

Article

Port Intelligent Transformation and Regional Economic Sustainability: Evidence from the Yangtze River Delta, China

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Abstract

The intelligent transformation of ports has become a critical pathway for advancing sustainable regional development in the context of rapid globalization and digitalization. While existing studies primarily focus on evaluating port intelligence, limited attention has been given to its role in fostering regional economic sustainability. To address this gap, this study examines the Yangtze River Delta (YRD) region as a representative case to explore the mechanisms through which port intelligent upgrading influences regional economic systems. An integrated analytical framework is developed in which the Analytic Hierarchy Process (AHP) is used to construct a composite index of port intelligence, and Principal Component Analysis (PCA) is employed to measure regional economic development. Furthermore, a Panel Vector Autoregression (PVAR) model is applied to capture the dynamic interactions between these two systems. The results indicate that port intelligence has increased significantly across the sampled ports, with the Port of Shanghai and the Port of Ningbo–Zhoushan exhibiting particularly notable growth, rising by 28% and 44%, respectively, over the period of 2011–2021. The PVAR results further reveal a sustained upward trend in regional economic development, suggesting a positive and persistent association between port intelligence and regional economic performance. These findings provide both theoretical and empirical support for understanding the role of port intelligent transformation in promoting regional economic sustainability and offer policy-relevant insights for fostering coordinated development between port systems and regional economies.

Keywords: port intelligent transformation; regional economic development; Yangtze River Delta; Panel Vector Autoregression



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1. Introduction

With the continued expansion of economic globalization, ports have become increasingly important nodes within global logistics and supply chain networks [1]. Maritime transport remains the dominant mode of international freight movement, supporting the large-scale circulation of bulk commodities and long-distance cargo flows [2]. In value terms, nearly half of global trade is transported by sea, making port efficiency closely linked to supply chain resilience and regional economic competitiveness [3].

At the same time, growing operational complexity and competitive pressure are accelerating the digital transformation of port systems. Technologies such as the Internet of Things (IoT), artificial intelligence (AI), and 5G are increasingly being integrated into port operations, promoting the development of intelligent ports as an important strategic

direction for the maritime industry [4]. Evidence from major Chinese ports, including Qingdao Port and Shanghai Port, shows that intelligent and automated systems can improve operational efficiency, shorten vessel turnaround time, and optimize resource allocation. Against this background, evaluating the level of port intelligence and examining its relationship with regional economic development have become issues of growing theoretical and practical significance. Such research can support more efficient resource allocation, evidence-based policymaking, and sustainable regional economic growth.

Early studies on the relationship between ports and regional economies mainly focused on the economic effects of port infrastructure investment and cargo throughput, together with their spatial spillover effects. Song and van Geenhuizen [5], for example, used a production function approach to demonstrate the positive contribution of port investment to regional economic growth in China. Bottasso et al. [6] further employed spatial econometric models to estimate both local and spillover effects generated by ports. However, these studies also present several limitations. Most focus primarily on seaports and rely on symmetric spatial weight matrices, which do not adequately capture the heterogeneous relationships between ports and their hinterland regions. As a result, differences in economic scale, geographical conditions, and functional roles are often overlooked [7]. Existing studies therefore remain limited in explaining the spatial boundaries of port-driven economic benefits and the uneven development patterns among regions.

To address these limitations, more recent research has shifted from viewing ports as isolated growth poles toward examining broader regional integration processes. Concepts such as port regionalization and port–region symbiosis have consequently received increasing attention. Notteboom and Rodrigue [8] argue that port competitiveness increasingly depends on integration with inland logistics networks rather than on port performance alone. Similarly, studies on Australian regional ports emphasize the mutual dependence between ports and regional development, suggesting that ports should play more active roles in regional planning, innovation, and governance [9]. Although these perspectives improve understanding of port–regional interactions, important gaps remain. Existing studies still lack effective analytical frameworks for dealing with governance complexity in regional port systems. In addition, while the strategic importance of ports has been widely acknowledged, quantitative approaches for evaluating their broader economic contributions remain relatively limited. This constrains the ability of current research to support coordinated regional policymaking and investment decisions.

Recent studies have increasingly examined how digital technologies and the digital economy influence port development and regional economic systems. Advanced econometric approaches have been widely adopted to explore these relationships. Zhao et al. [10], for instance, use a Spatial Durbin Model (SDM) and mediation analysis to show that the digital economy improves port resilience in the Bohai Rim region by enhancing innovation capacity, optimizing industrial structures, and improving resource allocation efficiency while also generating positive spatial spillover effects. Despite these advances, most existing studies still treat port performance as a one-directional outcome of digitalization. The dynamic and reciprocal interactions between port intelligent transformation and regional economic development have received far less attention. Moreover, regional heterogeneity and long-term feedback effects remain insufficiently explored. These gaps highlight the need for a more integrated analytical framework capable of capturing dynamic interactions over time.

