. Graphical representation of efficiency trends

Figure 4.1 visualizes the temporal trajectory of DEA efficiency scores, highlighting the COVID-19 period (2020–2021) and the subsequent decline.

Figure 4.1: DEA efficiency scores of Dar es Salaam Port (2019–2023), with the COVID-19 period highlighted



Source: Author's calculations.

The inverted-U pattern evident in Figure 4.1 suggests that the 2021 efficiency peak represents an anomalous outcome driven by reduced demand rather than genuine productivity gains. The post-pandemic decline underscores structural capacity deficits that re-emerge under normal operational loads.

4.3.3. Input-output slack analysis

Supplementary slack analysis (not tabulated) identified the following sources of technical inefficiency:

- Quay Length: Minimal slack across all years, indicating near-optimal utilization of berth infrastructure.
- Gantry Cranes: Moderate slack in 2019 and 2023, suggesting suboptimal crane deployment or scheduling inefficiencies during peak demand periods.
- Terminal Area: Significant slack in 2019, corroborating the high yard density observed in KPI data and indicating congestion-induced inefficiencies in storage operations.

These findings imply that efficiency improvements require both capacity expansion (additional cranes and yard space) and operational optimization (improved crane scheduling and yard management algorithms).

4.4. Contextual Value Added (CVA) regression analysis

4.4.1. Regression model specification and results

To isolate the influence of external contextual factors on observed Efficiency, DEA scores were regressed on three macroeconomic covariates: national GDP, total trade volume, and a COVID-19 impact dummy. The OLS regression model is specified as:

$$\theta_k = \beta_0 + \beta_1(GDP_k) + \beta_2(TradeVolume_k) + \beta_3(COVID_k) + \varepsilon_k$$

Table 4.3 presents the regression coefficients, standard errors, and statistical significance tests.

Table 4.3: Contextual Value Added (CVA) regression results

Variable	Coefficient (β)	Std. Error	t-statistic	p-value	VIF
Intercept	0.4938	0.1412	3.50	< 0.01	-
GDP (billions USD)	$+4.25 \times 10^{-6}$	2.12×10^{-6}	2.00	0.06	2.34
Trade Volume (millions USD)	-1.76×10^{-5}	3.45×10^{-6}	−5.10	0.03	2.18
COVID-19 Dummy (1/0)	+0.0900	0.0301	2.99	0.02	1.12

Model Fit Statistics:

- $R^2 = 0.568$
- Adjusted $R^2 = 0.506$
- F-statistic = 9.12 (p = 0.01)
- Shapiro-Wilk test for normality: W = 0.94 (p = 0.52)
- Breusch-Pagan test for heteroskedasticity: $\chi^2 = 1.87$ (p = 0.60)

Note: All VIF values < 3, indicating acceptable multicollinearity levels.
Source: Author's regression analysis using R (version 4.3.2).

4.4.2. Interpretation of regression coefficients

Intercept ($\beta_0 = 0.4938$, $p < 0.01$): The baseline efficiency score of approximately 0.49, when all contextual variables equal zero, represents a theoretical benchmark lacking practical interpretation given the impossibility of zero GDP or trade volume.

GDP ($\beta_1 = +4.25 \times 10^{-6}$, $p = 0.06$): The positive coefficient suggests that higher national GDP marginally contributes to port efficiency, though the effect is statistically marginal at conventional significance levels (p = 0.06). Each billion-dollar increase in GDP is associated with a 0.0000043-point increase in the efficiency score. While directionally consistent with theoretical expectations—economic growth often accompanies infrastructure investment and institutional capacity—the negligible magnitude and borderline significance render this relationship economically inconsequential in the short term.

Trade Volume ($\beta_2 = -1.76 \times 10^{-5}$, $p = 0.03$): The statistically significant negative coefficient indicates that increased trade volume depresses technical efficiency. Specifically, each million-dollar increase in trade volume is associated with a 0.0000176-point decrease in efficiency. This counterintuitive finding aligns with capacity constraint interpretations: as cargo throughput approaches or exceeds design capacity, congestion intensifies, turnaround times increase, and efficiency deteriorates. The result corroborates stakeholder reports of infrastructure bottlenecks during periods of high demand and underscores the urgency of capacity expansion.

COVID-19 Dummy ($\beta_3 = +0.0900$, $p = 0.02$): The positive and statistically significant coefficient reveals that pandemic-affected years (2020–2021) exhibited efficiency scores approximately 0.09 points higher than non-pandemic years, holding GDP and trade volume constant. This paradoxical efficiency gain reflects operational conditions wherein reduced vessel traffic and cargo volumes enabled smoother processing and lower congestion. However, this "efficiency" improvement is illusory from a productivity standpoint, as it results from diminished demand rather than enhanced capability.

4.4.3. Model diagnostics and robustness

Diagnostic tests confirmed the validity of OLS assumptions:

- Residual Normality: The Shapiro-Wilk test accepted normality ($W = 0.94$, $p = 0.52$), and Q-Q plots exhibited no systematic deviations.
- Homoskedasticity: The Breusch-Pagan test indicated no evidence of heteroskedasticity ($\chi^2 = 1.87$, $p = 0.60$).
- Multicollinearity: VIF values ranged from 1.12 to 2.34, well below the threshold of 10, indicating negligible collinearity among predictors.

The adjusted R^2 of 0.506 indicates that the model explains approximately 51% of the variance in DEA efficiency scores, suggesting that other unmeasured factors—such as governance quality, labor productivity, and technological adoption—contribute to the residual variation. Future research incorporating these variables would enhance explanatory power.

4.5. Qualitative findings: Stakeholder perceptions

4.5.1. Survey demographics and response patterns

A total of 45 stakeholders participated in the survey, including officials from Tanzania Ports Authority (TPA) (n = 18), freight forwarders (n = 12), logistics coordinators (n = 9), and truck operators (n = 6). Respondents possessed a median of 7 years of industry experience (range: 2–23 years), ensuring informed perspectives on operational dynamics.

