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The Impact of Automation on the Efficiency of Port Container Terminals

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Abstract

The increasing need to optimize efficiency in port container terminals has led to the transition of operations from manual to automated or semi-automated processes. Automation involves integrating or gradually adopting digital technologies and equipment that reduce human intervention, enhance productivity, safety and sustainability. This study investigates the impact of automation on port efficiency through a comparative analysis of 20 container ports in the wider Mediterranean region, using a two-stage modeling approach. In the first stage, Data Envelopment Analysis (DEA) is applied under constant and variable returns to scale to estimate port efficiency using infrastructure, equipment, and container throughput data. The second stage employs Tobit regression to assess the effect of automated operations or systems on port efficiency, including variables such as the automation index, TEUs per employee, TEUs per ship (call) and revenue. A key contribution of this study is the development of a methodological framework for qualitatively classifying and evaluating these ports based on their level of automation, the introduction of digital technologies or equipment, and investments in new technologies. The results indicate that automation alone does not necessarily lead to higher efficiency unless it is effectively integrated into operations accompanied by adequate staff training and supported by gradual investment strategies. By contrast, cargo intensity (TEUs per call), highlights the importance of vessel size and cargo concentration in improving port performance.

Keywords: automation; digitalization; containers; container port; efficiency; DEA; Tobit model

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1. Introduction

The global trend towards improving the efficiency and effectiveness of container terminal ports resulted in a gradual shift from manual labor processes to automated or semi-automated practices. Port automation refers to the introduction and deployment of new technologies, equipment, or digital systems that can replace human labor, either fully or partially, with the goal of increasing productivity [1].

An "automated port container terminal" (PCTs) is a port with automated yard operations and transport between the yard and the quay, such as the ECT Delta Terminal [2]. In these ports, crane-ship operations are manual, while the interaction between yard cranes and pickup/delivery vehicles is supported by remote controllers. However, this is just one of the many automation capabilities available in PCTs. Nowadays, the terms "automated container terminals" and "semi-automated ports" are commonly used [3]. Specifically:

- An automated port is a port system in which various functions and processes, such as container handling, crane operation, and transport using Autonomous Guided Vehicles (AGVs) are carried out with minimal or no human intervention. These functions are performed using automation technologies and digital systems.
- A semi-automated port refers to port facilities where some core operations are automated while others are done manually. Semi-automated container terminals can achieve significant or complete automation by introducing automated equipment such as Automated Stacking Cranes (ASCs) and AGVs. However, the term "semi-automated" can also refer to the use of remotely controlled equipment or the partial automation of certain equipment functions. A semi-automated terminal may have automated yard operations but conventional equipment for transporting containers between the yard and quay, or vice versa.

Globally, there are approximately 53 automated container terminals, representing about 4% of the total global container terminal capacity. Most of these terminals have emerged since the 2010s, following a gradual adoption process that began in the 1990s and continued into the 2000s. The majority of automated terminals are located in Asia (32%), Europe (28%), Oceania (13%), and the United States (11%). Ports like Shanghai Yangshan, Rotterdam Maasvlakte II, and Antwerp operate as fully or semi-automated terminals. In the Mediterranean region, the adoption of automation remains uneven, with significant progress observed in ports such as Valencia, Algeciras, and Tanger Med, while others are still in transitional stages [4,5]. Most of these ports are new (greenfield) terminals, with only a few converted from traditional terminals to automated ones (brownfield) [6].

The rationale behind port automation in container terminals is to improve operational efficiency, improve safety, and support sustainability. Automation allows for faster and more accurate cargo handling, reduces vessel dwell times at ports and increases throughput. The use of robotic systems and autonomous vehicles reduces human exposure to dangerous port areas and addresses labor shortages during night shifts and other difficult working hours [4]. Despite the high initial installation costs, automation leads to long-term savings in personnel and maintenance costs. Additionally, automated operations are usually more environmentally friendly, e.g., electric AGVs and optimal energy management. In the context of "smart ports", automation is essential for integrating technologies such as digital twins, the Internet of Things (IoT), and artificial intelligence. Improving port efficiency levels can potentially reduce average maritime transport costs by up to 14% and increase exports by up to 2.2% [7], enhancing the country's exporting capabilities [8]. Recent studies have highlighted the significance of high port efficiency in boosting resilience to disruptions, with East Asian ports demonstrating the highest levels of resilience and operational efficiency [9].

The process of container handling in ports includes all activities related to seaside operations (quay), yard operations, and landside operations. Quay operations involve loading and unloading containers from ships to the shore (or vice versa). This process can be further divided into four sub-processes: lashing, quay crane operation, twist-lock handling, and transport from the quay to the storage area. Yard operations involve temporarily storing containers and organizing them in designated storage areas in blocks. Landside operations include dispatching or receiving containers from trucks or other modes of transport. Therefore, the process encompasses all activities from the moment a vessel arrives at a container port until a truck (or train, ship, barge, etc.) carrying the container departs, and vice versa [10].

Large-scale or full automation of equipment is typically achieved through the integration of multiple technologies or systems, each of which may individually be considered a minor automation. In some cases, conventional equipment can be fully automated by

incorporating low-level automation components as part of an upgrade process. This approach offers a viable solution for operational terminals that have not yet recouped their initial investment in equipment [2].

This research aims to investigate the impact of automation on the efficiency of container terminals. The study focuses on a comparative analysis of twenty ports located in the wider Mediterranean region, each exhibiting a different level of automation. The goal is to understand how automation and the modernization of operations and equipment affect port performance indicators. To achieve this goal, a two-stage model is employed to quantify how different degrees of automation and digitalization relate to measured port efficiency. First, the Data Envelopment Analysis (DEA) is used to estimate the technical efficiency of the ports under both constant and variable returns to scale assumptions. Second, Tobit regression is used to investigate the relationship between automation level and the impact of new technologies, equipment or processes on port efficiency. A key innovation is the development of a methodology that qualitatively assesses the level of automation and digitalization of each port, enabling their classification for further statistical analysis in the second stage. However, this study does not address existing or emerging forms of automation in the shipping sector, such as autonomous vessels. It also excludes ship navigation services to ports, such as pilotage, towing, and berthing, as well as automation in inland transportation modes.