Against this background, this study investigates the relationship between port intelligent transformation and regional economic development in the Yangtze River Delta (YRD). An integrated analytical framework combining the Analytic Hierarchy Process (AHP), Principal Component Analysis (PCA), and the Panel Vector Autoregression (PVAR)

model is developed. First, AHP is employed to construct a composite index measuring port intelligence across multiple dimensions. Second, PCA is used to evaluate regional economic development. Finally, the PVAR model is applied to examine the dynamic and bidirectional relationship between port smartization and regional economic performance.

This study contributes to the existing literature in three main aspects. First, it extends previous research by explicitly linking port intelligent transformation with regional economic sustainability. Second, it provides empirical evidence on the dynamic interaction between smart ports and regional economies. Third, it combines multi-criteria evaluation methods with dynamic econometric analysis, offering a structured analytical framework for future studies on port digitalization and regional development. Due to data limitations, the analysis mainly focuses on dynamic associations rather than strict causal identification.

The remainder of this paper is organized as follows: Section 2 reviews the relevant literature. Section 3 introduces the research methodology. Section 4 presents the results and discussion. Section 5 concludes this study and suggests further research.

2. Literature Review

This section presents a systematic review of the extant literature on the relationship between ports and regional economies, with a particular focus on the construction of port intelligence evaluation indicators and the dynamic interactions between port development and regional economic growth.

2.1. Port Intelligence Evaluation Indicators

In the context of multidimensional comprehensive evaluation, scholars have developed systematic frameworks to holistically capture the overall developmental level of ports, thereby providing a robust analytical basis for port governance and strategic decision-making. Praharsi et al. [11], in their study of Indonesian ports, integrated the four perspectives of the Balanced Scorecard (BSC)—financial, customer, internal process, and learning and growth—with external macro-environmental factors derived from a PESTLE (political, economic, social, technological, legal, environmental) framework. Through three iterative rounds of the Delphi method, they distilled 114 effective indicators from an initial set of 127, resulting in a comprehensive index system encompassing ten dimensions: financial, customer, internal business processes, learning and growth, political, economic, social, technological, legal, and environmental. Rezaei et al. [12], from the perspective of port selection, employed the Best–Worst Method (BWM) to assign weights to 17 indicators spanning maritime, port, and inland segments. Their findings indicate that transportation cost and time carry dominant weights, while qualitative indicators such as satisfaction, reputation, and flexibility also exert substantial influence, thereby bridging traditional performance evaluation with user-oriented decision-making behavior. Alharbi et al. [13] proposed an evaluation methodology grounded in partial order set theory (LAPOS). This approach utilizes Hasse diagrams to reveal incomparability relationships among ports, enabling decision-makers to accommodate genuine multi-criteria trade-offs rather than imposing a forced ranking structure.

Regarding evaluation methodologies for port intelligence, both domestic and international studies have extensively employed multi-criteria decision analysis (MCDA) approaches and hybrid modeling frameworks to enhance the methodological rigor and practical applicability of evaluation indicator systems. Rodriguez Estevez et al. [14], focusing on dry ports in Spain, developed Smart Dry Port (SDP) indicators encompassing four principal dimensions—operations and economics, social aspects, institutional and political factors, and environmental considerations—and determined the weights of individual indicators using the Delphi method. Philipp [15] further proposed the Digital

Readiness Index for Ports (DRIP), adopting a maturity model framework that incorporates five dimensions—management, human capital, technology, information, among others—comprising 38 indicators to systematically assess the level of port intelligence. Makkawan and Muangpan [16], taking the Eastern Economic Corridor of Thailand as a case study, employed a triangulation-based research design integrating literature review, participatory observation, and in-depth interviews to identify 29 indicators across three key domains: smart port operations, smart port environment, and smart port safety. From a methodological perspective, Rodrigo Gonzalez et al. [17] utilized the Delphi method to construct a Smart Port Index for the Spanish port system and determined indicator weights using a hybrid AHP-Entropy framework. Chen et al. [18] applied the Interpretive Structural Model (ISM) to analyze the key determinants of green and smart port development, concluding that digital and intelligent technologies function as foundational enablers for achieving sustainable port development.

In the context of sustainable development, ports are increasingly conceptualized as complex socio-technical systems that necessitate a balanced integration of economic performance and ecological impacts. Accordingly, the construction of indicator systems in this domain is intended to provide a robust analytical foundation for environmental regulation, green technology investment, and the evaluation of emission reduction performance. In a comprehensive review of green port assessment methodologies, Fei et al. [19] systematically examined studies spanning the period from 2009 to 2024, highlighting a predominant emphasis on environmental performance metrics. Typical indicators identified in the literature include greenhouse gas and pollutant emissions, energy consumption structures and efficiency, waste and wastewater management, the utilization of water and land resources, and noise pollution control. Methodologically, Data Envelopment Analysis (DEA), widely employed for efficiency benchmarking, and the Analytic Hierarchy Process (AHP), primarily used for determining indicator weights, constitute the principal analytical tools within this body of research.