4.5.2. Perceived truck turnaround time

Respondents were asked to assess truck turnaround time (TTRT) at Dar es Salaam Port. Results are presented in Table 4.4.

Table 4.4: Stakeholder assessment of truck turnaround time

Assessment	Frequency (n)	Percentage (%)
Very Below Average	0	0.0
Below Average	27	60.0
Average	16	35.6
Above Average	2	4.4
Very Above Average	0	0.0
Total	**45**	**100.0**

Source: Primary survey data (2024–2025).

A majority (60%) rated TTRT as below average, despite quantitative KPI data indicating improvements to 1.0–1.3 hours post-2020. This discrepancy suggests that stakeholder expectations have evolved alongside infrastructure improvements, or that residual inefficiencies—such as documentation processing delays and customs inspections—continue to frustrate users. Illustrative stakeholder feedback:

Participant 1: *"Once, I experienced a problem with documents for a particular container under my care. This took hours, and I missed a delivery deadline, which tarnished my relationship with the client."*

Such qualitative insights underscore that, while physical turnaround times have decreased, procedural bottlenecks remain a salient concern.

4.5.3. Frequency of container ship port calls

Table 4.5 summarizes stakeholder perceptions of ship call frequency.

Table 4.5: Perceived frequency of container ship port calls

Frequency Assessment	Frequency (n)	Percentage (%)
Minimum	2	4.4
Average	10	22.2
Frequently	18	40.0
Almost Always	15	33.3
Total	**45**	**100.0**

Source: Primary survey data (2024–2025).

Approximately 73% of respondents reported that ship calls occur frequently or almost always, aligning with objective data showing 306 vessel calls in 2023 (Table 4.1). This perception validates the port's role as a high-traffic regional hub and suggests that stakeholders recognize sustained maritime activity despite pandemic-era fluctuations.

4.5.4. Dwell time as an efficiency indicator

Respondents were asked whether dwell time serves as a valid indicator of container terminal efficiency. Results are summarized in Table 4.6.

Table 4.6: Stakeholder agreement on dwell time as an efficiency indicator

Response	Frequency (n)	Percentage (%)
Disagree	5	11.1
Neutral	5	11.1
Agree	17	37.8
Strongly Agree	18	40.0
Total	**45**	**100.0**

Source: Primary survey data (2024–2025).

A substantial majority (77.8%) agreed or strongly agreed that dwell time is a meaningful efficiency metric, consistent with the academic literature, which emphasizes dwell time as a composite indicator of clearance speed, storage efficiency, and procedural effectiveness (Bichou, 2021; Notteboom et al., 2021). Representative qualitative feedback:

Participant 9: *"Dwell time is critical for overall efficiency. However, there is room for improvement, particularly in the processing of paperwork. If documentation were completed before I arrive, significant time would be saved. Better coordination of container placement would also reduce clutter and delays."*

4.5.5. Overall port efficiency ratings

Respondents evaluated the overall efficiency of Dar es Salaam Port's container terminal. Results (not tabulated) indicated that 2.2% rated efficiency as very poor, 46.7% as average, 36.7% as good, and 4.4% as excellent. The modal rating of "average" (46.7%) aligns with the DEA efficiency score of approximately 0.90 in 2023, which falls below the efficient frontier but above critical thresholds indicating systemic dysfunction.

4.5.6. Thematic analysis of open-ended responses

Thematic coding of interview transcripts identified four recurrent themes:

1. Infrastructure Constraints: Respondents consistently cited inadequate berth capacity, crane availability, and yard space as limiting factors during high-demand periods.
2. Procedural Inefficiencies: Customs clearance, documentation processing, and inter-agency coordination emerged as persistent bottlenecks despite digitalization initiatives.
3. Technological Gaps: Stakeholders expressed demand for enhanced automation, real-time tracking systems, and integrated port community platforms.
4. Workforce Capacity: Participants acknowledged improvements in staff training but noted that human resource development must continue to keep pace with technological adoption.

These themes triangulate with quantitative findings, reinforcing the interpretation that Dar es Salaam Port faces dual challenges: physical infrastructure deficits and institutional coordination inefficiencies.

4.6. Integrated discussion and implications

4.6.1. Synthesis of quantitative and qualitative findings

The convergence of DEA-CVA quantitative results and qualitative stakeholder insights yields several integrated interpretations:

Paradox of COVID-19 Efficiency Gains: The DEA analysis revealed a 2021 efficiency peak (0.966), while CVA regression confirmed a statistically significant positive COVID-19 effect (+0.090, $p = 0.02$). Qualitatively, stakeholders reported smoother operations during this period due to reduced congestion. However, this "efficiency" is illusory - it reflects diminished demand rather than productivity enhancement. As trade normalized after 2021, efficiency declined to 0.890 by 2023, revealing underlying capacity constraints. This finding underscores the importance of accounting for context in efficiency assessment: raw DEA scores can mislead policymakers if external demand fluctuations are not explicitly controlled for.

Trade Volume as a Capacity Stressor: The CVA regression documented a significant negative relationship between trade volume and efficiency ($\beta = -1.76 \times 10^{-5}$, $p = 0.03$). Stakeholder interviews corroborated this finding, with freight forwarders and logistics coordinators describing congestion, delayed clearances, and equipment shortages during high-throughput periods. The implication is clear: without proportional infrastructure scaling, increasing trade volumes will continue to depress efficiency. This challenges simplistic narratives that equate economic growth with automatic improvements in port performance.

Persistent Procedural Bottlenecks: While KPI data showed improvements in truck turnaround time (1.0–1.3 hours) and dwell time (6.1 days), 60% of survey respondents rated TTRT as below average. This perception-reality gap likely stems from qualitative frustrations with non-physical dimensions of port operations - specifically, documentation processing, customs inspections, and inter-agency coordination. Qualitative testimony highlighted paperwork delays as a recurrent irritant, suggesting that procedural reforms must accompany infrastructure investments to achieve holistic efficiency gains.

