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Thematic Section - Digital Transformation of Supply Chain Management

Efficiency determinants in Industry 4.0: a two-stage DEA approach in the Brazilian 3PL industry

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Abstract

Paper aims: The main objective is to determine which Industry 4.0 (I4.0) technologies significantly impact the scale efficiency of 3PLs' (Third Party Logistics).

Originality: This paper provides a significant academic contribution given that it is the first quantitative research endeavor to evaluate the influence of I4.0 applications on productivity within the Brazilian 3PL industry.

Research method: A two-stage Data Envelopment Analysis (DEA) model was adopted. The first stage of the DEA enabled the measurement of 3PL efficiency, and the second stage (Bootstrap Truncated Regression) allowed us to explore the relationship between efficiency and the I4.0 technologies. Secondary data from *Revista Tecnologística* provided the inputs, outputs, and contextual variables for this analysis.

Main findings: In the first stage of the analysis, a high average technical inefficiency was identified, suggesting managerial failures to efficiently use available resources. However, 3PLs demonstrated low-scale inefficiency, operating close to the optimal production scale. In the second stage, the contextual variables Drones, Big Data, and Business Intelligence were positively significant, while Internet of Things technology was negatively significant.

Implications for theory and practice: Our study enhances 3PL efficiency literature by applying DEA, considering contextual aspects, and exploring the adoption challenges of I4.0 technologies in emerging economies.

Keywords

3PL. Industry 4.0. Efficiency. DEA. Bootstrap Truncated Regression.

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The authors have no conflict of interest to declare.

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This research did not involve direct interaction with human participants and used only secondary data obtained from publicly available sources.

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1. Introduction

Efficiency remains a persistent challenge in logistics, as firms face growing pressure to deliver faster, more flexible, and lower-cost services while managing high operational expenses and meeting sustainability expectations (Rodrigues et al., 2018; Ivanov et al., 2019). To handle these demands, many companies outsource logistics activities to third-party logistics providers (3PLs), which are responsible for services such as transportation, storage, packaging, labeling, and distribution (Pishdar et al., 2021). When well-managed, outsourced logistics can offer cost savings, improved service quality, and environmental benefits (Wang et al., 2019). However, if 3PLs lack the capability or resources to operate efficiently, the consequences can include delays, increased costs, and reputational harm to client firms (Singh & Singh, 2023). This makes the efficiency of 3PLs a critical concern for individual companies and supply chains.

3PL providers worldwide face persistent efficiency challenges stemming from the growing demand for outsourcing, expansion of logistics services, and intensified competition, requiring continuous operational improvement (Min & Joo, 2006; Rodrigues et al., 2018; Sahay & Mohan, 2006). These challenges include managing rising supply chain costs, maintaining lean operations, coping with tax complexities, and meeting increasingly sophisticated customer demands (Wanke, 2012; Zhou et al., 2008). Operational constraints, such as limited scale, talent shortages, underutilized assets, and insufficient IT use, are recurrent issues that 3PLs face across regions (Min & Joo, 2006, 2009; Marchet et al., 2017). In emerging economies such as China and Brazil, such difficulties are intensified by inadequate infrastructure, regulatory inefficiencies, corruption, and bureaucratic barriers, resulting in high costs, narrow margins, and limited capacity for service sophistication (Zhou et al., 2008; Wanke, 2012). Despite regional differences, these structural and institutional constraints consistently undermine the efficiency and competitiveness of 3PL providers in both the developed and developing markets (Yang et al., 2024; Zhou et al., 2008; Wanke, 2012).

In response to these challenges, many 3PLs have turned to Industry 4.0 (I4.0) technologies as potential solutions. It has been argued that the implementation of I4.0 technologies, such as cloud computing, the Internet of Things (IoT), sensors and actuators, blockchain, and Artificial Intelligence (AI) has the potential to enhance the performance of companies and sustain their supply chains (SC) by offering opportunities for innovation and promoting competitive growth (Azadi et al., 2023; Fosso Wamba et al., 2015). Recent research indicates that I4.0 benefits companies in terms of improved product quality, reduced production costs, enhanced sustainability performance, flexible production, and minimized investment risk (Ivanov et al., 2018; Rosin et al., 2020; Tran et al., 2023). Additionally, studies have highlighted the positive effects of I4.0 on logistics, SC, and lean production (Azadi et al., 2023; Ivanov et al., 2018, 2019).

When assessing 3PLs' efficiency, some techniques are widely employed to identify logistic-suitable performance levels. For example, benchmarking is used owing to its simple application and practical results (Bogetoft & Otto, 2011). Increasingly, Data Envelopment Analysis (DEA) has been considered a key method for measuring performance and has been used to evaluate parts of SC performance or its total performance. Kalantary & Farzipoor Saen's (2019) study on SC assessment, Zhou et al.'s (2019) work on developing a sustainable SC, and Rodrigues et al.'s (2018) research on the efficiency of specialized 3PL providers are examples of studies that use DEA based on fuzzy theory. Nevertheless, this literature does not considered the specific context of 3PLs, nor has it focused on the underlying role of I4.0 technologies in these firms' efficiency. This knowledge is necessary to understand how I4.0 technologies impact 3PL efficiency, optimize resource use, and enhance performance.

To contribute to this knowledge generation, we focus on the Brazilian 3PL industry in a contextual setting. Specifically, we focus on the following research question: How do I4.0 technologies impact the logistics efficiency of Brazilian 3PLs? To achieve our objectives, a literature review was conducted to characterize the industry specificities and articulate the methodological choice of the two-stage modeling approach. Specifically, after calculating efficiency using the DEA technique, a Bootstrap Truncated Regression (BTR) was employed to assess the impact of contextual variables on the industry's scale efficiency. The information available in the *Revista Tecnologística* database was based on our analysis and findings.

This study is relevant for two reasons. First, 3PLs play a critical role in supply chains, especially those operating in an increasingly competitive environment that necessitates continuous efficiency improvements, such as Brazil. Two-thirds of Brazilian firms' logistics-related expenditures are for service providers, underscoring the importance of outsourced logistics in the country (Vivaldini & Pires, 2020). Second, given the capital-intensive nature of technological investments and the limited availability of resources for investments (especially for small and medium 3PLs), it is imperative to assess the strategic value of technology in enhancing productivity and competitiveness. However, there remains a gap in the literature regarding the extent to which I4.0 technologies impact 3PL performance. This study addresses this gap by empirically examining the relationship between the adoption of technologies such as Big Data, Business Intelligence, the IoT, and drones and the operational efficiency of 3PLs.

Our findings suggest that certain I4.0 technologies support more efficient operational scales within the 3PL industry. Since no previous studies have used DEA to examine the relationship between I4.0 adoption and 3PL performance, we address this gap by applying a two-stage DEA model to evaluate Brazilian 3PLs. This study sheds light on the specific challenges and operational realities faced by the 3PLs in emerging economies. While mainstream research has explored developed countries, our study focuses on the distinct dynamics of technology adoption in a developing context. Our contributions are threefold. First, we confirm previous findings that link I4.0 technologies to improved productivity in supply chains (Azadi et al., 2021, 2023; Pishdar et al., 2021; Woo et al., 2021). Second, we extend this knowledge by using DEA to assess how these technologies influence efficiency in the 3PL industry by considering local conditions and firm-specific factors. Third, by focusing on Brazil, we add to the limited but growing body of research on I4.0 in emerging economies (Rodrigues et al., 2018; Wanke, 2012; Yang et al., 2024). In doing so, we shift the conversation beyond the usual focus to developed countries, and highlight the opportunities and constraints that shape the adoption of new technologies in less-studied regions.

The remainder of this paper is organized follows. Section 2 discusses the Brazilian 3PL industry, I4.0 technologies, and efficiency. Section 3 presents the two-stage DEA model in detail. Section 4 analyzes the data and discusses the results. Section 5 concludes the paper and provides directions for future research.