Beyond environmental indicator construction, recent studies also clarify the operational channels through which intelligent transformation can support sustainable shipping. AI-assisted berth allocation, yard scheduling, and vessel traffic coordination can reduce waiting time, idling, and unnecessary equipment movements, thereby lowering fuel consumption and emissions during port calls [1,2]. Smart shore-power systems, digital energy management, and sensor-based monitoring further enable ports to shift energy use from shipborne auxiliary engines to cleaner grid electricity and to track emissions performance in real time. In this sense, port intelligence is not only a technological upgrading process but also a governance mechanism for linking operational efficiency with carbon reduction, resource conservation, and regional environmental sustainability [18,19].

In summary, research on port intelligence evaluation has evolved from the establishment of comprehensive performance assessment frameworks toward the development of specialized measurement systems that capture the distinctive features of smart transformation. Scholars have progressively constructed a systematic quantitative assessment toolkit through the integration of multidimensional modeling approaches and the development of digital readiness indices. The application of diverse methodologies, such as the Analytic Hierarchy Process (AHP) and Interpretive Structural Modeling (ISM), for determining indicator weights enables a more precise and fine-grained measurement of the progression of port intelligence [18].

2.2. Relationship Between Ports and Regional Economics

From the perspective of port–regional economic interactions, early studies primarily focused on developing quantifiable assessment frameworks to measure both the direct and

indirect contributions of port activities to regional economic performance. Research during this phase predominantly employed input-output analysis, characterized by its method of differentiating among “port-essential industries,” “port-attracted industries,” and “port-induced industries.” This approach aimed to precisely calculate the multiplier effects of port operations and associated industrial clusters on output, employment, and income [20,21]. As illustrated by Santos et al.’s [20] case study of the Port of Lisbon, while this methodology effectively reveals the significant economic contribution of ports to adjacent regions, it also reveals limitations, including difficulties in data acquisition, reliance on surveys, and challenges in conducting cross-regional comparisons. To address these issues, researchers began integrating top-down statistical data with bottom-up survey methods and attempted to establish unified industrial classification systems [20]. Nonetheless, much of this research treats the port as a relatively independent industrial sector, emphasizing static economic impact analysis while offering insufficient exploration of the complex, dynamic causal relationships between ports and regional economies.

Subsequent research has accordingly shifted its focus toward the dynamic and complex nature of port-regional economic interactions, recognizing that their underlying mechanisms evolve alongside the intelligentization of ports. On the one hand, ports are widely acknowledged as pivotal engines of regional economic growth, primarily by reducing transportation costs, facilitating trade flows, and fostering industrial agglomeration [6]. However, subsequent studies provide more nuanced insights that challenge this linear and deterministic narrative. For instance, Deng et al. [22], employing structural equation modeling across China’s five major port clusters, demonstrate that port supply does not exert a direct effect on regional economic growth. Instead, its influence is mediated through the stimulation of port demand, which in turn promotes value-added port activities and ultimately impacts the regional economy. Similarly, Song and van Geenhuizen [5] investigate the output elasticity of port investment, revealing substantial heterogeneity in its effects depending on regional economic structure, transport network connectivity, and port typology. Cong et al. [23], through panel data analysis of Chinese port cities, identify bidirectional Granger causality between port throughput and key urban economic indicators, such as GDP and industrial structure. This finding suggests the presence of a dynamic system characterized by mutual interaction and co-evolution, rather than a simplistic unidirectional relationship. Ferrari et al. [24] further substantiate this complexity by demonstrating that the employment effects of ports are mediated by governance structures and cargo composition. On the other hand, emerging evidence points to a gradual weakening of the traditional port-regional economic linkage. Jung [25], in a study of South Korean port cities, observes persistent economic underperformance in cities such as Busan and Incheon, suggesting that advanced port services do not necessarily translate into local economic prosperity. This decoupling of the “port-city interface” is attributed to multiple factors, including technological advancements in transport (e.g., containerization), industrial restructuring from manufacturing toward services, diminishing employment effects driven by the increasing capital intensity of port operations, and the growing prevalence of negative externalities such as congestion and environmental pollution.