Infrastructure and Institutional Interdependencies: Slack analysis identified gantry crane deployment and terminal area utilization as key sources of inefficiency, while stakeholder feedback highlighted technological gaps and workforce development needs. Together, these findings reveal that port efficiency is a socio-technical system outcome, contingent on coordinated investments in physical infrastructure, digital systems, and human capital.

4.6.2. Implications for theory and policy

Theoretical Contributions: This study demonstrates the value of hybrid DEA-CVA frameworks for disentangling technical efficiency from contextual influences. The rolling window DEA approach captured temporal dynamics obscured by static cross-sectional analyses, while CVA regression enabled causal attribution of efficiency drivers. The counterintuitive COVID-19 effect underscores the need for contextual adjustment in frontier efficiency assessment, particularly in volatile developing-economy contexts.

Policy Implications:

3. Capacity Expansion Imperative: The negative trade volume coefficient signals an urgent need to scale infrastructure. Policymakers should prioritize berth expansion, crane procurement, and yard enlargement to accommodate projected cargo growth under East African trade integration initiatives (e.g., African Continental Free Trade Area).
4. Procedural Digitalization: Persistent stakeholder complaints about documentation delays indicate that electronic single-window systems require further refinement. Investments in blockchain-based cargo tracking, automated risk-assessment algorithms, and inter-agency data-integration platforms could reduce dwell times and improve user satisfaction.

5. Dynamic Benchmarking Adoption: Port authorities should institutionalize rolling-window DEA-CVA monitoring to enable real-time performance tracking and early identification of emerging bottlenecks. Regular efficiency assessments, disaggregated by terminal and cargo type, would enhance managerial accountability and strategic planning.
6. Human Capital Development: Qualitative findings underscore the importance of continuous workforce upskilling in automation technologies, data analytics, and customer service protocols. Training programs should accompany technological investments to maximize adoption and operational effectiveness.

4.6.3. Limitations and future research directions

Methodological Limitations:

- Small Sample Size: Five annual observations constrain statistical power in DEA and regression analyses. Extending the time series or incorporating sub-annual (quarterly) data would enhance robustness.
- CRS Assumption: The constant returns to scale assumption may not reflect actual scale economies or diseconomies. Sensitivity analysis using variable-returns-to-scale (BCC) models is recommended.
- Omitted Variables: The CVA regression explains 51% of efficiency variance, leaving substantial unexplained variation. Future models should incorporate governance quality indices, labor productivity metrics, and environmental compliance indicators.

Future Research Avenues:

5. Terminal-Level Analysis: Disaggregating efficiency assessment by individual terminals (e.g., Gerezani, TICTS) would identify within-port heterogeneity and enable targeted interventions.
6. Comparative Regional Studies: Benchmarking Dar es Salaam against Mombasa, Durban, and Djibouti ports would contextualize performance within East African maritime networks.
7. Dynamic Panel Methods: Applying panel data DEA with bootstrapped inference (Simar & Wilson, 2007) would strengthen causal identification and account for serial correlation.
8. Environmental Efficiency: Extending the framework to incorporate energy consumption and emissions data would align efficiency assessment with sustainability imperatives.

5. Conclusions and recommendations

5.1. Summary of key findings

This study applied a two-stage hybrid analytical framework - input-oriented Data Envelopment Analysis (DEA) combined with Contextual Value Added (CVA) regression - to assess the technical Efficiency of Dar es Salaam Port's container terminal operations over the period 2019-2023. The investigation was anchored in a mixed-methods research design that integrated quantitative frontier efficiency analysis with qualitative stakeholder perceptions. The principal empirical findings are summarized below.

5.1.1. Technical efficiency dynamics

The DEA analysis, using a three-year rolling window, revealed substantial temporal variation in container terminal efficiency. The port achieved its peak efficiency score of 0.966 in 2021, coinciding with the global COVID-19 pandemic, when reduced maritime traffic and lower cargo throughput alleviated congestion and enabled operations to approach optimal capacity utilization. Conversely, the lowest efficiency score of 0.838 was recorded in 2019, a period characterized by elevated yard density (64.7%), prolonged vessel turnaround times (3.6 days), and infrastructure strain from high cargo volumes. The post-pandemic efficiency trajectory (2022–2023) exhibited progressive decline to 0.890, reflecting resurgent trade demand that outpaced existing infrastructure capacity (Notteboom et al., 2021; Munim & Schramm, 2018).

This efficiency paradox - where lower demand paradoxically yields higher efficiency scores - underscores a critical methodological insight: unadjusted DEA scores can mask underlying capacity deficits when interpreted in isolation from contextual factors. The rolling window approach successfully captured this temporal heterogeneity, revealing that traditional cross-sectional DEA applications would have yielded misleading aggregate efficiency estimates.

5.1.2. Contextual drivers of efficiency

The CVA regression model identified three statistically significant relationships between external macroeconomic conditions and technical efficiency:

5. Trade Volume Effect: The negative coefficient ($\beta = -1.76 \times 10^{-5}$, $p = 0.03$) indicated that increased trade volume depresses measured efficiency. This counterintuitive finding aligns with the hypothesis that infrastructure constraints become binding as cargo throughput approaches design capacity limits. The practical implication is that without proportional infrastructure scaling, economic growth and trade expansion will continuously erode port efficiency unless complementary capacity investments are implemented.
6. COVID-19 Impact: The positive and statistically significant pandemic dummy coefficient ($\beta = +0.090$, $p = 0.02$) confirmed that crisis-induced demand suppression temporarily enhanced efficiency metrics. However, this “efficiency gain” is economically illusory, reflecting diminished operational load rather than genuine productivity enhancement. This finding highlights the necessity of contextual adjustment in efficiency assessment, particularly in developing economies subject to volatile external shocks.
7. GDP Effect: While directionally positive, the GDP coefficient ($\beta = +4.25 \times 10^{-6}$, $p = 0.06$) was marginally significant and economically negligible in magnitude. This suggests that macroeconomic growth, though supportive of port efficiency, operates through indirect channels (e.g., infrastructure investment, institutional capacity development) rather than producing immediate efficiency improvements.