2. Literature review

2.1. Brazilian 3PL context

Since the 1980s, there has been a noticeable shift towards outsourcing non-core logistics activities (Arroyo et al., 2006). Companies have increasingly relied on 3PLs to handle logistics operations worldwide (Arroyo et al., 2006; Carbone & Stone, 2005; Lieb & Bentz, 2005; Lieb & Lieb, 2016; Rahman & Jim Wu, 2011). In recent years, there has been an increase in academic research and publications dedicated to understanding the various facets of 3PLs. This development can be explained by the growing trend of logistics outsourcing in the business domain, which has increased the service range provided by 3PLs (Zhou et al., 2008).

3PL can be defined as an integrated logistics service provider that is prepared to meet most, if not all, of a client's customized logistics needs (Figueiredo et al., 2000). The increase in outsourcing and use of 3PLs is due to various factors such as cost reduction, enhancement of service levels, improved operational flexibility, and the ability to concentrate on the core business (Wanke, 2012).

In Brazil, the implementation of Plano Real, an economic plan launched in 1994, along with the country's economic stability, has led to greater utilization of outsourced logistics functions by Brazilian shippers (Fleury & Ribeiro, 2003; Wanke et al., 2007). However, this trend was delayed compared to other contexts, such as those in the US and Europe. Currently, most logistics-related expenditures of Brazilian firms are allocated to logistics service providers, highlighting the significance of outsourcing for the country (Vivaldini & Pires, 2020). Therefore, 3PLs must constantly seek new ways to maintain their competitiveness (Panayides et al., 2009). Evaluation of efficiency techniques plays a crucial role in this endeavor.

The Brazilian 3PL industry comprises 159 medium and large firms, generating total annual revenue of R$ 44.3 billion (Associação Brasileira de Operadores Logísticos, 2023). Their average yearly revenue is approximately R$ 278.6 million per firm. The industry also contributes significantly to job creation – it employs 177,521 individuals directly and 532,563 indirectly. Indeed, an industry employing 710,084 people, collecting R$ 7.2 billion in taxes and R$ 2.0 billion in charges impacts the national economy significantly. Despite considerable legal uncertainty, this industry continues to grow significantly beyond the Gross Domestic Product, indicating its intention to invest approximately 5.7% of its total revenue (R$ 608.2 million) over the next three years.

In Brazil, 3PLs continue to search for alternatives to stay competitive (Rodrigues et al., 2018; Wanke, 2012). Brazilian shippers seek more tailored services; however, providers cite limited operational scales, hindering substantial investment (Rodrigues et al., 2018). This, coupled with slow revenue growth, compounds financial strains for 3PLs due to narrow profit margins. Amidst rising competition, the key to survival lies in maintaining lean operations (Wanke, 2012). However, sustaining this proves challenging amidst mounting cost pressures from heightened customer expectations, fuel expenses, insurance premiums, and expanded services. To address this problem, companies have adopted efficiency evaluation techniques and alternatives.

Brazilian law lacks a systematic approach to the logistics 3PLs concept, resulting in unambiguous treatment (Fleury & Ribeiro, 2003; Wanke, 2012). Consequently, 3PLs' activities are inherently subject to regulations regarding different modes of transportation and storage methods, as defined by law. This introduces legal uncertainty for 3PLs, hindering their ability to receive the benefits granted to other firms performing related activities, such as transportation and warehousing.

2.2. I4.0 technologies and 3PLs

I4.0 was initially introduced at an international fair in Germany and was officially embraced by the German government in 2013 as a strategic agenda to revolutionize the manufacturing industry (Caiado et al., 2021; Xu et al., 2018). As the development of advanced manufacturing systems in industrial organizations is advantageous, I4.0 has received significant attention in recent years (Raj et al., 2020).

The adoption of I4.0 in manufacturing organizations brings about changes in traditional skills, creates new working environments, and encourages employees to adapt to new job requirements with greater flexibility (Caiado et al., 2021; Sony & Naik, 2020). Moreover, I4.0 technologies enable monitoring and control of materials, products, equipment, and information flow through feedback mechanisms, thereby improving organizational efficiency (Dalenogare et al., 2018). These technologies also contribute to the sustainability of SCs through optimized resource allocation, information sharing, reduction in fuel consumption, and decreased production costs (Mastos et al., 2021). However, investment in I4.0 imposes significant financial pressures on companies and may not yield immediate economic returns. The literature highlights that lack of financial resources is the main challenge to the adoption of I4.0 technologies (Raj et al., 2020).

I4.0 technologies encompass a new paradigm and multiple innovative and smart technologies, including autonomous robots, the IoT, cybersecurity blockchain, Drones, cloud computing, Big Data (BD), and AI (Ivanov et al., 2019), as illustrated in Table 1. In advanced manufacturing systems, these technologies empower firms to adopt data-driven strategies for data collection and transformation, as well as for enhancing horizontally and vertically integrated manufacturing systems (Frank et al., 2019; Tao et al., 2018).

Table 1. I4.0 related technologies.

Technologies	Definitions
Additive manufacturing or 3D impression	Versatile machines for Flexible Manufacturing Systems, able to transform digital 3D models into physical products using additive manufacturing
AI	Computer-based algorithms using analytical and statistical methods to support data analysis and automated decision-making
Big Data (BD) Analytics	Computer-based predictive analytics, data mining and statistical analysis to treat large and unstructured data sets, generated by sensors
Computer-Aided Design and Manufacturing	Computer-based systems for product design, manufacturing planning and management
Cloud computing	Storage and processing of large data volumes in remote computers
Sensor-based digital automation	Automated systems with embedded sensor technology
Integrated engineering system	Integration of IT support systems for information exchange in product development and manufacturing
IoT	High-speed internet-based sensors that allow to remotely control equipment
Robotics	Application of programmable, autonomous manufacturing machines
Simulations/analysis of virtual models	Application of analytical methods in engineering projects and systems simulate their properties and outcomes
Unmanned aerial Vehicles (UAV)	Any unpiloted aircraft is commonly referred to as a “drone”

Source: Adapted from Muniz Junior et al. (2023) and Javaid et al. (2022).

In the Brazilian context, I4.0 technologies are fundamental to modern logistics. The increasing demand for agility, transparency, visibility, and accuracy, combined with the growing complexity of supply chains, presents significant logistical challenges. However, technological advancements also create new opportunities. The stage of Brazilian 3PLs regarding these technologies can be understood through clusters, grouped according to their implementation level and future investment potential (Instituto de Logistica e Supply Chain, 2024). The first cluster includes foundational technologies such as TMS (Transportation Management System), WMS (Warehouse Management System), and demand planning systems, which are essential for efficient logistics management (Rodrigues et al., 2018; Wanke, 2012). The second cluster consists of visibility-enhancing tools like Drones, BD, Business Intelligence, AI, and IoT, which have been rapidly adopted with the prospect of becoming standardized tools for the 3PL industry in the short term. The third cluster focuses on digitalization and virtualization, which are expected to transform logistics operations significantly in the medium term. Finally, the fourth cluster includes supply chain orchestration technologies, which will enable seamless global supply chain management in the long term.

This study focuses on technologies from the second cluster, as they represent a critical transition point for 3PLs in Brazil. These tools bridge the gap between traditional logistics management and more advanced digital capabilities, enhancing operational efficiency and decision-making (Instituto de Logistica e Supply Chain, 2024). Moreover, their increasing adoption by 3PLs indicates their immediate relevance, making them a strategic priority for companies aiming to remain competitive in an evolving logistics landscape.

This study focuses on key technologies for 3PLs: Drones, BD, Business Intelligence (BI), and IoT. Drones refer to UAVs or flying robots controlled by software applications. The first commercial drone - Unmanned Aerial Systems - was created by the U.S. Federal Aviation Administration (FAA) in 2006. In 2016, FAA authorized its application in many industries, resulting in accelerated marketing growth (Maghazei et al., 2022). Over time, they have become increasingly popular in various fields, including healthcare and the COVID-19 response (Abdel-Basset et al., 2021). Drones are considered emerging technologies in I4.0 context and SCM (Akbari & Hopkins, 2022; Maghazei et al., 2022). Their adoption is influenced by economic, strategic, operational, SC, organizational, and behavioral factors (Maghazei et al., 2022).