This research contributes to three key areas:

- Methodology: Introduces a combined DEA-Tobit approach to analyze the impact of automation on port performance.
- Empirical evidence: Analyzes container ports in the Mediterranean region with varying levels of automation. This study fills a research gap, by investigating and comparing the efficiency levels, automation maturity, and technological investments of these container ports.
- Innovative classification framework: Proposes and develops an innovative classification framework to qualitatively assess the level of automation, digital technology adoption, and overall technological maturity of container ports. This methodology combines qualitative processes with quantitative data to apply the second stage of the model.

The next section of the research includes an extensive overview of relevant studies on automation impacts and technological trends in container ports (Section 2), focusing on improvements in productivity, safety, and sustainability. Section 3 presents the theoretical background of the DEA and Tobit models. Section 4 describes the methodological approach, data, and results, while Section 5 presents the main conclusions and proposes recommendations for future research.

2. Literature Review

There is a significant body of literature that focuses on investigating the impact of automation on container ports. To assess the efficiency of a container port, several different parameters should be examined. This section reviews previous research and relevant literature regarding the impact of automation on container ports, based on (a) the effects on operational performance, (b) emerging technological trends in port automation and (c) methodological approaches implemented to assess port efficiency in relation to the integration of automation.

2.1. Impacts of Automation on Container Ports

Automation in container ports involves integrating new technologies and equipment, such as AGVs and ASCs, as well as digital operating systems to reduce human intervention

and improve productivity, operational activities and efficiency [11]. Several studies have examined the impact of automation on port productivity, costs, safety and the overall socio-political environment.

2.1.1. Productivity and Efficiency

Automated ports are generally considered to be more productive than non-automated terminals because they enable continuous daily operations with minimal performance (e.g., during shift changes, vessel dwell time or scheduling activities) [12]. The International Transport Forum [6] investigated the types of terminal activities that have been automated in various ports and those activities that could be automated in the future. This study assessed the effects of automation on port performance, handling costs, and safety, as well as the extent to which automation projects have achieved their goals, recognizing policy issues related to container terminal automation. The study reported that the examined container terminals have automated their yard operations through technologies such as RMG (Rail Mounted Gantry cranes), RTG (Rubber-Tyred Gantry cranes), or other ASC (Automated Stacking Cranes). Approximately one-third of the automated terminals used automated transfers from the quay to the yard via AGVs (Automated Guided Vehicles), automated transfer cranes, or other automated transport equipment. None of the automated container terminals have fully automated quay cranes, but some have remote crane operators and others have twin-lift cranes [13].

Chandra and Heaslip [14], evaluated the performance of AGVs by analyzing container dwell times and their effects on congestion in the surrounding transport networks, using the Long Beach Container Terminal as a case study. Their findings suggest that strategically using AGVs could significantly improve port operations, but it is essential to carefully assess their impact on local transport infrastructure. Similarly, Kon et al. [3] reviewed the literature on Automated Container Terminals (ACT) to address the research question about the Delta Terminal at the Port of Rotterdam and how to enhance ACT management. Through a systematic review and meta-analysis, they concluded that the adoption of ACT technology could improve productivity, cost efficiency and environmental performance.

2.1.2. Costs, Safety and Social Implications

Although automation typically leads to lower labor costs, it also requires higher capital expenditure for equipment acquisition and integration into port activities. Whether automation has led to lower handling costs depends on port location and consequently regional labor costs. Automation can deliver greater savings in developed economies with higher labor costs. In low-wage regions, however, labor cost savings may not justify automation investment [6]. According to the United Nations [15] automation could significantly change the quantitative relationships of capital/labor ratio (capital intensity), resulting in increased capital intensity and reduced need for manual labor.

From a safety perspective, automation can enhance workplace safety by reducing human exposure to hazardous areas and repetitive activities that cause strain. Walters and Wadsworth [16] argued that worker safety and health at terminals have improved with automation. However, automation at container terminals could reduce accidents related to automated equipment but could also require higher operational skills and training for operators, or it could lead to new types of human error [6].

The shipping industry is undergoing a transformation driven by the increasing integration of technology in business, redefining health, safety, and environmental practices in ports, as explained in Stickler [17]. This work tracks the evolution of port safety and explains how the semi-automated port is the next logical step for worker protection and

operational optimization shaping the future of port safety while increasing economic and environmental performance.

The transition to automation also has social implications, including changes to the labor force. At the Maasvlakte II terminal in Rotterdam, labor unions have opposed projects that aimed to automate and develop the terminal because they saw these projects as a threat to jobs [15]. Research conducted by the World Maritime University forecasts that, while automation will expand and be evolutionary, skilled human labor with appropriate qualifications will remain essential in the foreseeable future [18].

Automation and its economic impacts on ports were studied by Oliveira et al. [19], analyzing the costs and benefits of automation in ports. Specifically, the study examined the costs to labor markets and to each country's GDP, including compensation and benefits for dockworkers paid by the state. The research also applied these findings to Portuguese state policies and compared them with corresponding Swedish policies over a certain period.

2.2. Technological Trends in Port Automation

Automation in ports is becoming more widely supported by broader "smart ports" concepts and innovations. One such innovation is the digital twin (DT), a virtual replica or model of a physical entity (physical twin) that is interconnected with it through real-time data exchange. DTs are used for real-time monitoring, design, optimization, simulation, forecasting, maintenance, and remote access. DT technology is considered a cornerstone of Industry 4.0 because it can reduce errors, uncertainties, inefficiencies, and costs in any system or process. The primary goal of these innovative digital technologies is to optimize economic performance and energy demand, reduce resource consumption and waste, and improve service quality. In the maritime sector, digital twins can improve safety and increase the ability to predict potential risks or create optimal designs [20,21]. Integrating and adopting digital twins in port operational development makes ports better equipped to face challenges such as increasing cargo volumes, evolving regulatory requirements, and the need for greater efficiency [22].