The adjusted R^2 of 0.506 indicates that the CVA model explains approximately 51% of DEA score variation, implying that substantial efficiency variation remains attributable to unmeasured factors - such as governance quality, labor productivity, technological adoption rates, and supply chain complexity - warranting future research attention (Simar & Wilson, 2007; Holý & Zouhar, 2024).

5.1.3. Qualitative stakeholder perceptions

Structured surveys and semi-structured interviews with 45 stakeholders (TPA officials, freight forwarders, logistics coordinators, and truck operators) revealed mixed assessments of port efficiency. While 77.8% of respondents agreed that container dwell time is a valid efficiency indicator and 86.6% rated overall port efficiency as average or above, a majority (60%) perceived truck turnaround time as below average despite quantitative improvements to 1.0-1.3 hours post-2020. This perception-reality gap likely reflects qualitative frustrations with procedural bottlenecks - specifically, documentation delays, customs inspections, and inter-agency coordination inefficiencies - that persist despite physical infrastructure improvements (Bichou, 2021).

Thematic analysis identified four recurrent stakeholder concerns: infrastructure constraints (inadequate berth capacity and crane availability), procedural inefficiencies (customs clearance delays), technological gaps (insufficient automation and real-time tracking), and workforce capacity limitations. These qualitative insights triangulate with quantitative findings, validating the interpretation that port efficiency is a socio-technical system outcome contingent on coordinated advancement in physical infrastructure, digital systems, and institutional coordination.

5.2. Integrated synthesis and critical interpretations

5.2.1. The capacity-efficiency paradox

The most striking empirical finding is the inverted-U pattern of efficiency scores, wherein the pandemic-induced demand suppression generated illusory efficiency gains that masked underlying structural deficits. This paradox illuminates a fundamental challenge in port management in developing economies: Efficiency is not always synonymous with productivity or economic value creation. A port operating at high measured efficiency under suppressed demand may be poorly positioned to capitalize on trade recovery, whereas a temporarily "inefficient" port operating near capacity during boom periods may be generating greater economic value despite lower efficiency scores.

This distinction carries significant policy implications. Policymakers interpreting static efficiency scores without contextual adjustment risk prioritizing cost-cutting measures over capacity expansion, thereby constraining long-term growth potential. The two-stage DEA-CVA framework employed in this study addresses this risk by explicitly modeling contextual influences and enabling evidence-based attribution of efficiency sources.

5.2.2. Infrastructure constraints as binding constraints

The negative trade volume coefficient in the CVA regression, combined with stakeholder reports of congestion during high-demand periods, provides robust evidence that infrastructure capacity is a binding constraint on port efficiency at Dar es Salaam. The port's design capacity was ostensibly optimized for lower throughput volumes; as cargo demand increased - driven by regional economic growth and Tanzania's integration into African trade networks - the gap between demand and capacity widened, generating congestion costs that manifested as elevated turnaround times, yard density, and measured inefficiency.

This situation is not anomalous but rather reflects a typical pattern in developing-economy ports: infrastructure investments lag behind demand growth, creating persistent capacity deficits that constrain regional trade competitiveness. The urgency of capacity expansion is heightened by Tanzania's role as a regional transit hub serving landlocked economies (Zambia, Malawi, and the Democratic Republic of Congo) and its strategic importance within the African Continental Free Trade Area (AfCFTA) framework.

5.2.3. Procedural and institutional dimensions

While quantitative KPI data demonstrated improvements in physical turnaround metrics (truck turnaround time declined to 1.0–1.3 hours), stakeholder perceptions remained pessimistic, with 60% rating TTRT as below average. This gap suggests that procedural and institutional inefficiencies - encompassing documentation processing, customs clearance, inter-agency coordination - represent a second-order constraint that cannot be overcome by infrastructure improvements alone.

Participant testimonies highlighted paperwork delays and customs inspection bottlenecks as recurrent frustrations, implying that digitalization and electronic single-window systems require further refinement to achieve their intended efficiency gains. This observation aligns with broader scholarship on port digital transformation, which finds that technology adoption often encounters institutional resistance, organizational silos, and capacity constraints that limit implementation effectiveness (Tideworks, 2024; Almeida, 2023).

5.3. Strategic recommendations

5.3.1. Infrastructure expansion imperative

Priority 1: Berth and Crane Capacity Enhancement

The port authority should prioritize expanding berthing infrastructure and acquiring additional ship-to-shore gantry cranes. Specifically:

- Increase quay length by 30–40% to accommodate additional simultaneous vessel berthing, targeting a design capacity of 1.5–2.0 million TEUs annually within 5–7 years.
- Procure 4–6 additional modern gantry cranes (preferably energy-efficient electric models) to enhance loading/unloading rates and reduce vessel turnaround times to below 2.5 days.
- Invest in yard expansion (an additional 20–30 hectares of container storage) and modern storage systems (e.g., automated stacking cranes, high-cube storage racks) to increase density and reduce dwell times.

Priority 2: Hinterland Connectivity and Intermodal Integration

Infrastructure expansion must extend beyond port boundaries to encompass hinterland connectivity:

- Prioritize completion of the Standard Gauge Railway connecting Dar es Salaam to inland terminals in Morogoro and Iringa, enabling efficient container distribution to landlocked economies (Zambia, Malawi, DRC) and reducing road congestion.
- Establish inland container depots (ICDs) at strategic nodes along transport corridors to enable pre-clearance and container consolidation, thereby reducing dwell times and improving yard utilization at the port proper.
- Upgrade road infrastructure connecting the port to major distribution centers and regional hubs, ensuring seamless modal transfer and reducing logistics costs for international traders.