Recent studies have increasingly emphasized the spatial dimension of ports’ economic impacts, acknowledging that the benefits generated by ports can extend to surrounding areas through complex network linkages, commonly referred to as spillover effects. Bottasso et al. [6], employing a spatial panel model, demonstrate that port activities not only exert positive effects on their host regions but also generate significant spatial spillovers to adjacent areas. Notably, these spillover effects may even exceed direct local impacts, thereby providing a theoretical basis for interregional collaborative development and cost-sharing mechanisms. Furthermore, the scope of research has expanded beyond conventional seaports to encompass

inland ports. Wu et al. [7], in their study of ports along the Yangtze River, demonstrate that the development of inland ports also produces substantial direct and spillover effects on both local and neighboring regions. Although the magnitude of these effects differs from that observed in seaports, the strategic importance of inland ports in fostering regional development remains considerable. Similarly, Mudronja et al. [26], in their analysis of European Union port regions, confirm that ports exert a positive influence on regional GDP and generate substantial spillover effects that benefit neighboring non-port areas.

Recent cluster-oriented studies further enrich this spatial perspective by shifting the unit of analysis from individual ports to inter-port networks and competitive groups. Li et al. [27] use network analysis of the Bohai Bay port cluster to show that regional coordinated development depends on the pattern of functional connections among ports, rather than on the capacity of a single hub alone. Cabral and Ramos [28], through a cluster analysis of Brazilian container ports, demonstrate that ports with similar competitive characteristics can be grouped according to operational scale, connectivity, and market positioning. These studies suggest that port intelligence should be evaluated together with regional network structure and cluster competitiveness, which is consistent with the present study's focus on the Yangtze River Delta port system [29].

In summary, scholarship on the port–regional economy nexus has undergone a pronounced paradigm shift, transitioning from static assessments of economic contributions toward a more rigorous examination of dynamic interaction mechanisms. Early contributions predominantly relied on input-output analytical frameworks to quantify the direct and indirect economic multipliers generated by port activities. Subsequent research has incorporated advanced econometric methodologies, including Structural Equation Modeling (SEM) and Panel Vector Autoregression (VAR) models, thereby elucidating complex bidirectional causal linkages and indirect transmission mechanisms between port activity and regional economic growth. This stream of research further suggests that structural factors, such as industrial upgrading, can catalyze the transformation of the traditional “port-city symbiosis” relationship. More recent studies have extended this line of inquiry by incorporating the spatial dimension, employing spatial econometric techniques to demonstrate that port development generates substantial spatial spillover effects across hinterlands and neighboring regions.

2.3. Summary

In summary, the extant literature has developed a relatively comprehensive analytical framework for evaluating port intelligence and has systematically elucidated the multifaceted interactions between ports and regional economic systems. However, a direct and empirically robust quantitative nexus between these two domains has yet to be rigorously established. Consequently, a rigorous investigation into the dynamic causal relationships and underlying mechanisms linking port intelligence levels with regional economic performance is essential for accurately capturing the substantive value of digital port transformation and for providing a sound theoretical underpinning for evidence-based policymaking. Accordingly, this line of inquiry constitutes the central research objective of the present study.

3. Methodology

This study proposes an integrated analytical framework to examine the relationship between port intelligence and regional economic development. The approach combines multi-criteria evaluation methods with econometric modeling, enabling both the measurement of key variables and the analysis of their dynamic interactions. The structure of the framework is presented in Figure 1.

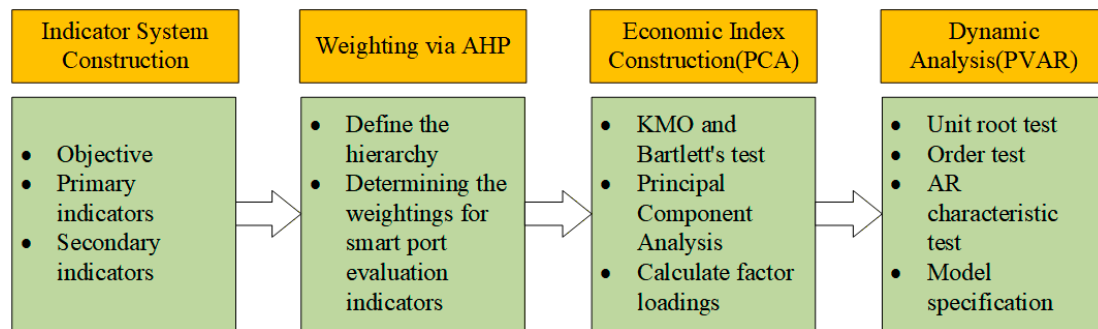


Figure 1. Methodology Framework.

3.1. Indicator System Construction

The multidimensional nature of port intelligence transformation introduces complex interdependencies among influencing factors, posing challenges for empirical analysis. The core task, therefore, is to construct an evaluation system that captures key features of port intelligence while remaining aligned with practical development needs. Drawing on prior studies and guided by the principles of representativeness, comprehensiveness, scientific rigor, and applicability, this study develops a three-tier evaluation system grounded in Port Ecosystem Theory, Port–City Interaction Theory, and Regional Growth Pole Theory. The system comprises three primary dimensions and seven secondary indicators, which is shown in Figure 2.