The concept of "smart ports" and the integration of technologies such as the Internet of Things (IoT), cybersecurity, AI, machine learning techniques and cloud computing are crucial for improving operational efficiency. Heikkila et al. [23] explored the concept of "smart ports" within Industry 4.0, categorizing them by automation, sustainability, and collaboration. Using scenario theory, they proposed four potential futures for smart ports, each emphasizing different digital innovations in these areas. Leading automated ports include Brisbane, Antwerp, Shanghai, Hamburg, Rotterdam, Singapore, Dubai, and Los Angeles, among others. These ports have deployed smart systems for cargo handling, energy management and coordination [16].

2.3. Methodological Approaches in Port Efficiency Research

Several studies have examined various methods and models to assess operational efficiency in container ports, focusing on technological advancements and operational factors that impact port performance. One such method is Data Envelopment Analysis (DEA), which allows for comparisons between ports using inputs and outputs. DEA is widely used to measure scale efficiency. Some studies use a combination of DEA and other regression models, such as the Tobit regression model, to examine how external factors, such as automation or hinterland connectivity, influence efficiency levels.

Moschovou and Kapetanakis [24] examined the efficiency of Mediterranean container ports using DEA, considering factors such as port size, equipment, productivity, and revenue. Their findings identified the most and least efficient ports, grouped by market size. Bichou [25] studied how changes in operational conditions affect port efficiency by

analyzing 420 container ports from 2004 to 2010 using DEA. The results indicated that operational shifts significantly impact efficiency, suggesting that future research should consider port structure and operational mechanisms.

Ghiara and Tei [26] investigated the effect of automation technology on port efficiency using a two-stage DEA and regression approach, highlighting automation as a key factor in terminal productivity improvements. Zhu [27] applied a two-stage DEA-Tobit approach to evaluate port efficiency. They found that external trade volume strongly influences port development and emphasized the importance of optimizing resource allocation. Yen et al. [28] examined the impact of port design on maritime efficiency, using DEA-Tobit and AHP to study automation, environmental factors, and intelligence in smart ports. Environmental controls were found to positively affect efficiency, while intelligence-related factors had mixed effects due to their complexity.

Knatz et al. [10,29] conducted empirical analyses with terminal operators, revealing that automation decisions depend on multidimensional parameters and that the expected benefits generally materialize post-implementation. Pamungkas and Gurning [30] used the Best Worst Method (BWM) to rank parameters influencing automation readiness, emphasizing container throughput, storage capacity, investment costs, and environmental management. They noted constraints such as high investment costs and low labor costs in Indonesia. Hsu et al. [31] assessed smart port service quality post-pandemic using SERVQUAL and multi-criteria decision methods (AHP and DEMATEL). They identified critical success factors such as accurate cargo delivery, electronic documentation, integrated logistics, and the utilization of big data. Paraskevas et al. [32] reviewed how smart ports leverage IoT, cybersecurity, and cloud computing to optimize operations, identifying research gaps and emerging trends through a systematic literature review. Habri [33] compared automation levels at Antwerp and Rotterdam ports, showing that historical context, absorptive capacity and strategic priorities crucially determine automation intensity, despite similar size and technology access.

Beyond the classical DEA and second-stage regressions, there are several methodological extensions to DEA that address efficiency assessment in general. However, these extensions have not yet been applied to port container terminal efficiency, but rather to evaluate the performance of public transport. Among these, Iterative DEA recalculates efficiency frontiers iteratively and identifies gradual improvements [34], while eXplainable DEA (X-DEA) uses AI to explain why a DMU is efficient or inefficient [35]. Applying these with a focus on strategy-oriented performance, can help answer questions such as how automation investments can be gradually implemented in line with operational and sustainability goals.

Overall, these studies emphasize the importance of combining advanced efficiency measurement techniques with considerations of technology, operational conditions, and strategic factors to improve container port performance and guide smart port development. The literature review revealed a significant amount of research focused on assessing the readiness of container terminals to implement automation functions and evaluating the performance of ports that already utilize automated systems. Various factors influencing port efficiency and productivity were identified, including costs, safety, working conditions, and sociopolitical implications. While earlier studies have estimated port efficiency and automation, few have integrated a qualitative assessment of technological maturity into a two-stage DEA–Tobit framework. This study fills that gap by combining quantitative efficiency estimation with a qualitative automation index, providing a more comprehensive understanding of how technology adoption and operational modernization interact to influence port performance in the Mediterranean context. The study aims to examine the impact of automation on port operational efficiency and to determine if transitioning

to a modernized, and automated container port, including the necessary investments, is beneficial. By employing a two-stage model, first DEA, then Tobit regression, this study aims to quantify the effects of new technologies, equipment, and automated processes on port performance.

3. Materials and Methods

The first stage involved systematically collecting relevant data and information on 20 container ports located in the Mediterranean area primarily from Eurostat. The next step was to verify the reliability of the data and fill in any gaps using the official websites of each port as well as Google Earth. The collected data included information on the land, infrastructure, and equipment used by the ports (inputs), as well as the ports' productivity and financial results (outputs).

After collecting all data, the first stage of the modeling process involved applying the DEA models. Both Constant Returns to Scale (CCR) and Variable Returns to Scale (BCC) were used to estimate the efficiency level of each port. In the second stage, the Tobit model was applied. This model used the DEA-BCC efficiency score as the dependent variable (y) and parameters related to automation and the status of the examined ports as independent variables.

3.1. Data Envelopment Analysis Models

To understand the operation and usefulness of DEA in this research context, it is important to clarify some basic concepts.

1. Decision-Making Units (DMUs): The entities evaluated and compared efficiency within the DEA method. DMUs are production units that use inputs to produce outputs. Efficiency is calculated based on the ratio of resources used to produce results. In this research, the DMUs are individual container ports, compared in terms of their effectiveness in utilizing infrastructure and equipment [36].
2. Inputs/Outputs: Inputs for a production unit can include all resources (labor, capital, raw materials, etc.) used to produce goods or services. Outputs are the end products or services generated by the production unit.
3. Efficiency: The ability of a production unit to effectively use available and limited resources (inputs) to produce goods or services (outputs). A unit is considered efficient when it achieves the maximum possible output with the given inputs or when it uses the minimum possible inputs to achieve specific outputs [37].