BD refers to a large data set generated from various independent systems that cannot be processed using traditional BI tools. BD extracts meaningful insights and transforms them into informative and actionable information. Analyzing vast amounts of data and extracting valuable insights, BD can provide valuable observations that can be used for decision-making, forecasting, and strategic planning purposes, to name a few (Akbari et al., 2023; Singh et al., 2024).

BI refers to the use of technologies to collect, analyze, and interpret data to support decision-making and improve business performance. It involves gathering data from various sources and from large volumes, transforming raw data into meaningful insights, and presenting it in a format that can be used to drive strategic actions and achieve organizational goals. BI systems allow organizations to get a better understanding of their operations, customers, and market trends with tools and techniques enabling them to identify opportunities for improvement. BI is relevant in the I4.0 context, leveraging the use of co-related technologies such as BD, AI, and the IoT to drive operational efficiency, enhance customer experiences, and gain competitive advantage (Chen et al., 2023; Rajnoha & Hadač, 2024).

IoT connects physical devices to the digital environment, enabling real-time visibility. In SCs, it improves process efficiency, such as tracking, predictive maintenance, and accurate forecasting (Akbari & Hopkins, 2022). It provides a collection of data that enables more informed decision-making, enhances business models in industrial organizations, improves knowledge management, and increases SC capacity, especially in highly dynamic settings (Akbari et al., 2023).

2.3. I4.0 efficiency studies with DEA

Research on I4.0 technologies utilizing DEA models is in its initial phase. To ensure the quality of the knowledge base used in this study, we followed systematic procedures to find relevant literature. We reviewed articles on I4.0 technologies efficiency from 2000 to 2023 in Web of Science and Scopus databases, identifying 38 unique documents after removing duplicates. However, we have only found five articles that indirectly evaluate the impact of I4.0 technologies: Azadi et al. (2021, 2023, 2024), Pishdar et al. (2021), and Woo et al. (2021). They used DEA models to assess efficiency in different industries and settings as we explore next.

In the context of Supply Chain Finance (SCF), Azadi et al. (2021) used DEA to assess the sustainability of financing resources for investing in I4.0 technologies. Specifically, they developed an advanced DEA model incorporating economic, environmental, and social factors to measure sustainability. Then, the DEA model was used in SCF to identify inefficiencies in inputs and outputs for investing in I4.0 technologies.

Moreover, Azadi et al. (2023) evaluated cloud computing providers for I4.0 using DEA to address existing methodological shortcomings and assess sustainability. Their research not only highlights the role of I4.0 in shaping sustainable supply chains and the challenges of integrating I4.0 principles with sustainability measures but also emphasizes the need for effective cooperation and integration throughout the supply chain. As such, the study offers relevant managerial insights for evaluating the sustainability of cloud computing providers, providing practical guidance for industry professionals.

Similarly, Azadi et al. (2024) conducted a comprehensive study using DEA to evaluate cloud service providers' efficiency in an entire supply chain, where multiple organizational actors, processes, and services interact to achieve business objectives. They found that taking undesirable outputs, integer-valued, and stochastic data into account changes service providers' efficiency and enables the identification of an optimal portfolio of providers that best suit a customer's priorities and requirements.

Using a different approach, Woo et al. (2021) used DEA to assess companies' maturity levels in applying smart manufacturing and smart factories within the shipbuilding industry. As a result, they developed a diagnostic framework for smart shipyard maturity level assessment, which has been applied to eight shipyards in South Korea. Given that this is a built-to-order industry, models that allow measuring efficiency levels are crucial. By comparing DEA models with conventional ones, the authors found that DEA models perform better.

Finally, Pishdar et al. (2021) explore the role of I4.0 in shaping sustainable supply chains and the challenges faced in integrating I4.0 principles with sustainability measures. For this, they apply DEA but present I4.0 technologies only as a context. Their research emphasizes the need for effective cooperation and integration of machines, workers, and systems throughout the supply chain to achieve I4.0 logic and implement circular economy strategies. Additionally, the authors highlight that I4.0 research has overlooked the use of DEA, resulting in a lack of standardized metrics for efficiency assessment, indicating the need for further exploration and development. This work aims to contribute to this knowledge generation by focusing on the Brazilian 3PL industry.

The limited number of studies that use DEA in 3PLs demonstrates a lack of standardized models and variables to evaluate efficiency. Therefore, we concluded that there is no single set of efficiency measurements for this type of operation, given its multifaceted and complex nature. Furthermore, we have not identified works that applied the DEA methodology to identify contextual variables that significantly impact efficiency. Thus, given the theoretical gap and practical relevance of the topic, we decided to analyze Brazilian 3PL operators using a two-stage DEA model. The following section details our methodological choices, and the techniques used.

3. Methodology

This study investigates the impact of I4.0 (I4.0) technology adoption on logistics efficiency within the Brazilian 3PL industry. To achieve this, we employ a two-stage approach that combines DEA with BTR. We chose DEA and BTR because of their ability to address the specific statistical characteristics of efficiency scores, as extensively discussed in the seminal literature (Simar & Wilson, 2000, 2007, 2011). The main reasons include: (i) comprehensive efficiency measurement, as this approach allows for a detailed assessment of the efficiency of 3PL providers; (ii) analysis of contextual variables with BTR is employed to explore the relationship between the efficiency scores obtained with DEA and various contextual variables, specifically the adoption of I4.0 technologies, considering the truncated and estimated nature of these scores; (iii) reduction of statistical noise, unlike traditional methods such as OLS or Tobit, which can produce biased and inconsistent estimates when applied to DEA efficiency scores, BTR is superior in reducing sampling bias and statistical noise, providing a more reliable regression coefficient estimation technique (Simar & Wilson, 2007, 2011); and (iv) the robustness of the results with the use of BTR, as the calculation of confidence intervals for the efficiency estimates adds a layer of statistical rigor to the analysis (Simar & Wilson, 2011).

Two primary methodological frameworks exist for evaluating efficiency: mathematical programming, exemplified by DEA and its variants; and stochastic frontier analysis (SFA), rooted in econometric principles (Bogetoft & Otto, 2011). Although DEA's slack-based approach provides valuable insights into resource allocation for efficiency enhancement, SFA focuses on the economic rationale underlying a specified production function. However, SFA relies on parametric assumptions regarding the error and inefficiency components, which can be limiting. DEA offers advantages owing to its non-parametric, distribution-free nature and capacity to handle multiple outputs simultaneously. Critically, DEA excels at identifying benchmarks. By pinpointing efficient peer units for each inefficient unit, the DEA facilitates the development of targeted strategies for improvement. However, DEA alone lacks the statistical rigor to analyze the direct influence of contextual variables on inefficiency. Therefore, to complement the DEA results, we adopt a two-stage approach that enables a deeper investigation of the determinants of efficiency in the Brazilian 3PL context.

To address the statistical limitations in analyzing the influence of contextual variables on DEA efficiency scores, we employ BTR. This approach is crucial for overcoming the shortcomings of methods like Ordinary Least Squares (OLS) and Tobit, which are not appropriate for dependent variables that are truncated estimates, such as DEA efficiency scores (Simar & Wilson, 2000, 2007, 2011). Bootstrapping, as a powerful and non-parametric resampling technique (Simar & Wilson, 2011), overcomes the lack of direct statistical properties in DEA efficiency scores. By repeatedly resampling the original data, bootstrapping generates an empirical distribution of efficiency scores, enabling the calculation of bias-corrected estimates and robust confidence intervals for regression coefficients (Cooper et al., 2007).