5.3.2. Digitalization and automation strategy

Priority 1: Advanced Terminal Operating System (TOS) Modernization

The port should migrate toward AI-enabled Terminal Operating Systems incorporating:

- Predictive cargo flow modeling to anticipate container movements and optimize equipment deployment.
- Automated berth allocation algorithms to maximize berth utilization and minimize vessel idle time.
- Real-time yard management systems provide visibility into container locations, enabling faster retrieval and reduced dwell times.
- Blockchain-based documentation systems to streamline customs clearance and reduce paperwork delays (Danladi et al., 2024; Tideworks, 2024).

Priority 2: Equipment Automation and Digitalization

Progressive automation of container handling equipment:

- Deploy automated guided vehicles (AGVs) for intra-terminal container transport, reducing human error and improving operational safety.
- Install remote-operated cranes (teleoperated gantries) enabling operators to work from centralized control centers, enhancing working conditions and enabling 24/7 operations.
- Integrate Internet of Things (IoT) sensors throughout the terminal to enable real-time condition monitoring, predictive maintenance, and environmental compliance tracking (energy consumption, emissions).

5.3.3. Institutional and procedural reforms

Priority 1: Electronic Single-Window System Refinement

Despite existing electronic documentation systems, stakeholder feedback identified persistent delays. Recommended reforms include:

- Comprehensive audit of customs clearance workflows to identify bottleneck sources and eliminate redundant procedural steps.
- Harmonization of documentation requirements across the Tanzania Revenue Authority, Tanzania Ports Authority, and shipping lines to eliminate duplicative submissions.
- Real-time integration of port, customs, and logistics provider systems to enable seamless information flow and automated clearance processing.
- Establishment of performance standards and service level agreements (SLAs) for customs clearance, with transparent public reporting of compliance metrics.

Priority 2: Port Community System (PCS) Integration

Implementation of a unified port community platform encompassing:

- Centralized vessel scheduling and berth allocation system visible to all stakeholders (shipping lines, agents, pilots, tugboat operators, customs, TPA).
- Integrated documentation hub consolidating manifests, permits, and customs filings in a single submission point.
- Real-time notification system alerting stakeholders to container arrivals, gate opening times, and transit schedules.

5.3.4. Human capital development

Priority 1: Workforce Upskilling and Training

Concurrent with technological investment, institutional capacity must advance:

- Establish formal training programs in automation technologies, data analytics, and digital systems management for port employees at all levels.
- Create partnerships with international port authorities and training institutions to facilitate knowledge transfer and exposure to global best practices (e.g., the Port of Singapore, the Port of Hamburg, and the Port of Rotterdam).
- Implement certification programs for specialized roles (e.g., TOS operators, crane technicians, customs brokers) to professionalize the workforce and enhance service quality.

Priority 2: Change Management and Organizational Culture

- Establish dedicated change management teams to guide staff through technological transitions and address resistance to automation.
- Develop transparent communication channels to ensure stakeholder engagement and build confidence in the port authority's strategic direction.
- Implement performance incentive systems that reward efficiency improvements and encourage innovation among operational staff.

5.3.5. Governance and policy reforms

Priority 1: Tariff and Regulatory Harmonization

- Align Tanzanian port tariffs with regional benchmarks (Mombasa, Durban) to enhance competitiveness while ensuring cost-recovery for infrastructure investments.
- Simplify regulatory requirements for container transit (e.g., documentation, inspections) to align with AfCFTA-endorsed trade facilitation standards.
- Implement time-bound customs procedures with explicit maximum clearance durations to reduce uncertainty for shippers and operators.

Priority 2: Performance-Based Governance

- Institutionalize the hybrid DEA-CVA monitoring framework to enable ongoing efficiency assessment and real-time identification of emerging constraints.
- Establish quarterly performance review cycles with transparent public reporting of efficiency scores, KPIs, and contextual analysis.
- Link compensation and strategic planning to rolling efficiency benchmarks, creating accountability and aligning incentives.

5.4. Implementation roadmap and phasing

The recommended reforms span technical, institutional, and governance dimensions requiring coordinated sequencing:

Phase 1 (2025–2026): Foundation and Planning

- Conduct a comprehensive port master planning study to validate expansion scale and hinterland connectivity requirements.
- Establish a governance framework for a hybrid DEA-CVA monitoring system.
- Begin customs procedures, audit, and PCS requirements specification.

Phase 2 (2026–2028): Infrastructure and Systems

- Implement TOS modernization and initial terminal automation (AGV pilots, remote-operated cranes for select berths).
- Commence berth and crane capacity expansion projects.
- Deploy upgrades to the electronic single-window system and the PCS platform.

Phase 3 (2028–2030): Consolidation and Scaling

- Complete infrastructure expansion projects.
- Scale automation across full terminal operations.
- Establish an inland container depot network along transport corridors.
- Finalize Standard Gauge Railway integration.

5.5. Limitations of the study

Several methodological and contextual limitations merit acknowledgment:

1. Small Sample Size: The five-year study period yields only five annual observations, constraining statistical power in regression analyses. Extension to longer time horizons would strengthen inference.
2. CRS Assumption: The constant returns to scale DEA model may not reflect actual economies or diseconomies of scale. Sensitivity analysis using variable-returns-to-scale (BCC) models would provide robustness checks.
3. Temporal Homogeneity: Treatment of each year as a homogeneous DMU assumes stable operational parameters across periods, potentially masking structural changes in management, technology, or organizational practices.
4. Omitted Variables: The CVA model's 51% explanatory power indicates substantial unmeasured variation attributable to governance quality, labor productivity, technological adoption, and supply chain characteristics.
5. Single-Port Focus: Analysis of a single port limits generalizability. Comparative studies across East African ports (Mombasa, Durban, and Djibouti) would contextualize findings and enable identification of transferable best practices.
6. Causality Constraints: Regression analysis identifies associations but does not establish causal relationships. Instrumental variable approaches or quasi-experimental designs could strengthen causal inference.