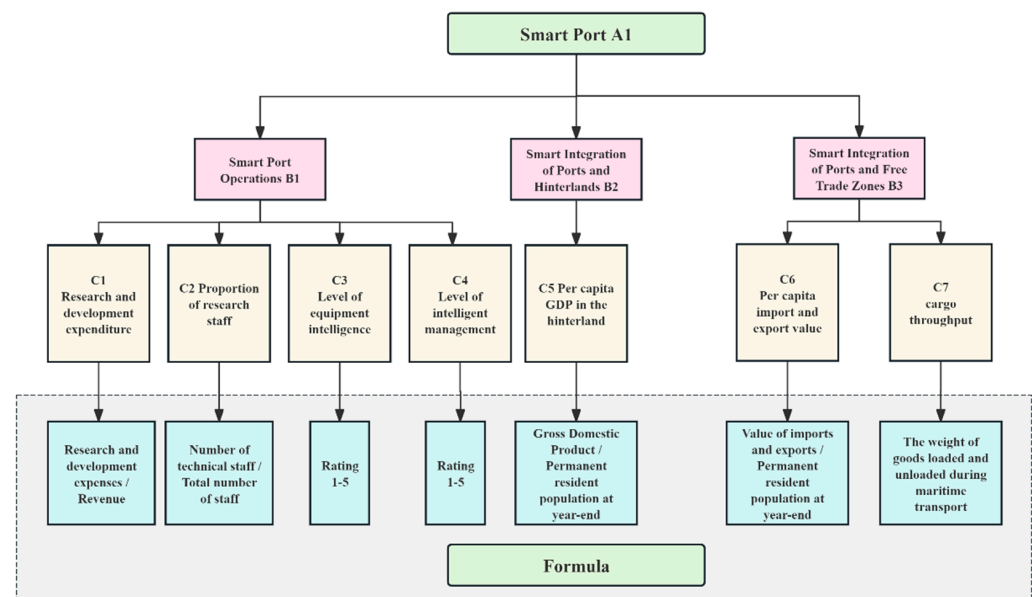


Figure 2. Port Intelligence Composition.

In this study, intelligent port transformation is defined as the transition from a digitally recorded port system to an adaptive, data-driven, and regionally connected port system. A traditionally digitized port mainly converts information, documents, and operational records into electronic form, whereas an intelligent port integrates sensing infrastructure, automated equipment, AI-assisted scheduling, real-time data platforms, green energy management, and inter-organizational coordination to support autonomous or semi-autonomous decision-making. Therefore, the proposed framework does not treat port intelligence as a single technology indicator. Instead, it conceptualizes smart-port development as a socio-technical transformation reflected in three linked dimensions: internal operational intelligence, port–hinterland integration, and port–free-trade zone integration.

Port Ecosystem Theory views ports as complex systems that extend beyond port operators to include hinterland economies and free-trade zones [30]. Port–City Interaction Theory emphasizes reciprocal relationships between ports and cities, while Regional Growth Pole Theory explains how policy-driven zones promote industrial concentration and spillovers [31]. Based on these theoretical perspectives, port intelligent transformation is conceptualized as a multi-level process involving coordinated development across ports, hinterland cities, and free-trade zones. Accordingly, three core dimensions are defined: intelligent port operations (B1), port–hinterland integration (B2), and port–free-trade zone integration (B3) [32].

At the operational level, port performance is closely related to infrastructure capacity, management efficiency, and digital investment [33]. This study therefore emphasizes efficiency-oriented indicators. Research funding (C1) reflects the intensity of technological innovation, while the proportion of research personnel (C2) indicates the capacity to adopt advanced technologies. Equipment intelligence (C3) improves operational efficiency and safety, and intelligent management (C4) supports data-driven decision-making. At the integration level, port–hinterland linkage is represented by hinterland economic strength (C5), measured by per capita GDP. Port–free-trade zone integration is captured by trade openness (C6), proxied by per capita import and export volume. Cargo throughput (C7) is included as a key indicator reflecting both port activity and its linkage with regional economic vitality [34]. Regional economic development is measured using three indicators: total economic output, economic structure, and logistics connectivity, as detailed in Table 1.

Table 1. Selection of Three Key Economic Indicators.

Indicators	Variable	Unit
Economic output	Regional GDP	100 million yuan
Economic structure	Percentage of regional GDP accounted for by the tertiary sector	%
Logistical accessibility	Maritime freight turnover	100 million tones

3.2. The AHP Model

Local GDP reflects the overall scale of economic development, while the share of the tertiary sector captures the structural characteristics of the economy. Waterborne freight turnover is used to represent the intensity of logistics interactions between ports and cities. The AHP model structures the evaluation system into three hierarchical levels: the objective level, representing the overall goal; the criterion level, consisting of key dimensions; and the indicator level, comprising measurable variables. This hierarchical structure facilitates systematic weighting and ensures consistency in evaluation (Figure 2).