In this study, BTR is applied to examine the influence of I4.0 technology adoption (i.e., our contextual variables) on three dimensions of efficiency: technical, managerial, and scale. This approach offers a nuanced understanding by distinguishing between (1) technical efficiency, assessed using the CCR model, which reflects the overall input-output conversion under constant returns to scale; (2) managerial efficiency, estimated via the BCC model, which isolates pure operational performance by allowing variable returns to scale; and (3) scale efficiency, calculated as the ratio between the two, which identifies the optimal operational scale. This methodology not only strengthens the analytical rigor of the study but also adds valuable empirical evidence to the ongoing debate in Brazil's 3PL industry, where concerns about potential capacity constraints have emerged. It helps clarify how the adoption of Industry 4.0 technologies relates to efficiency outcomes.

These methodological choices, along with the steps followed in the research process, are summarized in Figure 1 and further discussed in the following sections.

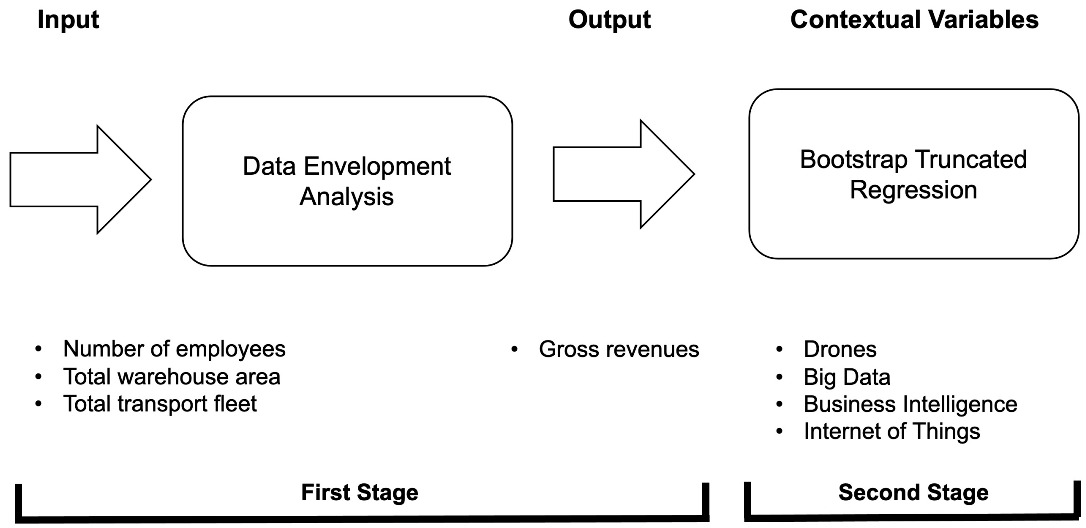

Figure 1. Model and research construction.

3.1. DEA models

DEA is an approach initially introduced by Charnes et al. (1978). This technique has attracted substantial attention from scholars in different fields (Cooper et al., 2011). DEA is based on linear programming and is used to calculate the relative efficiency of a group of business units, known as Decision-Making Units (DMUs), using multiple input and output measures. Given a set of DMUs, inputs, and outputs, DEA determines, for each DMU, an efficiency measure derived as a ratio of weighted outputs to weighted inputs. There are several variations of this technique, differing, for example, in terms of scale gains and how the distance of inefficient DMUs to the frontier is computed (Cook et al., 2014)

Consider $s=1..S$ production units with $x_s^T=(x_{s1},...,x_{sn})$ inputs and $y_s^T=(y_{s1},...,y_{sn})$ outputs. The column vectors x_s and constitute the s-th column of matrices X and Y. Furthermore, let $\lambda^T=(\lambda_1,...,\lambda_s)$ be a non-negative vector, and $e^T=(1,...,1)$ ò R^s be a vector of unit values. The DEA-CCR (Charnes et al., 1978) and DEA-BCC (Banker et al., 1984) models are represented by Equations 1 and 2.

$DEA-CCR$

$Input\,orientation$

$min_{\theta,\lambda}\theta$

$s.t.\theta x_s - X\lambda \geq 0$ (1)

$Y\lambda \geq y_s$

$$\lambda \geq 0$$

$$DEA - BCC$$

$$Input\ orientation$$

$$min_{\theta,\lambda}\theta$$

$$s.t.\theta x_s - X\lambda \geq 0 \quad (2)$$

$$Y\lambda \geq y_s$$

$$e\ \lambda = 1$$

One of the main advantages of DEA is that it does not require *a priori* specification of weights for inputs and outputs, unlike several multi-criteria decision-making methods (e.g., AHP, TOPSIS). Furthermore, in contrast to parametric methods such as Stochastic Frontier Analysis (SFA), DEA does not require assumptions about functional form or statistical distributions (Cook et al., 2014). In addition to providing efficiency measures, DEA under the variable returns to scale assumption - commonly referred to as the BCC model - offers other relevant information about inefficient DMUs. It identifies the efficient facet used for comparison, the combination of inputs inefficiently utilized, and the deviation of specific outputs from the efficient level. It is important to note that efficient DMUs typically do not exhibit any slack, which is only reported for inefficient DMUs (Cooper et al., 2007, 2011).

The scale inefficiency arises from the increase or decrease in scale returns, which can be determined by examining the sum of the weights according to the specifications of the CCR model. If this sum equals 1, the law of constant returns to scale prevails. However, if the sum is less than or greater than 1, respectively, increasing returns to scale or decreasing returns to scale prevail in the input-oriented model. Cooper et al. (2011) also emphasize that to identify how much inefficiency within a DMU is caused by conducting inefficient operations or by its scale size, the scale efficiency is defined by the following ratio (Equation 3):

$$SE = CCR / BCC \quad (3)$$

It's crucial to note that the maximum value of SE is 1, indicating that the DMU is operating at the most productive scale size.

3.2. Bootstrap Truncated Regression

This study employs the BTR method put forth by Simar & Wilson (2007), which has demonstrated superior efficacy compared to Tobit regression. Compared with a Monte Carlo experiment, this method yielded higher outcomes attributable to a reduction in statistical noise. Nevertheless, traditional two-step approaches lack a clearly defined data-generating mechanism (Simar & Wilson, 2007). The model that was tested takes the following form:

$$\theta_i = a + Z_j\delta + \varepsilon_j, j = 1, \ldots, n, \quad (4)$$

where θ_i denotes the *true* (but unobservable) efficiency score for each DMU, a is a constant, Z_j is the vector of contextual variables, δ is the vector of parameters associated with these variables, and ε_j is statistical noise. The distribution of ε_j is conditioned by the restriction $\varepsilon_j \geq 1 - a - Z_j\delta$.

Following Simar & Wilson (2011), it is assumed that the distribution is normal with zero mean and unknown variance. However, since θ_i is not directly observable, we replace it with the efficiency scores estimated by DEA. This leads to the following empirical model:

$$\hat{\theta}_i \approx a + Z_j\delta + \varepsilon_j, j = 1, \ldots, n. \quad (5)$$

where $\hat{\theta}_i$ represents the DEA-estimated efficiency score.

This formulation follows the approach proposed by Simar & Wilson (2007), recognizing the difference between the theoretical model (4) and its empirical counterpart (5).

$$\varepsilon_j \sim N\left(0, \sigma_\varepsilon^2\right), such\,that\, \varepsilon_j \geq a - Z_j \delta, j = 1, \ldots, n,, j = 1, \ldots, n. \quad (6)$$

The efficiency estimators were calculated using the maximum likelihood method given δ and σ_ε^2. Bootstrap consistent estimators were used to calculate confidence intervals for the estimates of δ and σ_ε^2 to at a given significance level. The algorithms used in the estimation of the parameters were deliberately omitted for the sake of brevity and can be found in Simar & Wilson (2007).