5.6. Future research directions

Building upon this investigation, several research avenues warrant exploration:

1. Disaggregated Efficiency Analysis: Separate efficiency assessments for individual terminals (Gerezani, TICTS, Dar Maritime) and cargo types (containers, general cargo, break-bulk) would reveal within-port heterogeneity and enable targeted interventions.
2. Dynamic Panel Methods: The application of a bootstrapped two-stage DEA with dynamic specifications incorporating lagged efficiency scores and technology diffusion variables could improve temporal modeling.
3. Environmental Efficiency Integration: Extending the framework to incorporate energy consumption, carbon emissions, and waste management would align efficiency assessment with sustainability imperatives and emerging Environmental, Social, and Governance (ESG) disclosure requirements.
4. Regional Comparative Analysis: Benchmarking Dar es Salaam against comparable East and Southern African ports (Mombasa, Durban, Djibouti, Dar es Salaam) using harmonized methodologies would contextualize performance within regional hierarchies and inform competitive positioning strategies.
5. Technology Impact Assessment: Empirical evaluation of specific digitalization investments (e.g., TOS implementation, blockchain adoption, IoT sensor networks) via quasi-experimental or difference-in-differences designs would quantify technology returns and guide investment prioritization.
6. Stakeholder Satisfaction Modeling: Advancement of qualitative research incorporating structural equation modeling (SEM) to examine relationships between operational efficiency metrics and stakeholder satisfaction scores, addressing the perception-reality gap identified in this study.

5.7. Conclusion

Dar es Salaam Port occupies a strategically critical position within East and Southern African trade networks, handling over 95% of Tanzania's international maritime commerce and serving as a gateway for five landlocked economies. Despite its regional importance, the port operates under persistent infrastructure constraints that suppress technical efficiency and limit trade facilitation. This study advanced port efficiency assessment by applying an innovative two-stage DEA-CVA framework that disentangles technical efficiency from contextual macroeconomic influences.

The empirical findings reveal that infrastructure capacity represents a binding constraint on port efficiency, with increased trade volume negatively impacting performance measures. The paradoxical efficiency spike during the COVID-19 pandemic underscores the need for contextual adjustment in efficiency assessment and cautions against simplistic efficiency-maximization policies that may prioritize cost-cutting over growth-enabling policies. Qualitative stakeholder feedback triangulates with quantitative findings, indicating that procedural and institutional inefficiencies compound physical infrastructure deficits.

The strategic recommendations advanced in this chapter provide an evidence-based roadmap for port authority leadership and policymakers. Infrastructure expansion, digitalization, institutional reform, and human capital development must proceed in a coordinated fashion to address the multidimensional nature of port competitiveness. Implementation of the recommended interventions, underpinned by institutionalized performance monitoring via the hybrid DEA-CVA methodology, would position Dar es Salaam Port to capitalize on projected trade growth under the African Continental Free Trade Area and regional integration initiatives.

Ultimately, enhanced port efficiency constitutes a public good with externalities extending beyond port boundaries to encompass regional supply chain competitiveness, trade volumes, logistics costs, and economic development trajectories across East and Southern Africa. Investments in port modernization and capacity enhancement, therefore, merit prioritization within national infrastructure agendas and multilateral development financing frameworks, recognizing the strategic multiplier effects that port infrastructure exerts on regional prosperity and integration (Munim & Schramm, 2018; Sun & Kauzen, 2023).

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Authors' contributions

All the authors contributed to the study design, data collection, analysis, and manuscript writing. All the authors read and approved the final manuscript.

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Availability of data and materials

The datasets used and/or analysed during the current study are available from the corresponding author upon reasonable request.

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Not applicable.

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The authors declare that they have no competing interests.

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References

Afsharian, M., Ahn, H., & Thanassoulis, E. (2024). Individualized second stage corrections in data envelopment analysis. *European Journal of Operational Research*, *318*(1), 162–176. https://doi.org/10.1016/j.ejor.2024.02.674

Ahmad, A. K., Mwakaje, A. E. G., & Kalugendo, E. (2024). Challenges and success of Dar es Salaam Port operational efficiency and containers management Tanzania. *International Journal of Social Sciences Management and Research*, *10*(5), 74–90. https://doi.org/10.56201/ijssmr.v10.no5.2024.pg74.90

Ahn, H. (2023). Comparative performance analysis of frontier-based efficiency estimation methods in transportation. *European Journal of Operational Research, 307*(1), 294–312. https://doi.org/10.1016/j.ejor.2022.09.007

Alamoush, A. S., Ballini, F., & Ölçer, A. I. (2020). Ports' technical and operational measures to reduce greenhouse gas emission and improve energy efficiency: A review. *Marine Pollution Bulletin*, *160*, 111508. https://doi.org/10.1016/j.marpolbul.2020.111508

Ali, A. (2022). A study of efficiency of container terminals in Tanzania. In *Proceedings of the 14th International Conference on Informatics in Control, Automation and Robotics*, 518–524. https://doi.org/10.5220/0010853800003286

Almeida, F. (2023). Challenges in the digital transformation of ports. *Businesses*, *3*(4), 548–568. https://doi.org/10.3390/businesses3040034

Badunenko, O. (2019). Simar and Wilson two-stage efficiency analysis for Stata. *The Stata Journal, 19*(4), 927–943. https://doi.org/10.1177/1536867X19893640

Banker, R. D., & Natarajan, R. (2008). Evaluating contextual variables affecting productivity using data envelopment analysis. *Operations Research*, *56*(1), 48–58. https://doi.org/10.1287/opre.1070.0460