Since the early 1960s, there has been a growing need for more effective management and planning business operations. In 1957, Farrell [38] articulated the need for a method to estimate business efficiency. In 1978, Charles et al. [39] introduced the DEA method in their study comparing the efficiency of non-governmental organizations to that of the public sector. DEA enables the evaluation of production units' efficiency and allows for comparative analysis between DMUs using multiple inputs and outputs. DEA focuses on analyzing the processes that units use to convert inputs into outputs, and as a comparative method, the calculated efficiency is relative. In 1984, Banker et al. [40] applied a variation in the CCR model using variable returns to scale making the efficiency frontier different. This frontier is the convex hull of the decision-making units.

The objective of DEA is to determine the production frontier of a unit. Specifically, a frontier or efficient boundary is created to define the optimal combination of inputs and outputs, meaning the ideal combination in which maximum outputs are produced with minimum inputs. There are two types of returns to scale: Constant returns to scale (CCR) and variable returns to scale (BCC), which can be input or output oriented. As previously mentioned, ports are considered decision-making units (DMUs), and the methodology

focuses on port productivity. Therefore, it is essential to use both CCR and BCC models with an output orientation, as the objective is to maximize the output produced with fixed inputs. Applying both models together allows for a more thorough evaluation of efficiency by enabling comparison under both constant and variable returns to scale assumptions, providing a more accurate representation of each port's capabilities.

3.1.1. Constant Returns to Scale (CCR)

Consider j as a DMU (j = 1, 2, …, n) which uses m inputs and produces s outputs where each unit has different weighting coefficients for inputs and outputs. Let's define:

- x_{ij}: The input i = 1, 2, …, m used by DMU j,
- y_{rj}: The output r = 1, 2, …, s produced by DMU j,
- λ_j: intensity variable

Using the output-oriented CCR model involves maintaining inputs while maximizing outputs. In the CCR model, constant returns to scale (CRS) are assumed. If φ is the optimal output index of DMU_0 then the efficiency formula is as follows:

$$\max_{\varphi,\lambda} \varphi \tag{1}$$

subject to:

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{i0}, \qquad i = 1, \ldots, m \tag{2}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq \varphi y_{r0}, \; r = 1, \ldots, s \tag{3}$$

$$\lambda_j \geq 0, \quad j = 1, \ldots, n \tag{4}$$

3.1.2. Variable Returns to Scale (BCC)

The BCC model assumes variable returns to scale (VRS). An additional constraint leads to the following formulas for the BCC model:

$$\max_{\varphi,\lambda} \varphi \tag{5}$$

subject to:

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{i0}, \quad i = 1, \ldots, m \tag{6}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq \varphi y_{r0}, \quad r = 1, \ldots, s \tag{7}$$

$$\sum_{j=1}^{n} \lambda_j = 1, \tag{8}$$

$$\lambda_j \geq 0, j = 1, \ldots, n \tag{9}$$

Then, the technical efficiency (θ_{BCC}) results from:

$$\theta_{BCC} = \frac{1}{\varphi} \tag{10}$$

while scale efficiency (SE) is measured as:

$$SE = \frac{\theta_{CCR}}{\theta_{BCC}} \tag{11}$$

3.2. Tobit Regression Model

The Tobit regression, also known as the censored regression model [41,42] is widely used in the second stage of DEA to analyze the effect of external factors, which are unrelated to physical inputs, on the efficiency calculated by the first stage model. The Tobit regression model is an alternative to classical linear regression (OLS) when the dependent variable is restricted within a specific range and cannot fall below a minimum or rise above a maximum value. In the context of DEA efficiency scores range between 0 and 1, and often many DMUs achieve a value of 1, indicating full efficiency. This results in aggregation only at the upper bound, which is known as right-censoring. OLS ignores this boundary constraint of the dependent variable and produces biased results. Tobit regression addresses this issue by modeling a latent variable and estimating the model's parameters (β) through Maximum Likelihood Estimation instead of the sum of squared errors.

Let's define:

- y_j*: A latent (unobserved) variable transformed from the original y.
- y_j: The efficiency values of port j from the DEA-BCC model.
- x_j: The vector of independent variables for DMU j.
- β: The unknown parameters of the independent variables,
- ε_j: The error term (independently and normally distributed with $\varepsilon_j \sim N(0,\sigma^2)$.

The general formulation of the Tobit model is as follows [43]:

$$y_j^* = \beta x_j + \varepsilon_j \tag{12}$$

For the second stage of analysis, efficiency values (y_j), derived from the DEA-BCC model are employed. The selection of the BCC model is justified as it assesses technical efficiency while disregarding scale effects. Since automation primarily affects a port's operation and resource management rather than its scale, it is methodologically appropriate to use BCC efficiency as the dependent variable in the Tobit model. The efficiency values (y_j), estimated from the first stage of the DEA model, are defined as follows:

$$y_j = 0, \quad \text{if } y_j^* \leq 0, \tag{13}$$

$$y_j = y_j^*, \quad \text{if } 0 < y_j^* < 1, \tag{14}$$

$$y_j = 1, \quad \text{if } y_j^* \geq 1 \tag{15}$$

The efficiency values of the DEA-BCC model are censored between 0 and 1 with many values near or equal to 1, so Tobit regression can produce biased results. To avoid this issue, the results are interpreted by focusing on the signs and magnitudes of the coefficients rather than relying on the *p*-values. To ensure the reliability of the results, alternative techniques could be applied, such as a fractional response model [44] which treats censored values at 0 and 1 as proportions between 0 and 1, or a two-stage model and double bootstrap procedure for DEA values [45] separating the fully efficient ports from less than fully efficient ones.

4. Analysis

This section outlines the methodology used to collect and process data, apply models, and analyze and interpret results. The study explores the impact of automation on the efficiency of 20 different Mediterranean ports and analyzes relevant data. This data includes geographic characteristics (such as area and quay length) and technical characteristics (such as the number of quay cranes, number of containers (TEUs), and turnover). The primary objective is to determine the efficiency rate of the ports based on their level of automation. Data collection was time-consuming because much of the data on the ports was not publicly available. Sources of data included the Eurostat website, official port websites, mapping applications like Google Earth and Google Maps, scientific studies, and articles with reliable and real data. The data came from multiple sources, so were cross-checked to ensure data reliability and reduce measurement errors. All variables were harmonized to a common reference year and maintained unit consistency, for example, quay length was expressed in meters and area in hectares. Official sources were given priority in cases of outliers and were compared to widely used container port performance indices [9]. Twenty container ports in the broader Mediterranean region were selected based on data availability to identify input and output variables.