3.3. Input, output, and contextual variables

The variables used in this study were collected from *Revista Tecnologística's* special issues dedicated to 3PLs for 2019 and 2020. We used data from these periods as they are the most recently available in the database. The survey of these data has been conducted annually since 2000, ensuring robust and consistent data collection and guaranteeing the quality and reliability of the information. Additionally, it is worth noting that the number of respondents was representative of the 3PL industry in Brazil, reinforcing the validity and generalizability of the findings. Although the dataset provided by *Revista Tecnologística* may not have been collected within the framework of a theoretical model, it model can still be identified and applied. This is mainly because the data include objective measures based on explicit criteria represented by metrics (inputs and outputs) and nominal scales (for most contextual variables). As single-item indicators of these objective measures, the data can be considered valid and reliable indicators of the variables. In addition, the reliability and applicability of this dataset are demonstrated by its use in previous academic studies, including those by Rodrigues et al. (2018), Wanke (2012), and Wanke & Affonso (2011) examined the 3PL performance. Although these aspects ensured the validity of the dataset, data limitations were also considered in our analysis.

After refining the original database, the final sample comprised of 38 observations, representing the maximum number of cases available. Three inputs and one output, widely recognized in 3PL research, were selected for DEA modeling based on their relevance in the literature (Cooper et al., 2011). DEA is particularly well-suited for small sample sizes, as its non-parametric nature does not require assumptions about statistical distributions (Bogetoft & Otto, 2011; Cooper et al., 2007). Moreover, previous studies have successfully applied DEA with similarly limited samples, demonstrating its effectiveness in identifying efficiency patterns and areas for improvement, even with constrained datasets (Marchetti & Wanke, 2017; Wanke & Barros, 2016; Wanke, 2012; Yang et al., 2024).

In terms of inputs, the 3PL's total number of staff members involved in either strategic or operational activities is the measure used to represent labor force utilization (Min et al., 2013; Wanke, 2012). Beyond this, a selection of measures is also necessary to translate how 3PLs handle warehousing (Wanke, 2012). In the Brazilian 3PL industry, warehousing services are more abundant than transportation services, highlighting the total owned warehouse area as an essential input for the model (Wanke, 2012). Recognizing the circumstances in which the 3PL manages the storage facility is crucial given the significant influence of modifications in storage procedures within the context of I4.0. The literature highlights the increased value of companies that adopt new technologies in this transformative process (Rodrigues et al., 2018). Finally, evaluating the overall transport fleet size is essential, as more efficient transportation methods drive market expansion and bolster profit margins. Transportation and warehousing are among the most frequently outsourced logistics functions, underscoring their centrality in 3PL operations (Rodrigues et al., 2018; Wanke, 2012). Incorporating these variables into the DEA model ensures a comprehensive assessment of the efficiency with which 3PLs utilize their fundamental operational resources. In terms of output, gross revenue is understood as a representation of the services delivered (Min et al., 2013; Wanke, 2012).

In the Brazilian context, I4.0 technologies are becoming increasingly vital to modern logistics operations. The rising demand for agility, transparency, and accuracy, along with growing supply chain complexity, presents a significant challenge for companies. However, these challenges are met by the opportunities offered by technological advancements. The Brazilian 3PL industry is progressing through various stages of technology adoption, with particular emphasis on technologies from the second cluster, such as Drones, BD, BI, and IoT. These technologies are essential for improving efficiency by enabling better decision making, real-time monitoring, and process optimization. As they are rapidly gaining traction and are expected to be standard in the short term, they represent a critical point of transition for 3PLs, helping them bridge the gap between traditional logistics management and more advanced digital solutions and ultimately enhancing operational capabilities and positioning companies for sustained competitiveness in an evolving logistics environment. These variables were used as regressors to identify the determinants of the SE of the Brazilian 3PLs.

Finally, free R software (version 3.2.2) and the rDEA package were used to calculate the efficiency scores for the classical DEA models. The package also allowed for the implementation of Simar & Wilson's (2007) algorithm using the BTR model (Simm & Besstremyannaya, 2020).

4. Data analysis and results discussion

The number of DMUs should surpass the larger value between the product of the number of inputs and outputs and three times the sum of the number of inputs and outputs (Cook et al., 2014). To enhance the discriminatory power of the DEA models, each 3PL-year combination was treated as an individual DMU, yielding a total of 38 DMUs. This methodology has been employed by some researchers (Rodrigues et al., 2018; Wanke, 2012).

To assess the potential reduction of variables considered in the analysis, correlation coefficients between the model's inputs and outputs were examined. Figure 2 shows the correlation coefficients between pairs of outputs. Given that the correlations between the sets are relatively low, all inputs were retained for the analysis.

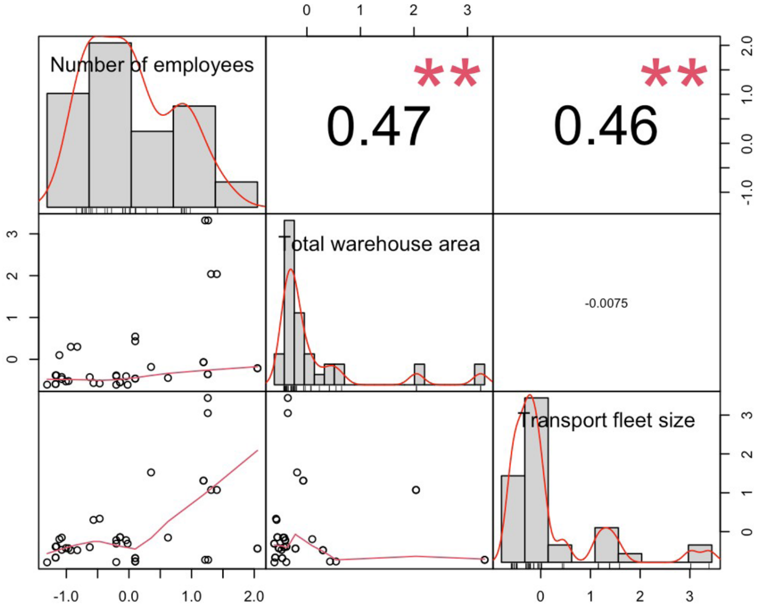

Figure 2. Correlation coefficient.
Note: * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

4.1. Efficiency, SE and RTS analysis

The DEA CCR and DEA BCC models were calibrated, as demonstrated in Table 2. A wide range of data dispersion is apparent, reflecting 3PL's varying operational scales.

The initial stage of the DEA model involved an analysis of the DEA CCR and DEA BCC efficiency models (Table 3). These models were oriented towards outputs, as the overall performance of 3PLs can be assessed through their financial outcomes (Min et al., 2013). Output orientation allows production to vary while keeping inputs constant. Hence, 3PLs strive to optimize their outputs within existing resource constraints to respond more effectively to demand. This entails answering the question: 'To what extent can a DMU's production (gross revenue) be increased proportionally without altering the quantity of inputs used (number of employees, warehouse area, and fleet)?' Table 3 presents the scale efficiencies (SE) and returns to scale (RTS) for each DMU in the sample.

Table 2. Data statistics - inputs and output.

	Input 1	Input 2	Input 3	Output
	Number of employees	Total warehouse area	Transport fleet size	Gross revenues
Minimum	38	14000	2	1650000
Median	1000	109500	19.5	101550000
Mean	1117.16	285229.32	376.76	200502026.32
Maximum	2812	1765000	2010	1500000000
Standard deviation	826.24	445706.63	474.69	265429319.21
DMUs = 38				

Table 3. Efficiency scores - DEA CCR and DEA BCC models, SE, $\sum(\lambda)$, and RTS.