The Analytic Hierarchy Process (AHP) is employed to determine the weights of the port intelligence indicators [35,36]. As a structured multi-criteria decision-making method, AHP enables the systematic evaluation of relative importance among indicators through pairwise comparisons and consistency verification. In this study, the previously constructed indicator system is organized into a three-level hierarchy, consisting of the objective level, criterion level, and indicator level. Pairwise comparison matrices are then established based on expert judgment to assess the relative importance of indicators within each level [37]. A nine-point scale is adopted to quantify the comparison results, where values from 1 to 9 (and their reciprocals) represent increasing degrees of importance. The weights of the indicators are derived from the normalized eigenvectors of the judgment matrices. Consistency tests are conducted to ensure the reliability of the comparisons. Specifically, the consistency ratio (CR) is calculated, and matrices with CR values below 0.10 are considered acceptable. When the consistency condition is not satisfied, the judgment matrix is revised accordingly. Through this procedure, the relative weights of all indicators are obtained, providing a

quantitative basis for the subsequent evaluation of port intelligence. The mathematical formulations of the model are presented and analyzed as follows:

Because the port intelligence index is intended to measure a multidimensional socio-technical transformation, AHP is theoretically appropriate for deriving indicator weights from a structured hierarchy rather than from the statistical dispersion of single variables alone. The selected indicators cover both directly measurable variables, such as R&D investment and cargo throughput, and judgment-based dimensions, such as equipment intelligence and intelligent management. For such mixed indicators, expert pairwise comparison can incorporate domain knowledge about functional importance, operational relevance, and logical relationships among dimensions. To improve reliability, this study aggregates pairwise comparisons from multiple experts, reports the dispersion of expert judgments, and applies the consistency ratio (CR) as a formal validity criterion; only matrices with CR values below 0.10 are accepted. Therefore, the AHP procedure provides a transparent and theoretically grounded basis for constructing the port intelligence index.

For the AHP procedure, a six-expert panel was used because the weighting task requires specialized judgment rather than population-level statistical inference. In Delphi/AHP-based evaluation, the key requirement is not a large random sample but whether the panel covers the main knowledge domains of the decision problem and whether the judgments are sufficiently consistent. In this study, the experts covered port operations, intelligent management, shipping logistics, port economy, regional economic planning, and transport policy, which provided practical judgment saturation for the indicator-weighting task. Their judgments were aggregated rather than used individually, and dispersion statistics together with the consistency ratio (CR) were used to assess whether the comparison matrices reached an acceptable level of agreement and reliability.

To protect anonymity while clarifying credibility, the expert panel is described by professional background rather than by personal identity. The panel included two specialists with port operation and intelligent management experience, two specialists with shipping logistics and port economy research backgrounds, and two specialists familiar with regional economic planning and transport policy. The final comparison values were obtained by aggregating valid pairwise-comparison judgments using the arithmetic mean; dispersion statistics were then reported to identify areas of agreement or disagreement before the consistency test was performed.

For each element at the subsequent level of the hierarchical structure, pairwise comparisons are conducted with the corresponding elements in the preceding level to which it is related, thereby constructing a series of decision matrices.

$$B = (\beta_{ij})_{m \times n} \quad (1)$$

where β_{ij} represents the relative importance of indicator B_i over indicator B_j with respect to their common parent indicator; β_{ji} represents the relative importance of indicator B_j over indicator B_i with respect to their common parent indicator, where $\beta_{ji} = \frac{1}{\beta_{ij}}$. The judgment matrix B represents the comparison results for all elements between these two levels.

In practice, the values of β_{ij} are typically determined based on scores assigned by experts in relevant fields. To avoid unnecessarily increasing the complexity of the assessment, a nine-point scale is adopted as the optimal approach. Specifically, the numbers 1–9 and their reciprocals are used to perform pairwise comparisons, thereby rating the relative importance of each factor within the system. The scale and its corresponding interpretations are presented in Table 2. The scoring criteria for the first- and second-level indicator layers are derived from the study entitled “Research on the Construction of an Evaluation Indicator System for Smart Ports in the Context of China’s Pilot Free Trade Zones” [38].

Table 2. Nine-point scale.