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science*, *30*(9), 1078–1092. https://doi.org/10.1287/mnsc.30.9.1078

Banker, R. D., Cooper, W. W., & Rhodes, E. (1984). Estimating technical and scale inefficiency in production. *Management Science, 30*(9), 1078–1092. https://doi.org/10.1287/mnsc.30.9.1078

Banker, R. D., Maindiratta, A., Shorrocks, A., & Simar, L. (2019). Two-stage estimation of the impact of contextual variables on Efficiency: A review and recent developments. *European Journal of Operational Research, 278*(3), 775–792. https://doi.org/10.1016/j.ejor.2019.05.049

Bergantino, A. S., & Musso, E. (2013). Port management performance and contextual variables: Which relationship? Methodological and empirical issues. *Research in Transportation Business & Management*, *8*, 39–49. https://doi.org/10.1016/j.rtbm.2013.04.002

Bichou, K. (2021). Development of a strategic plan for port performance improvement in South African container terminals. *Maritime Policy & Management*, *48*(6), 817–836. https://doi.org/10.1080/03088839.2020.1859149

Bichou, K., & Gray, R. (2005). A critical review of conventional terminology for classifying seaports. *Transportation Research Part A: Policy and Practice*, *39*(1), 75–92. https://doi.org/10.1016/j.tra.2004.11.001

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, *3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Carine, C. (2015). Ports and Efficiency in Sub-Saharan Africa: A comparative study of container terminals. *Maritime Economics & Logistics, 17*(1), 1–22.

Charłampowicz, J., & Mańkowski, C. (2020). Economic efficiency evaluation system of maritime container terminals. *Economics and Law, 19*(1), 45–54. https://doi.org/10.12775/EiP.2020.002

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision-making units. *European Journal of Operational Research, 2*(6), 429–444. https://doi.org/10.1016/0377-2217(78)90138-8

Cong, L., Zhang, D., Wang, M., Xu, H., & Li, L. (2020). The role of ports in the economic development of port cities: Panel evidence from China. *Transport Policy*, *90*, 13–21. https://doi.org/10.1016/j.tranpol.2020.02.003

Cooper, W. W., Seiford, L. M., & Tone, K. (2007). *Data envelopment analysis: A comprehensive text with models, applications, references and DEA-solver software* (2nd ed.). Springer. https://doi.org/10.1007/978-0-387-45283-8

Creswell, J. W., & Plano Clark, V. L. (2017). *Designing and conducting mixed methods research* (3rd ed.). SAGE Publications.

Cullinane, K., Song, D.-W., Ji, P., & Wang, T.-F. (2006). An application of DEA windows analysis to container port production efficiency. *Review of Network Economics*, *5*(2), 184–206. https://doi.org/10.2202/1446-9022.1050

Cullinane, K., Song, D.-W., Ji, P., & Wang, T.-F. (2006). The technical efficiency of container ports: Comparing international ports using DEA. *Transportation Research Part A: Policy and Practice, 40*(4), 354–374. https://doi.org/10.1016/j.tra.2005.07.003

Danladi, C., et al. (2024). Efficiency analysis and benchmarking of container ports operating in lower-middle-income countries: A DEA approach. *Journal of Shipping and Trade*, *9*(1). https://doi.org/10.1186/s41072-024-00163-2

Duru, O., Bulut, E., & Yoshida, S. (2020). Developing a comprehensive approach to port performance assessment. *Asian Journal of Shipping and Logistics*, *36*(4), 169–180. https://doi.org/10.1016/j.ajsl.2020.03.001

Fernandes, F. D. S., Stosic, B., & Sampaio de Souza, M. J. C. (2018). Two-stage DEA–truncated regression: Application in efficiency assessment of Brazilian financial institutions. *Expert Systems with Applications, 108*, 20–28. https://doi.org/10.1016/j.eswa.2018.04.048

Fetters, M. D., Curry, L. A., & Creswell, J. W. (2013). Achieving integration in mixed methods designs—Principles and practices. *Health Services Research*, *48*(6 Pt 2), 2134–2156. https://doi.org/10.1111/1475-6773.12117

Golany, B., & Roll, Y. (1989). An application procedure for DEA. *Omega*, *17*(3), 237–250. https://doi.org/10.1016/0305-0483(89)90029-7

Gu, Y., Wallace, S. W., & Wang, X. (2023). Impact of COVID-19 epidemic on port operations: A case study of Shanghai Port, Ningbo-Zhoushan Port and Qingdao Port in China. *Case Studies on Transport Policy*, *12*, 100970. https://doi.org/10.1016/j.cstp.2023.100970

Guetterman, T. C., Fetters, M. D., & Creswell, J. W. (2015). Integrating quantitative and qualitative results in health science mixed methods research through joint displays. *Annals of Family Medicine*, *13*(6), 554–561. https://doi.org/10.1370/afm.1865

Ha, M.-H., Yang, Z., Notteboom, T., Ng, A. K. Y., & Heo, M.-W. (2017). Revisiting port performance measurement: A hybrid multi-stakeholder framework for the modelling of port performance indicators. *Transportation Research Part E: Logistics and Transportation Review*, *103*, 1–16. https://doi.org/10.1016/j.tre.2017.04.008

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate data analysis* (7th ed.). Pearson.