DMU	CCR	BCC	SE	$\sum(\lambda)$	RTS	DMU	CCR	BCC	SE	$\sum(\lambda)$	RTS
1	0.358	0.367	0.976	0.355	Increasing	20	0.830	0.882	0.941	0.134	Increasing
2	0.973	1	0.973	1.759	Decreasing	21	1	1	1	1	Constant
3	0.536	0.597	0.897	0.216	Increasing	22	0.925	0.925	1	1	Constant
4	0.576	0.645	0.893	0.241	Increasing	23	0.131	0.131	0.999	0.944	Increasing
5	1	1	1	1	Constant	24	0.142	0.142	0.999	0.976	Increasing
6	0.568	0.620	0.916	0.347	Increasing	25	0.346	0.364	0.951	0.498	Increasing
7	0.389	0.484	0.804	2.099	Decreasing	26	0.214	0.225	0.951	0.498	Increasing
8	0.389	0.484	0.804	2.099	Decreasing	27	1	1	1	1	Constant
9	0.132	0.154	0.860	0.096	Increasing	28	0.736	0.736	1	1	Constant
10	0.147	0.177	0.832	0.082	Increasing	29	0.521	0.523	0.996	0.673	Increasing
11	1	1	1	1	Constant	30	0.489	0.491	0.996	0.706	Increasing
12	0.367	0.675	0.543	2.903	Decreasing	31	0.277	1	0.277	0.016	Increasing
13	0.367	0.675	0.543	2.903	Decreasing	32	0.042	0.05	0.854	0.094	Increasing
14	0.492	0.497	0.990	0.455	Increasing	33	0.415	0.419	0.990	0.890	Increasing
15	0.243	0.263	0.923	0.165	Increasing	34	0.672	0.674	0.996	1.025	Decreasing
16	0.331	0.351	0.941	0.205	Increasing	35	0.415	0.419	0.990	0.890	Increasing
17	0.292	0.326	0.898	1.756	Decreasing	36	0.708	0.714	0.992	0.880	Increasing
18	0.269	0.306	0.879	1.864	Decreasing	37	0.001	0.001	1	1	Constant
19	0.941	1	0.941	0.134	Increasing	38	1	1	1	1	Constant

The primary source of inefficiencies observed in 3PLs can be attributed to technically inefficient DMUs that exhibit increasing returns to scale, accounting for 57.89% of the analyzed DMUs. Within the logistics industry, many 3PLs demonstrate a high degree of inefficiency. The exponential increase in demand for logistics services in specific industry segments, driven by the growth in e-commerce and humanitarian logistics, can be attributed to the outbreak of the SARS-CoV-2 virus and the subsequent health crisis. Many shortcomings in the management of companies within the industry were identified during this period. These shortcomings were primarily a result of entrenched processes and insufficient logistical flexibility to accommodate the surge in demand (Rodrigues et al., 2018)

Table 4 presents the descriptive statistics derived from the results obtained using the DEA CCR, DEA BCC, and SE models. Substantial asymmetry is evident among the analyzed DMUs, with the minimum identified value being 0.001 and the maximum reaching 1. The CCR model revealed a low average efficiency of 0.506, indicating an overall inefficiency of 49.38%. Similarly, the BCC model identifies a low average efficiency of 0.561, representing an overall inefficiency of 43.9%. The average scale inefficiency is 9.09%, suggesting that managerial inefficiency surpasses scale inefficiency in both the models. Managerial inefficiency, distinct from scale inefficiency, highlights the inability of management to optimize resource utilization, pointing to opportunities for improvement in allocation and management. This finding aligns with those of Associação Brasileira de Operadores Logísticos (2023), which emphasizes the need for significant investments in the 3PL industry. Specifically, these investments should focus on technological innovation to reduce costs and enhance operational efficiency. Furthermore, there should be strong emphasis on capacity building among personnel within the industry, as it is crucial to address these inefficiencies.

Figure 3 represents the 5 DMUs with SE lower than the pure technical efficiency found in the DEA BCC model, which is located above the diagonal line in the graph. This result underscores the conclusion that management

Table 4. Descriptive Statistics - DEA CCR and DEA BCC scores and SE.

	DEA CCR	DEA BCC	SE
Average	0.506	0.561	0.909
Minimum	0.001	0.001	0.277
First quartile	0.281	0.332	0.894
Median	0.415	0.510	0.962
Third quartile	0.729	0.846	0.998
Maximum	1	1	1
% of inefficient DMUs	49.38%	43.90%	9.09%

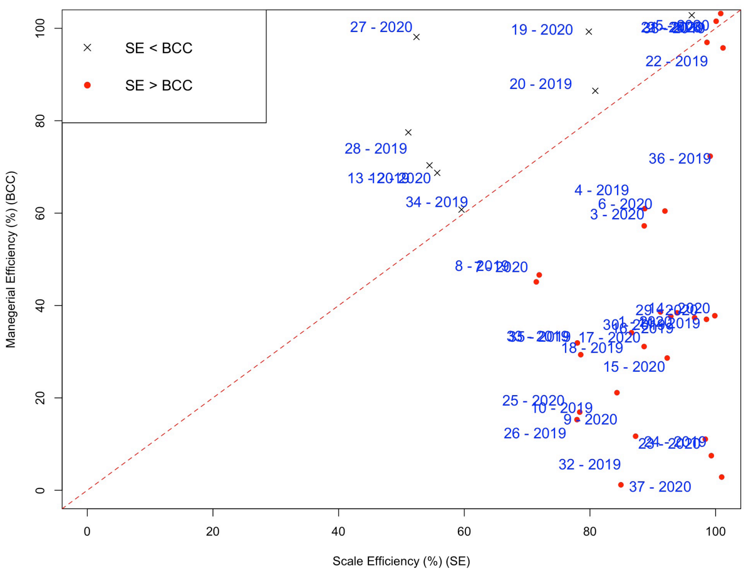

Figure 3. Pure Technical Efficiency (%) x Scale Efficiency (%).

inefficiency is more widespread than scale inefficiency in DMUs operations when attempting to explain the overall technical efficiency of the DMUs in the sample (28 DMUs below the diagonal line in the graph).

Only 13.1% of the DMUs (five DMUs) are located on the efficiency frontier of the DEA CCR model. These five DMUs are strongly efficient (vertex units) and thus serve as unique benchmarks for inefficient DMUs as they define the extreme points of the production possibility set under constant returns to scale. Their performance represents the best practices in the sample. These 3PLs specialize in transporting and storing products primarily from the automotive, parts, supplies, and beverage industry, conducting operations nationwide, predominantly in the southern and southeastern regions. On average, these companies have been active in the market for over 30 years and possess certifications that attest to their operational quality.

The efficiency frontier in the DEA BCC model, represented by convex linear combinations of the production possibilities set with variable returns of scale, comprises of 21% of the DMUs in the sample (eight DMUs). Among these eight DMUs, the same five CCR-efficient units are strongly efficient (vertex points), whereas the remaining three DMUs are weakly efficient (non-vertex points) under the BCC model. Although technically efficient, these three DMUs lie on the frontier owing to convex combinations under variable returns to scale and cannot act as unique benchmarks. Five DMUs garnered an efficiency score equal to one in the DEA CCR model, thus operating with an SE rated as optimum, and three DMUs were ranked as efficient in the DEA BCC model (albeit inefficient in the DEA CCR model) with a sub-optimum SE.

Figure 4 categorizes the 3PL based on their similar characteristics by conducting a combined analysis of the efficiency of the CCR results and the RTS of the DMUs in the sample (detailed in the Supplementary Material). The plotted points represent the efficiency scores in the CCR model on the y-axis and the RTS type of each DMU on the x-axis, where IRS is denoted in black, CRS in red, and DRS by blue. The groups are formed by considering the efficiency scores for the mean value and RTS type. Group E represents the benchmark 3PL for other inefficient DMU.

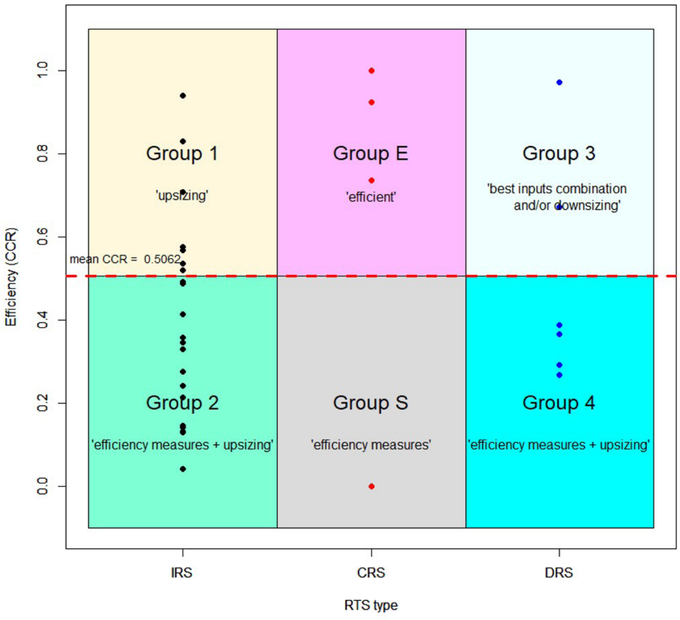

Figure 4. Efficiency x RTS type and similar 3PL groups (clusters).