4.1. Development of DEA Models

4.1.1. Data Collection

The minimum number of DMUs should follow one of the following restrictions:

1. The product of the number of inputs times the number of outputs [46].
2. At least twice the sum of the number of inputs and outputs [47,48].
3. At least three units for each input and output variable [49].
4. At least twice the product of the number of inputs and outputs [50].

For this research, we have chosen to follow the restriction set by [47]. Since there are four input variables and one output variable, the minimum number of DMUs required would be:

$$\text{DMUs} \geq (N_{\text{inputs}} + N_{\text{outputs}}) \times 2 = (4 + 1) \times 2 = 10$$

For the purposes of this research, data from 20 container ports were used to make conclusions more comprehensive. The selected ports met the following criteria:

- Be in the wider Mediterranean region.
- Handle at least 800,000 TEUs in 2023.
- Be container terminal ports and not general cargo commercial ports. Ports with passenger terminals were excluded from the calculations.

Table 1 shows the final selected DMUs.

Table 1. Selected container ports included as Decision Making Units (DMUs).

a/a	Container Ports	Country	a/a	Container Ports	Country
1	Tanger Med	Morocco	11	Alexandria	Egypt
2	Valencia	Spain	12	Marseilles Fos	France
3	Genoa	Italy	13	Sines	Portugal
4	Algeciras	Spain	14	Koper	Slovenia
5	Piraeus	Greece	15	Port Said	Egypt
6	Barcelona	Spain	16	Casablanca	Morocco
7	Gioia Tauro	Italy	17	Haifa	Israel
8	Marsaxlokk	Malta	18	Ambarli	Turkey
9	Mersin	Turkey	19	Constanța	Romania
10	La Spezia	Italy	20	Damietta	Egypt

The first stage of the model involved developing a DEA model to estimate port efficiency. The second stage of the model involves investigating the impact of automation and digitalization systems on container port efficiency. This is achieved by introducing the relevant variables and applying the Tobit model.

4.1.2. Variable Selection for the DEA Models

Port efficiency is often measured by technical efficiency, which is the relationship between the inputs and outputs of port operations [51]. The variables used in the first stage of DEA models must reflect the purpose and productivity of each port. After investigating and collecting data from the literature, one output and four inputs were selected:

Output

- Productivity in TEUs (annual container port throughput): This is the most important output of a port and serves as an indicator of its production efficiency.

Inputs

- Total quay length (in meters, m).
- Terminal area (in hectares, ha).
- Number of quay cranes (Ship to Shore cranes, mobile cranes).
- Number of stacking cranes in the yard (RTGs and RMGs).

Other input variables were also examined during the research analysis, included (a) the number of AGVs (Automated Guided Vehicles), which are widely used in industry, warehouses, and modern ports for automatic cargo transport without direct human intervention, (b) hinterland connectivity, which refers to the degree to which a port is connected to the wider inland area it belongs to and to transportation networks such as rail and road networks and, (c) CO_2 emissions, which represent the amount of carbon dioxide released into the atmosphere due to various port activities. These variables were excluded from the DEA to maintain comparability, due to limited, inconsistent, or non-public data. This issue is identified as a data availability constraint and is addressed in Section 6 where the limitations of this study are described and suggestions for future work are provided. Table 2 presents the descriptive statistics of the selected variables for the first stage (DEA) of the modeling process.

Table 2. Descriptive statistics of input and output variables for the first stage modeling (DEA).

	Output	**Inputs**			
	Throughput (TEUs)	**Quay Length (m)**	**Terminal Area (ha)**	**Quay Cranes (Number)**	**Yard Cranes (Number)**
Mean	2.622.852	2.514	106	20	46
Standard Deviation	2.055.370	1.264	68	10	33
Minimum	2.800	695	27	5	0
Maximum	8.617.410	4.812	231	43	113

4.2. Development of the Tobit Regression

4.2.1. Variable Selection for the Tobit Regression

The variables included in the Tobit model are as follows (Table 3):

- y: Efficiency of each port, as determined by the results of the first stage of the model using DEA-BCC.
- x_1: Automation index, indicating the level of technological maturity and technological advancement of each port. This variable is determined separately following an

innovative methodological framework described in the next section. This framework is based on the qualitative and quantitative characteristics of each port, as well as on available data and information from reliable sources.

- x_2: TEUs per ship call (TEUs/call): The number of containers handled during the arrival and departure of ships (ship calls). This variable expresses the number of containers moved per ship call. Data was collected from the Eurostat database and from the official websites of the ports, to compute the ratio with total annual TEUs in the numerator and the annual number of ship calls in the denominator [52]. For ports not listed in Eurostat (non-European ports), the relevant figures were obtained from the official website of each port for the same reference year (2023). This variable is also related to the types of vessels that each port serves.
- x_3: TEUs per worker per container port (TEUs/worker): This variable expresses the productivity of the labor force. It is calculated as the ratio of total annual TEUs to the total workforce of each port. Information on the number of employees for each port was collected from the ports' official websites or their published financial reports. This variable is related to automation because ports with a higher level of automation generally tend to employ fewer workers.
- x_4: Revenue, representing the financial performance of each port in terms of annual turnover. This variable indicates the economic status of each port and refers to its annual income. Port efficiency depends on the share of revenue allocated to investments in automation technologies.

Table 3. Variables used in the Tobit model.