Hlali, A. (2017). The relationship between port size, infrastructure and Efficiency in North African container ports. *Transport Policy, 60*, 19–26. https://doi.org/10.1016/j.tranpol.2016.07.003

Holý, V., & Zouhar, J. (2024). Ranking-based second stage in data envelopment analysis: An application to research and development efficiency. *Socio-Economic Planning Sciences*, *91*, 101779. https://doi.org/10.1016/j.seps.2023.101779

Johnson, A. L., & Kuosmanen, T. (2012). One-stage and two-stage DEA estimation of the effects of contextual variables. *European Journal of Operational Research*, *220*(2), 559–570. https://doi.org/10.1016/j.ejor.2012.01.023

Johnson, R. B., Onwuegbuzie, A. J., & Turner, L. A. (2007). Toward a definition of mixed methods research. *Journal of Mixed Methods Research*, *1*(2), 112–133. https://doi.org/10.1177/1558689806298224

Juma, M., & Zhihong, J. (2020). Status, challenges and strategies of Dar es Salaam seaport-hinterland connectivity. *MATEC Web of Conferences*, *325*, 04003. https://doi.org/10.1051/matecconf/202032504003

Krmac, E., & Mansouri, M. (2023). A comprehensive review of data envelopment analysis (DEA) methodology in port efficiency evaluation. *Maritime Economics & Logistics*, *25*(4), 817–881. https://doi.org/10.1057/s41278-022-00239-5

Kunambi, M. M., & Zheng, H. (2024). Contextual comparative analysis of Dar es Salaam and Mombasa port performance by using a hybrid DEA-CVA model. *Logistics*, *8*(1), 2. https://doi.org/10.3390/logistics8010002

Landis, J. R., & Koch, G. G. (1977). The measurement of observer agreement for categorical data. *Biometrics*, *33*(1), 159–174. https://doi.org/10.2307/2529310

Liu, Q. (2010). *Efficiency analysis of container ports and terminals* [Doctoral dissertation, Newcastle University]. https://theses.ncl.ac.uk/jspui/bitstream/10443/1049/1/Liu10.pdf

Maneno, F. H. (2019). *Assessment of factors causing port congestion: A case of the port Dar es Salaam* [Master's thesis, Mzumbe University].

Morgan, D. L. (2014). Pragmatism as a paradigm for social research. *Qualitative Inquiry*, *20*(8), 1045–1053. https://doi.org/10.1177/1077800413513733

Morse, J. M., & Niehaus, L. (2009). *Mixed method design: Principles and procedures*. Left Coast Press.

Munim, Z. H., & Schramm, H.-J. (2018). The impacts of port infrastructure and logistics performance on economic growth: The mediating role of seaborne trade. *Journal of Shipping and Trade*, *3*(1), 1. https://doi.org/10.1186/s41072-018-0027-0

Notteboom, T., Pallis, T., & Rodrigue, J.-P. (2021). Disruptions and resilience in global container shipping and ports: The COVID-19 pandemic versus the 2008–2009 financial crisis. *Maritime Economics & Logistics*, *23*(2), 179–210. https://doi.org/10.1057/s41278-020-00180-5

Patton, M. Q. (2015). *Qualitative research & evaluation methods* (4th ed.). SAGE Publications.

Perez, I., Diaz-Hernandez, J. J., & Trujillo, L. (2016). Efficiency determinants of container terminals in Latin America and the Caribbean. Utilities Policy, 41, 1–14. https://doi.org/10.1016/j.jup.2016.06.002

Peykani, P., Mohammadi, E., Jabbarzadeh, A., Rostamy-Malkhalifeh, M., & Pishvaee, M. S. (2021). Window data envelopment analysis approach: A review and bibliometric analysis. *Expert Systems*, *38*(7), e12721. https://doi.org/10.1111/exsy.12721

Poitras, G. (1996). Measuring port efficiency: An application of data envelopment analysis. MPRA Paper No. 113953.

Raballand, G., Refas, S., Beuran, M., & Isik, G. (2012). *Why does cargo spend weeks in sub-Saharan African ports? Lessons from six countries*. World Bank. https://doi.org/10.1596/978-0-8213-9499-1

Ramsey, J. B. (1969). Tests for specification errors in classical linear least-squares regression analysis. *Journal of the Royal Statistical Society: Series B (Methodological)*, *31*(2), 350–371. https://doi.org/10.1111/j.2517-6161.1969.tb00796.x

Shawtari, F. A., Ariff, M. S. M., Abdul Razak, S. H., & Mazumder, M. N. H. (2018). Decomposition of Efficiency using DEA window analysis: A comparative evidence from Islamic and conventional banks. *Benchmarking: An International Journal*, *25*(6), 1681–1705. https://doi.org/10.1108/BIJ-12-2016-0183

Simar, L., & Wilson, P. W. (2007). Estimation and inference in two-stage, semi-parametric models of production processes. *Journal of Econometrics*, *136*(1), 31–64. https://doi.org/10.1016/j.jeconom.2005.07.009

Sun, B., & Kauzen, R. (2023). The impact of port infrastructure and economic growth in Tanzania: Adopting a structural equation modelling approach. *SAGE Open*, *13*(1), 1–17. https://doi.org/10.1177/21582440221145894

Tanzania Ports Authority. (2016–2023). *Annual reports and statistics*. Dar es Salaam, Tanzania: TPA.

Tanzania Revenue Authority. (2023). *Trade facilitation and customs modernization report*. Dar es Salaam, Tanzania: TRA.

Tideworks. (2024). *Adopting AI in terminal operating systems, port strategy*. Retrieved from https://tideworks.com/adopting-ai-in-terminal-operating-systems-port-strategy/

Tongzon, J. L. (1995). Determinants of port performance and efficiency. Transportation Research Part A: Policy and Practice, 29(3), 245–252. https://doi.org/10.1016/0965-8564(94)00032-6

UNCTAD. (2020). *COVID-19 and maritime transport: Impact and responses*. United Nations Conference on Trade and Development. https://unctad.org/system/files/official-document/dtltlbinf2020d1_en.pdf

Wang, X., Yuen, K. F., Wong, Y. D., & Li, K. X. (2022). Quantitative analysis of the impact of COVID-19 on ship traffic and port operations. *Ocean & Coastal Management*, *229*, 106325. https://doi.org/10.1016/j.ocecoaman.2022.106325