Scale	The Relative Importance of Row Factor i Compared to Column Factor j
1	Factor i is just as important as factor j.
3	Factor i is slightly more important than factor j.
5	Factor i is significantly more important than factor j.
7	Factor i is much more important than factor j.
9	Factor i is extremely more important than factor j.
2, 4, 6, 8	As an interpolation of the adjacent matrices above
Reciprocal of scales	If the comparison between factor i and factor j yields the result B_{ij} , then the comparison between factor j and factor i yields the result $B_{ji} = \frac{1}{B_{ij}}$

Let λ_{max} denote the maximum eigenvalue of the decision matrix B , and ω the corresponding eigenvector. The eigenvalues of the decision matrix B are then computed. After normalization, ω becomes the weight vector, representing the relative importance of elements at the same hierarchical level with respect to a specific element in the preceding level. Subsequently, the root mean square method is employed to calculate the weights.

Calculate the product M_i of each element in every row of the decision matrix B , that is:

$$M_i = \prod_{j=1}^n \beta_{ij} \quad (i, j = 1, 2, 3, \dots, n) \quad (2)$$

Compute the n th root $\bar{\omega}_i, \bar{\omega}_i = \sqrt[n]{M_i} \quad (i, j = 1, 2, 3, \dots, n)$

Perform positive normalization on the vectors $\bar{\omega}_r = (\omega_1, \omega_2, \omega_3, \dots, \omega_n), \omega_i = \omega_i / \sum \bar{\omega}$.

To compute the largest eigenvalue λ_{max} of matrix B , we have:

$$\lambda_{max} = \frac{1}{n} \sum_{i=1}^n \frac{(BW)_i}{\omega_i} \quad (3)$$

Here, $(BW)_i$ denotes the i -th element of the product of matrix B and vector W .

Owing to the complexity of objective phenomena and the ambiguity and diversity inherent in human judgment, the constructed judgment matrices cannot achieve complete consistency; therefore, a consistency check is required after the weights have been derived. When $\lambda_{max} = n$, the matrix is perfectly consistent; when $\lambda_{max} > n$, the matrix exhibits inconsistency. The consistency index is calculated as follows:

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad (4)$$

Here, λ_{max} is the largest eigenvalue, and n is the order of the judgment matrix.

The formula for calculating the random consistency ratio CR is:

$$CR = \frac{CI}{RI} \quad (5)$$

If the random consistency ratio $CR < 0.10$, the judgment matrix is deemed to exhibit acceptable consistency, and the resulting weight allocations are considered reasonable; otherwise, it indicates that the assessment of the relative importance of each indicator is unreliable, and the elements of the judgment matrix must be revised until acceptable consistency is attained. The corresponding values of the random consistency index RI are presented in Table 3.

Table 3. Comparison of Average Random Consistency Metrics.

Order	1	2	3	4	5	6	7	8	9	10
RI	0.00	0.00	0.52	0.89	1.12	1.26	1.36	1.41	1.46	1.49

Finally, the weights of the various evaluation indicators for smart ports are ranked.

$$\omega_{Indicators} = \omega_{Guidelines} \times \omega_{Indicators}' \quad (6)$$

3.3. Principal Component Analysis

Principal Component Analysis (PCA) is a statistical method whose core principle is to project the original n -dimensional data space onto a k -dimensional orthogonal basis through an orthogonal transformation. It transforms multiple correlated indicators into a smaller set of uncorrelated composite variables with minimal information loss, thereby simplifying the data structure, extracting essential features, and enhancing computational efficiency [39]. For this reason, PCA is adopted in this study.

PCA is used only for the measurement of regional economic development rather than for the construction of the port intelligence index. Its purpose is to synthesize three correlated regional economic indicators—local GDP, the share of the tertiary sector, and waterway freight turnover—into a composite economic development score. In this way, the regional economic variable used in the PVAR model is derived from the observed variance structure of the data, while the port intelligence variable remains based on the theoretically grounded AHP indicator system.

First, SPSS 26 software was employed to conduct the KMO and Bartlett's tests on the selected urban economic indicators to assess their suitability for principal component analysis. Based on the results of the KMO and Bartlett's tests, principal component analysis was subsequently conducted. The formula for the coefficient of determination is:

$$\eta_j = \frac{\lambda_j}{\sum_{i=1}^p \lambda_i} \quad (j = 1, 2, \dots, p) \quad (7)$$

The proportion of variance explained reflects the extent to which a given factor captures information from the original variables, i.e., its explanatory power. Here, the eigenvalue λ_j represents the variance in the j th principal component, thereby reflecting the amount of information embodied in that component.

Subsequently, the weights are calculated based on the proportion of variance explained by each variable relative to the total cumulative variance explained. Finally, the evaluation indicators are linearly weighted to compute the composite score representing the city's level of economic development.

$$\eta = \alpha \times \eta_1 + \beta \times \eta_2 + \varepsilon \times \eta_3 \quad (8)$$

Here, η represents the score for local economic development; α represents local GDP; β represents the percentage of GDP accounted for by the tertiary sector; and ε represents waterway freight turnover.