These findings indicate that managers should adopt a specific set of objectives for each efficiency cluster that categorizes 3PLs based on their similar performance in terms of overall technical efficiency, SE, and RTS. The objectives are detailed below. The first group, referred to as "upsizing," is characterized by efficiency above the mean and IRS. This group requires increased inputs, such as the number of employees, total warehouse area, transport fleet size, and operating assets, to expand their activities. In contrast, the second group, "efficiency measures and/or upsizing," has efficiency below the mean and IRS. To improve their performance, this group needs to enhance their management practices (specifically, production management) and track infrastructure upgrades to boost asset turnover. In addition, they should consider expanding their new inputs and operating assets. It is worth noting that more than individual measures are needed to effectively address the various sources of inefficiency. In its turn, the third group, labeled as "combination of best inputs and/or downsizing," exhibits efficiency above the mean and DRS. To optimize their performance, this group should take steps to reduce inputs and/or achieve a more balanced combination of inputs, particularly for more efficient members. The fourth group ("efficiency measures and/or downsizing") has efficiency below the mean and DRS. Collaborative efforts are required to improve management practices, track infrastructure upgrades, and decrease input.

Despite operating at an optimal scale, Group S ("efficiency measures") still demonstrates technical inefficiency. This implies that it is possible to reduce input usage while maintaining the same production level or, alternatively, to increase production using the same inputs. By eliminating technical inefficiencies, DMUs can achieve efficiency with constant return. Group E ("efficient") consists of three 3PLs that serve as benchmarks for others. This group is less reliant on incentives, in terms of the scale of their activities, as they already possess better management practices and track infrastructure upgrades. However, discussion regarding incentives to sustain activities at a pace that matches rising demand remains a topic of consideration.

The results suggest that DMUs in Groups II and V, and Group S, with efficiencies below the mean, are most exposed to competitive pressures and the arrival of more efficient new 3PLs.

4.2. Significance of contextual variables on DMU's efficiency

The inefficiencies observed in 3PLs predominantly arise from technically inefficient DMUs that demonstrate increasing returns to scale, accounting for 57.89% of the analyzed DMUs. To identify the determinants of efficiency among 3PLs in Brazil, an investigation was conducted on technologies 4.0 employed by companies using the *Revista Tecnologística* database. These determinants serve as control variables in this study, representing attributes rather than inputs or outputs for operational processes.

The binary control variables were the Drones, BD, BI, and the IoT. These variables have a value 1 when the technology is present and 0 otherwise. Recognizing the need for k - 1 dummy variables to represent a variable with k categories (Gujarati, 2021), the base category is the absence of this characteristic.

Table 5 shows the regression coefficients and significance levels for contextual variables, with a confidence interval of 95% and a set of 2000 resampling iterations, a suitable value according to Simar and Wilson (2007), for constructing confidence intervals in the BTR. The interpretation of the results relies on confidence intervals to deduce parameter significance. For example, suppose alpha is 0.05, and the value of 0 is not within the confidence interval. In this case, the bootstrap samples suggest that the coefficient for the specific environmental variable is significant at the 0.05 (alpha) level. In this analysis, a positive regression coefficient indicates that the variable negatively impacts scale efficiency, whereas a negative coefficient indicates a positive impact (Balcombe et al., 2008).

Table 5. Coefficients and confidence interval (5%) of the BTR - constant RTS.

Coefficients	Value	Low limit (2.5%)	Upper limit (97.5%)
(Intercept)	-28.102	-56.370	-54.318*
Drones	-6.671	-13.669	-11.931*
BD	-3.969	-8.323	-6.723*
BI	-16.396	-32.426	-30.223*
IoT	6.081	11.114	12.809*

Note: *significant.

The BCC model was used to analyze the BTR results. This model allows for a more equitable comparison considering small DMUs with increasing returns and large DMUs with decreasing returns to scale. When considering the variable returns to scale, Table 5 shows that all contextual variables analyzed hold significance in the efficiency scores of the DMUs. Drones, BD, and BI are positively correlated with the scale efficiency of DMUs, whereas the IoT variable demonstrates a negative association.

Consistent with the literature (Abdel-Basset et al., 2021; Maghazei et al., 2022), drones positively impact the firm efficiency (-6.671*). The benefits of using drones are linked to their key role in Logistics 4.0. They allow companies to deliver more quickly and efficiently, which is crucial given the growing demand for e-commerce. Drones also enable rapid responses when delivering spare parts and help reach remote or hard-to-access locations (Abdel-Basset et al., 2021). Additionally, drones facilitate asset inspection, maintenance, and inventory management, thereby improving operational efficiency and safety (Javaid et al., 2022). Furthermore, their use offers benefits in terms of warehouse digitalization. This includes improving storage processes by monitoring conditions, identifying and retrieving hard-to-reach products, and assisting employees in navigating warehouse spaces (Maghazei et al., 2022).

We found a positive impact of utilizing BD (-3.969*), which is consistent with the study by Fosso Wamba et al. (2015). This indicates that BD has the potential to revolutionize management practices by transforming processes and enabling innovation, leading to increased efficiency in various operational and strategic business issues. This can be explained by the considerable number of data companies manage within the context of I4.0. The integration of BD offers numerous opportunities to enhance logistics processes. Companies can store delivery data, identify patterns, and improve their efficiency improvements. Moreover, when combined with predictive analysis, BD allows companies to anticipate issues, optimize delivery routes, enhance the quality of perishable goods transportation, and facilitate warehouse automation through the implementation of smart autonomous systems that manage significant data flows (Rajnoha & Hadač, 2024).

The results indicate a positive impact (-16.396*) of BI on the efficiency of 3PLs. This is consistent with the work by Chen et al. (2023), BI serves as a cornerstone for organizations seeking to streamline operations, enhance decision-making, and drive sustainable growth in the current data-driven business landscape. BI systems analyze large datasets to extract valuable insights, allowing organizations to make informed decisions quickly and accurately (Chen et al., 2023; Singh et al., 2024). By implementing BI solutions, companies can improve processes, monitor operations, and ensure real-time data availability for informed decision making (Chen et al., 2023). Furthermore, organizations can better meet customer needs by leveraging BI to understand consumer behavior, preferences, and trends, leading to more personalized products and services (Singh et al., 2024).

On the other hand, we found a negative impact (6.081*) associated with using the IoT, which contradicts much of the prevailing literature. Concerns over privacy and security are central to this contradiction (Rajnoha & Hadač, 2024). IoT involves interconnected devices that continually collect, share, and store data. However, the data involved often include sensitive information and privacy risks. Moreover, security vulnerabilities can open the door to cyberattacks, allowing malicious actors to infiltrate seemingly harmless devices such as batteries and use them as entry points to access increasingly restricted data throughout the network (Azadi et al., 2023).

Additionally, the implementation of IoT in Brazil is still at a nascent stage (Associação Brasileira de Operadores Logísticos, 2023). One of the main hurdles in adopting new technologies is the high acquisition costs during the initial phase. Regulatory barriers in Brazil also pose a significant challenge by delaying the rollout of IoT technologies in the country. The data analyzed in this research refers to 3PLs operations from 2019 to 2020, pointing to the relatively recent emergence of the IoT concept in the country. An example that supports this is the establishment of the '*Plano Nacional de Internet das Coisas*' in 2019 through Decree No. 9.854 to guide the development of machine-to-machine communication systems and the IoT infrastructure (Brasil, 2019). Only in 2020, *Agência Nacional de Telecomunicações* (ANATEL) take steps to ease regulatory constraints for IoT (Brasil, 2020). These developments point to the early stage of IoT implementation in Brazil, which probably influenced the operations of the 3PLs during the research period.