Variable	Description	Unit
Port efficiency (y)	Dependent variable extracted from the DEA-BCC model	Efficiency values (0–1)
Automation index (x_1)	Continuous index, represents technological maturity and automation level.	Derived from qualitative criteria
TEUs per ship call (x_2)	Average container throughput per vessel call.	Total annual TEUs/total annual ship calls
TEUs per worker per container port (x_3)	Labor productivity indicator	Total annual TEUs/total number of employees
Revenue (x_4)	Economic performance indicator	Annual turnover (million €)

The final equation for the second stage modeling and application of the Tobit model is as follows:

$$y_j^* = \beta_0 + \beta_1 DV_{auto,j} + \beta_2 TEUs/Call_j + \beta_3 TEUs/Worker_j + \beta_4 Revenue_j + \varepsilon_j \quad (16)$$

4.2.2. Automation and Technological Maturity Index of Ports

To determine variable x_1 (the automation index), a methodological framework for qualitative assessment was followed. The evaluation was based on the level of automation of operations and equipment at each port, the use and implementation of digital systems, and the potential for future application of automated and digitalized systems. Specifically, the evaluation was based on the following criteria indicating a level of automation maturity:

1. Availability and use of advanced automation systems.
2. Investment in advanced machinery and automation of flows and processes.
3. Integration of AI systems into port services, such as software.
4. Participation in research projects related to sustainability commitments and innovations aimed at reducing the carbon footprint and increasing operational efficiency.

5. Partial or full automation of container handling (transitioning from manual processes to automated or semi-automated practices).

Based on these criteria, ports were classified into two indicative categories (Table 4) that reflect high and moderate automation maturity and represent their relative positioning along a continuous Automation Index scale. Category 1 includes ports with high levels of automation and digital integration while Category 2 includes ports that are at transitional levels of automation and invest in automation and advanced technologies. This classification was based on a systematic collection of information from multiple sources, including official port authority websites, annual reports, press releases, published announcements, and other available documentation related to automation and digitalization initiatives. This qualitative evaluation relied only on verified and publicly available sources and data while the description provided the empirical basis for assigning relative weights to each criterion when constructing a continuous Automation Index, as described below.

Table 4. Classification of container ports based on automation maturity level.

Port Category	Description
Category 1	Advanced automation and digital integration
Category 2	Investment in advanced equipment and digital expansion

Category 1 includes ports that already use advanced automation systems or AI-based systems and have implemented functional digital systems. The following ports belong to this category:

- Haifa (Israel): Utilizes a smart port management system and technology from Shanghai International Port Group (operational since 2021).
- Valencia (Spain): Utilizes AI for truck traffic forecasting and port operation optimization, focusing on digitalization and machine learning models.
- Alexandria (Egypt): Uses a fully integrated AI terminal operating system, gate automation system, full electronic documentation and digital monitoring.
- Mersin (Turkey): Utilizes an integrated digital management system for terminal operations and 24/7 container tracking, wireless network coverage, and camera surveillance.
- Koper (Slovenia): Utilizes multiple digital systems, including integrated platforms for management, truck appointments and scheduling, warehouse management and client-side integration platforms (e.g., e-container).
- Tanger Med (Morocco): Utilizes cloud computing for cybersecurity and smart systems for port and industrial facilities and digitalization.
- Algeciras (Spain): Uses advanced RTG automation, automatic positioning and guidance systems, automated gates and container identification systems, a truck appointment system, and real-time API data sharing.
- La Spezia (Italy): Implements automation of processes and flow management, customs documents, mediation with authorities, and telematics activation for service optimization.
- Ambarli (Turkey): A "smart port" applying various technologies aimed at increasing efficiency and sustainability. It is equipped with modern cranes and cargo handling equipment, exploring automated systems and IoT devices.

Category 2 includes ports that are investing in automation and advanced equipment and focusing on strategic plans for sustainability and smart transformation as well as those that are in the early or transitional stages of infrastructure modernization.

- Genoa (Italy): Ordered a first-generation ecological crane in 2022 and relies on automated and digital operational systems for modernization, improved performance, and energy efficiency.
- Gioia Tauro (Italy): Engaged in modernizing container facilities and forming strategic partnerships to enhance efficiency and competitiveness.
- Marsaxlokk/Malta Freeport (Malta): Significant investments (over €320 million) have been made in infrastructure, equipment, and digitalization since privatization in 2004.
- Barcelona (Spain): Aiming to become a "smart" logistics hub by using advanced digital scanning platforms (such as mobile X-ray units) for logistics.
- Marseille Fos (France): Aiming to establish itself as a maritime data hub by investing in smart port digital infrastructures and submarine cables.
- Sines (Portugal): Committed to environmental sustainability and innovation to reduce its carbon footprint and increase operational efficiency.
- Port Said (Egypt): New terminals are expected in the second half of 2025, including multi-purpose, general cargo, dry bulk, and ro-ro terminals as well as a vehicle management line with an annual capacity of 800,000 vehicles.
- Casablanca (Morocco): Investment in digital transformation starting in December 2024 focusing on developing and implementing digital solutions.
- Constanța (Romania): Transforming into a "smart port," by incorporating technologies to enhance efficiency, reduce its environmental footprint, and improve overall operations. This includes creating a new Port Community System and investing in upgrades to the port's electrical infrastructure.
- Damietta (Egypt): Strengthening the strategic framework to expand port customers and increase throughput capacity by offering operational and logistical facilities while organizing workflows to ensure the continuity and efficiency of terminal operations.
- Piraeus (Greece): There is insufficient published data indicating the full adoption of advanced and automated systems, the complete implementation of digitalization projects, smart management, or the upgrading of infrastructure for energy efficiency.

To address the heterogeneity among ports the Automation Index (x_1) was recalculated on a continuous scale between 0 and 1. The Index was based on the same five qualitative criteria described earlier (availability and use of advanced automation systems, investment in automated machinery and process control, integration of AI systems into port operations, participation in innovation and sustainability projects, and the degree of automation in container handling). Each criterion was assessed on a three-level scale. The final index value represents the weighted average of these five scores, reflecting the relative technological maturity and automation intensity of each port. So, the Automation Index for each port j is calculated as follows:

$$x_{1j} = \sum_{k=1}^{5} w_k s_{jk}, \qquad 0 \leq x_{1j} \leq 1 \tag{17}$$

where s_{jk} denotes the score of port (DMU) j for criterion k and w_k the respective weight.

5. Results

5.1. DEA Results

Table 5 presents the results and efficiency level values derived from the CCR and BCC models as well as the scale efficiency and types of returns to scale for the examined container ports. The lower average efficiency value derived from the CCR model (0.62) compared to the BCC model (0.72) is because the BCC model measures technical efficiency, while the CCR model captures both technical efficiency and scale efficiencies. This explains why the two models characterize different ports as fully efficient (efficiency values equal

to 1.00). Specifically, the CCR model identifies 3 ports as efficient, while the BCC model identifies 7.