4.3. Discussion

The results of the model demonstrated the impact of adopting I4.0 technologies on the logistics efficiency of 38 Brazilian 3PLs, and this impact can offer opportunities for innovation and promote competitive growth (Azadi et al., 2023; Fosso Wamba et al., 2015). This study also revealed substantial room for improvement, particularly regarding technical efficiency, as both the CCR and BCC models indicated a high average inefficiency. Based on Panayides et al. (2009), 3PLs require continuous innovation to sustain their competitive edge.

However, confidence interval analysis using BTR highlighted that contextual variables as Drones, BD, and BI positively impacted the efficiency of DMUs, whereas IoT had a negative impact. These findings partially contribute to Chen et al., (2023), and Rajnoha & Hadač, (2024). These authors state that BI is relevant in the I4.0 context, such as BD and IoT.

We also find that adopting I4.0 technologies in 3PL is becoming increasingly critical because of their perceived benefits and potential to further optimize logistics processes. However, these technologies are still in their early stages, as demonstrated by the negative impact of the IoT on efficiency, indicating the need for further conceptual and technical developments. As stated by Raj et al. (2020), the main challenge to adopting I4.0 technologies is the lack of financial resources.

Corroborating with Ivanov et al., (2018), Rosin et al., (2020), and Tran et al., (2023) these findings suggest that incorporating I4.0 technologies, when combined with effective management, can significantly enhance the efficiency of 3PLs. However, these technologies must be used effectively to ensure that their costs are within their limits.

4.4. Managerial implications

The growing competitiveness of the 3PL industry necessitates continuous improvements in operational efficiency to sustain market relevance. This study offers actionable insights for both 3PL providers and shippers by outlining a strategic roadmap for decision-making in the context of I4.0. For 3PL managers, these findings provide a valuable reference for prioritizing technology investments and refining service portfolios. The efficiency benchmarks established herein enable self-assessments by comparing firm-specific performance with industry averages (see Tables 3 and 4). These insights are particularly useful when considering growth strategies, whether through organic expansion or mergers and acquisitions.

The classification of 3PLs into distinct efficiency clusters (see Figure 4) has several managerial implications. Firms operating under increasing returns to scale may benefit from strategic upsizing supported by digital tools that enhance scalability. Firms exhibiting inefficiency (yet operating at a suboptimal scale) should prioritize improvements in production management and infrastructure, leveraging predictive analytics, and digital monitoring. Conversely, firms with decreasing returns to scale should focus on input rationalization. Even those operating at the optimal scale but with technical inefficiencies can benefit from continuous process improvement. In turn, benchmark firms should aim to sustain their advantages through the ongoing integration of emerging technologies and process innovation. These differentiated strategies emphasize the importance of aligning technological adoption with the operational maturity and efficiency profile of each 3PL provider.

Regarding I4.0 technologies, drones can be deployed for inventory management within distribution centers and predictive monitoring of logistics assets, including storage conditions and fleet inspection. BD Analytics supports dynamic route optimization by integrating data on traffic, fuel consumption, and delivery history.

BI tools—such as real-time KPI dashboards—enhance operational visibility. The adoption of IoT technologies requires a cautious approach, starting with pilot projects focused on noncritical assets, cost-efficient "as-a-service" models, and robust cybersecurity training programs.

These recommendations should be tailored according to the efficiency profiles identified in this study. Firms in Clusters I–II (Increasing Returns to Scale) may gain more from investments in drones and BD as enablers of expansion, whereas those in Clusters III–IV (Decreasing Returns to Scale) should prioritize BI tools to optimize asset utilization. Benchmark firms (Cluster E) are well positioned to explore emerging technologies to maintain their competitive edge. These strategies are consistent with the Instituto de Logistica e Supply Chain (2024), which highlights the underutilization of analytics (only 32% adoption) and drones (15%) among Brazilian logistics companies, signaling significant opportunities for early adopters.

The empirical findings of this study provide shippers with a robust framework to evaluate and select 3PL providers. Although the analysis does not establish direct causal relationships between scale efficiency, operational costs, and service levels, the significant positive associations between specific I4.0 technologies (drones, BD analytics, and BI) and scale efficiency scores suggest an important indirect linkage.

5. Conclusion

This study demonstrates how the adoption of I4.0 technology influences the logistics efficiency of Brazilian 3PL. The study indicated that incorporating I4.0 technologies, when effectively managed, can lead to substantial improvements in the efficiency of 3PLs. Drones, BD, and BI had positive effects on the efficiency of 3PLs. These technologies facilitate better data management, real-time tracking, and improved decision making, which are crucial for enhancing logistics performance. Regarding the IoT, interestingly, while many I4.0 technologies are beneficial, the study found that the IoT has a negative impact on efficiency. This indicates that despite its potential, IoT technologies may still be in their early stages of implementation or may not be fully optimized within the Brazilian 3PL context.

The contributions of this study are threefold. First, the results corroborate evidence that I4.0 technologies in the SC may favor an operation that is close to the most productive scale size (Wanke, 2012). Second, it expands the research that applies the DEA model to analyze the efficiency of companies in the 3PL industry (Rodrigues et al., 2018). Third, exploring Brazilian 3PLs, contributes to the understanding of the unique specificities of emergent economies. While mainstream research focuses on the relationships between efficiency and I4.0 technologies mostly in developed contexts such as the United States or European countries, this paper provides different realities and challenges in adopting I4.0 technologies in developing contexts. This study provides valuable insights for practitioners in the logistics industry, guiding them in decisions related to the adoption of I4.0 technologies. This emphasizes the need to understand the impact of these technologies to improve efficiency and resource management.

Regarding limitations, it is worth noting that this study used secondary data from *Revista Tecnologística*. Based on our findings, future research could explore the relationships between I4.0 technologies and efficiency by collecting and analyzing the primary data of 3PLs. Qualitative research may help uncover the underlying aspects of I4.0 and efficiency in a complementary manner. Although we recognize that the operational challenges and market dynamics of Brazilian companies may not apply directly to other regions with different economic and regulatory conditions, we believe that our findings can offer valuable insights for other similar settings (e.g., emerging economies). Therefore, we recognize the limitations in generalizing these results and suggest that future research should explore this topic in other countries or regions to validate and/or refine our findings. Additionally, our analysis is limited to the period covered in the dataset used (2019-2020) and to the firms involved in the research. Future studies should adopt a longer timeframe to understand this phenomenon longitudinally and use a larger sample size to enhance the generalizability of the results. Furthermore, research avenues include incorporating other contextual variables, which could help identify factors affecting efficiency. Additionally, while binary indicators capture the presence of technologies, they do not account for heterogeneity in scale, quality, or operational costs. Future studies could improve this approach by incorporating quantitative measures to assess their impact on efficiency better. Finally, studies could segment 3PLs by type (e.g., different areas of operation) to provide insights into the potential unique challenges that each group may face.

As an additional reflection, it is worth noting that *Revista Tecnologistica*'s data collection was in progress when the Covid-19 pandemic hit. Therefore, our findings may have been influenced by profound changes brought about by the pandemic worldwide. In particular, the importance of the 3PL industry has increased significantly, given the increase in online shopping due to lockdown measures, as highlighted by works such as Kumawat (2024). Although we were not able to capture and measure such an impact, we believe that our findings remain valid and relevant to the contemporary reality of Brazilian 3PLs (post-pandemic), given that the industry has continuously faced ongoing uncertainties and challenges, leading to technology adoption to improve efficiency. Future research could investigate the Covid-19 effect of on the 3PLs technology adoption.

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Data availability

Research data is only available upon request.

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Supplementary Material

Supplementary material accompanies this paper.

Supplementary Material – DEA Concepts and Returns to Scale Classification

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