Of the 20 ports, 4 ports Gioia Tauro (Italy), Port Said (Egypt), Sines (Portugal) and Alexandria (Egypt) exhibit constant returns to scale. This means that these ports operate at an optimal scale. However, although the Port of Alexandria (Egypt) shows constant returns, it records low efficiency scores under both models (0.40). This suggests that its inefficiency is likely due to poor management of inputs and resources. In other words, the port could enhance its overall performance by making better use of its available equipment and implementing organizational improvements. The remaining 16 ports exhibit increasing returns to scale, suggesting that enhancing their efficiency could be achieved by increasing their physical inputs (e.g., length of berth, yard equipment, ship call to raise TEUs per call).

Table 5. Comparative overview results of port efficiency from CCR and BCC DEA models.

Container Ports	Port Category	Container Throughput (TEUs)	Efficiency		Scale Efficiency	Returns to Scale
			DEA-CCR	DEA-BCC		
Tanger Med	1	8,617,410	0.70	1.00	0.70	increasing
Piraeus	2	4,825,813	0.88	1.00	0.88	increasing
Valencia	1	4,780,666	0.37	0.56	0.66	increasing
Algeciras	1	4,733,526	0.73	0.91	0.80	increasing
Gioia Tauro	2	3,548,827	1.00	1.00	1.00	constant
Port Said	2	3,528,611	1.00	1.00	1.00	constant
Barcelona	2	3,268,911	0.45	0.60	0.75	increasing
Ambarli	1	3,170,000	0.68	0.77	0.88	increasing
Marsaxlokk	2	2,800,000	0.58	0.66	0.88	increasing
Genoa	2	2,419,829	0.33	0.43	0.77	increasing
Damietta	2	1,969,429	0.46	0.50	0.92	increasing
Mersin	1	1,942,071	0.45	0.48	0.94	increasing
Sines	2	1,665,308	1.00	1.00	1.00	constant
La Spezia	1	1,663,071	0.61	0.62	0.98	increasing
Marseille Fos	2	1,471,761	0.68	0.73	0.93	increasing
Haifa	1	1,470,000	0.56	0.63	0.89	increasing
Alexandria	1	1,324,947	0.40	0.40	1.00	constant
Casablanca	2	1,300,000	0.41	0.43	0.95	increasing
Koper	1	1,047,779	0.62	1.00	0.62	increasing
Constanța	2	884,598	0.61	1.00	0.61	increasing
Average			0.62	0.72	0.87	

Of the 16 ports, some are medium-sized in terms of annual TEUs handled, such as Damietta (Egypt), Marseille Fos (France), Koper (Slovenia) and Constanța (Romania), while others are large ports such as Tanger Med (Morocco), Piraeus (Greece), Valencia (Spain) and Algeciras (Spain). The inclusion of large ports in this group, suggests that they can still exploit economies of scale through capacity enhancement, productivity upgrades, and improved berth–yard coordination. The persistence of increasing returns among large ports likely reflects ongoing automation transitions and the underutilization of newly developed terminal capacities. On the other hand, ports operating under constant returns to scale Gioia Tauro (Italy), Port Said (Egypt), Sines (Portugal), Alexandria (Egytp), indicate that they operate close to their optimal capacity. For these ports, further efficiency is more likely to arise from managerial and technological improvements (e.g., scheduling optimization or digital integration) than from infrastructure expansion. Previous research [24], has shown that scale efficiency in Mediterranean ports increases with port size and operational maturity.

Specifically, while the Port of Tanger Med (Morocco) is efficient under the DEA-BCC model, it has a scale efficiency of 0.70 and operates under increasing returns to scale.

Despite its large container throughput (8,617,410 TEUs), this indicates that there is still room for improvement. Similarly, Piraeus Port in Greece, which has a high container volume (4,825,813 TEUs), is fully efficient under the DEA-BCC model but has a scale efficiency of 0.88, suggesting potential for further enhancements. Smaller ports such as Koper (Slovenia), Casablanca (Morocco), and Constanța (Romania), which handle lower container volumes, also demonstrate significant potential for improving efficiency.

5.2. Tobit Regression Results

The second stage of the analysis applied the Tobit model to investigate the impact of efficiency and automation related variables on the overall operational performance of the studied container ports. The dependent variable in the model was the efficiency scores obtained from the DEA-BCC model. Two Tobit models were estimated and are referred to as Tobit-I and Tobit-II:

- Tobit-I included all independent variables: Automation Index (x_1), TEUs per Call (x_2), TEUs per Worker (x_3), and Revenue (x_4).
- Tobit-II excluded the variable Revenue (x_4) to assess the effect of the remaining variables.

To ensure accurate results, the independent variables were normalized as an initial step. Each variable was transformed to have a mean of 0 and a standard deviation of 1, which helped in the convergence of the estimation of maximum likelihood. The normalization equation used was:

$$x'_{kj} = \frac{x_{kj} - \overline{x_k}}{s_{kx}} \tag{18}$$

where

$\overline{x_k}$ is the mean and s_{kx} the standard deviation of variable x_k.

The results of the two models are presented in Table 6.

Table 6. Results of Tobit-I and Tobit-II Models.

	Tobit-I	**Tobit-II**
Coefficients		
β_0 (Intercept)	0.8366 ***	0.8432 ***
β_1 Automation	−0.0399	−0.0832
β_2 TEUs/Call	0.1900	0.1861
β_3 TEUs/Worker	−0.0415	−0.0583
β_4 Revenue	−0.0921	not applicable
Pseudo-R^2	0.1559	0.1795
σ	0.2584	0.2786

*** indicates significance at the 1% level ($p < 0.01$).

As shown in Table 6, the coefficient for automation is negative in both Tobit models ($\beta_1 = -0.0399$ in Tobit-I and -0.0832 in Tobit-II) indicating that higher levels of automation do not directly correlate with higher efficiency. As discussed earlier, this variable describes the technological maturity level of each port. The negative impact could be explained by the fact that having automated equipment or processes does not necessarily mean they are utilized effectively. This could be due to a lack of staff training or insufficient integration into port operations. Similar findings are reported in studies such as [53], which noted an 11% drop in efficiency in automated ports [6] or [26] indicating that the presence of automated technology cannot be considered a standalone factor that enhances port efficiency, rather, it should be considered in association with the overall port context. Furthermore, ports may use both conventional equipment and automated machinery simultaneously, which could hinder adaptability.

TEUs per call (β_2 = 0.1900 in Tobit-I and 0.1861 in Tobit-II) show a positive, and significant association with efficiency. This indicates that handling higher container volumes per vessel call leads to better port performance. The variables TEUs/worker (β_3) and Revenue (β_4) have negative effects. This outcome could be explained by the fact that technologically advanced or automated ports invest significantly in advanced equipment and systems, but these investments do not immediately result in efficiency gains. Instead, benefits may only materialize over the long term, eventually improving efficiency and DEA scores. High revenue ports often invest heavily in advanced systems and equipment, but this does not necessarily translate into immediate operational efficiency, as seen in the findings of [8]. As ports are highly capital intensive, investments in new equipment or automation systems often result in increased expenditure and reduced revenue before efficiency is fully shown. Previous research has shown that there is an adjustment period for automation transitions, during which productivity may temporarily decline [54,55]. Competition among ports can drive operators to make aggressive investments and governance changes, sometimes leading to operating levels exceeding their capacity or to lower use of the new facilities. Overall, the negative signs in both automation and revenue may not be due to port inefficiency but rather transitional investment, capacity scaling, or under-absorption of new assets [56]. In both models, the Pseudo-R^2 values are satisfactory, indicating reasonable explanatory power, with Tobit-II providing a slightly better fit after removing Revenue.

6. Discussion and Conclusions

6.1. Key Findings

This study compared container ports with different levels of automation to understand how introducing automation and new digital technologies affects their performance and efficiency. To achieve this objective, a two-stage model was applied to the DEA, using the CCR, BCC models, and Tobit model. The innovation of this work lies not only in the application of the two-stage model, but also in the development of a qualitative methodology to evaluate and classify the level of automation maturity of the examined ports.

Application of the DEA models revealed that the ports of Gioia Tauro (Italy), Sines (Portugal), and Port Said (Egypt) were characterized as fully efficient based on the CCR model. According to the BCC model, seven ports were identified as fully efficient: Tanger Med (Morocco), Piraeus (Greece), Gioia Tauro (Italy), Sines (Portugal), Koper (Slovenia), Port Said (Egypt), and Constanța (Romania). The ports of Valencia (Spain) and Genoa (Italy) exhibited the lowest efficiency scores (below 0.40), indicating the need for extensive reorganization and optimization of their operations. Furthermore, scale efficiency analysis revealed that 16 out of 20 ports exhibit increasing returns to scale. This suggests that their efficiency could be improved through investments in infrastructure and equipment or by increasing the volume of TEUs handled. For example, although fully efficient, container ports with large handling volumes of TEUs showed lower scale efficiency values, indicating potential for improvement. In smaller ports such as Casablanca (Morocco), Koper (Slovenia) and Constanța (Romania), efficiency was found to be affected by input size, requiring strategic planning to enhance operational capacity.

Further analysis using the Tobit model revealed interesting findings regarding the factors affecting efficiency in relation to the level of automation. Specifically, the variable related to automation showed a negative effect on port efficiency, suggesting that the adoption of advanced technologies does not automatically lead to increased efficiency. This phenomenon may be due to the insufficient or incomplete integration of systems into daily operations or inadequate training of personnel. The TEUs/call variable, which reflects the quantity of containers per ship call, showed a positive and significant effect, highlighting the importance of cargo concentration and the efficient use of port infrastructure. Similar

findings by [6,10] revealed that automation in port terminal operations replaces not only equipment and vehicles, but also requires a long adaption period and is not dependent on its physical attributes.

Tobit regression identifies relationships rather than causal effects. Therefore, coefficients should be interpreted as indicative relationships rather than direct impacts. Realizing the potential efficiency benefits of automation depends strongly on systemic integration, managerial adaptation, and workforce training, all of which require coordinated planning across technical and human domains. Overall, the study demonstrates that efficiency depends not only on technological progress or investments but also on the ability to integrate them into operational and management processes, an essential factor for port competitiveness in the post-pandemic era.

6.2. Recommendations for Further Research

Examining port efficiency using more data would be particularly useful. The lack of certain variables due to data unavailability limited the analysis. Adding more variables and increasing the number of ports could strengthen the model's results and generalize the findings. Focus should be on extending this analysis beyond the Mediterranean area to include extra-regional ports, in Asia or North America. This expansion would enable country comparisons and the capture of different technological patterns. While the DEA–Tobit framework is a consistent and widely adopted approach for assessing efficiency and its determinants, future research could focus on applying alternative models. For example, comparing DEA with alternative methods such as Stochastic Frontier Analysis (SFA) to assess the stability of the results or extending the DEA model into a dynamic form (Dynamic DEA) to study port performance over time to further test the robustness and temporal stability of the results. The use of the Technology Readiness Level (TRL) index for quantitative evaluation of digitalization and automation levels or the addition of a ratio of automated to total equipment in addition to TRL, and the addition of environment-related variables such as energy consumption and CO_2 emissions could also be considered for future research to integrate environmental and social dimensions (kWh/TEU, CO_2e/TEU, safety rates). Lastly, a significant addition would be investigating the social impacts of automation, such as its effects on employment and acceptance of technology by workers.

This study was limited by the availability of certain data, particularly related to equipment and energy or environmental data. All data was carefully validated using public sources; however, these limitations may affect the generalizability of the findings beyond Mediterranean ports. Expanding the dataset to include broader geographic coverage and more detailed automation indicators (e.g., ratio of automated to total equipment, digital readiness metrics) would improve the robustness of future analyses.

The results of this study also provide valuable insights for port policy and management. As automation becomes more common in container terminals, it is crucial to integrate efficiency goals with social responsibility. Ports should plan automation and investment in phases, considering also available financial resources and labor cooperation. All stakeholders, port authorities, terminal operators, and labor unions could support the adoption of automation technologies, for example, through training programs. This transition could also be encouraged by creating planning frameworks or labor agreements to ensure that automation enhances both productivity and employment [57].

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