3.4. Panel Vector Autoregressive Model

To examine the dynamic interaction between port intelligence and regional economic development, a Panel Vector Autoregression (PVAR) model is employed. Unlike traditional regression models, the PVAR framework treats all variables as endogenous and captures their interdependencies over time [40,41]. Prior to estimation, panel unit root tests are conducted to ensure stationarity. Non-stationary series are transformed through first-order differencing where necessary. The optimal lag order is determined based on information criteria such as AIC and BIC. Model stability is verified using the characteristic root test.

The PVAR model is applied to a balanced panel dataset covering five port-city units in the Yangtze River Delta: Shanghai, Ningbo–Zhoushan, Hangzhou, Nantong, and Taizhou. The observation period extends from 2011 to 2021, producing a panel structure with five

cross-sectional units ($N = 5$), eleven annual periods ($T = 11$), and 55 total observations. This data structure allows the model to capture dynamic interactions between port intelligence and regional economic development across the YRD port system.

Based on the estimated PVAR model, three types of dynamic analyses are conducted. First, Granger causality tests are applied to examine the direction of influence between port intelligence and regional economic development. Second, impulse response functions (IRFs) are used to trace the response of one variable to shocks in another over time. Third, variance decomposition is performed to evaluate the relative contribution of each variable to the system's dynamics. Through this framework, this study captures both the short-term dynamics and long-term interactions between port intelligent transformation and regional economic systems.

4. Data

4.1. Field Data Selection

The empirical sample consists of five representative YRD port–city units: Shanghai, Ningbo–Zhoushan, Hangzhou, Nantong, and Taizhou. Shanghai is included as the regional core hub, while Ningbo–Zhoushan, Hangzhou, Nantong, and Taizhou represent major neighboring ports and related hinterland cities within the YRD port system. The observation period covers 2011–2021, and the final dataset forms a balanced panel with $N = 5$ cross-sectional units and $T = 11$ annual observations.

To better capture regional interactions within the Yangtze River Delta (YRD), this study further includes neighboring ports and related hinterland cities, including Ningbo–Zhoushan, Hangzhou, Nantong, and Taizhou. Incorporating both core hub ports and surrounding regional ports helps reflect the broader spatial structure of the YRD port system and improves the representativeness of the analysis.

The port intelligence evaluation framework developed in this study requires data on both port intelligence and regional economic development. Accordingly, three principles guided the data collection process. First, data availability and continuity were prioritized to ensure that long-term panel data could be obtained. Second, indicator selection was based on previous literature and theoretical relevance in order to maintain scientific rigor. Third, representative ports with different functional roles and development levels within the YRD were included to improve the generalizability of the analysis.

The data were collected from multiple public sources, including the Global Port Development Report (2011–2021), publications of the General Administration of Customs of China, the Shanghai International Shipping Research Center, statistical yearbooks of port cities, annual reports of port enterprises, audit reports, and official government and port authority websites. Detailed data is discussed in the following sections.

Some indicators, particularly R&D expenditure (C1) and the proportion of technical personnel (C2), were not consistently disclosed across all ports. For Hangzhou Port, Nantong Port, and Taizhou Port, missing values were estimated using the arithmetic mean of comparable ports within the sample. Over the period from 2011 to 2021, a balanced panel dataset containing 55 observations was constructed for the five selected ports.

To improve data consistency and comparability, several preprocessing procedures were conducted. First, ports with substantial missing information were excluded during sample screening. Second, missing values were supplemented using mean interpolation methods. Third, data collected from different sources were unified in terms of measurement units and statistical standards. Finally, all indicators were standardized using min–max normalization to eliminate the influence of dimensional differences and facilitate subsequent empirical analysis.

4.2. Data for Evaluating Port Intelligence

This study mainly uses indicators related to port intelligent transformation. The core explanatory variable is the Port Intelligence Index (PII), which is constructed using the Analytic Hierarchy Process (AHP) and subsequently incorporated into the PVAR model to measure the level of port smartization. The evaluation framework includes seven indicators: R&D investment (C1), proportion of R&D personnel (C2), equipment intelligence level (C3), intelligent management level (C4), hinterland per capita GDP (C5), per capita import and export trade volume (C6), and cargo throughput (C7). The source materials for the port-level indicators include port development reports and shipping databases [42,43], customs statistics for trade-related variables [44], enterprise annual reports for port-specific information [45,46], and the China Ports Yearbook for port statistical data [47]. Among them, the evaluation criteria for equipment intelligence and intelligent management are adapted from the framework proposed in Research on the Construction of a Smart Port Evaluation Index System in the Context of China's Pilot Free-Trade Zones, which helps ensure the consistency and reliability of the measurement system.

Because the port intelligence index combines heterogeneous indicators, the aggregation process was designed to avoid direct comparison of raw variables with different units and meanings. First, indicators were grouped according to the theoretical hierarchy of port operations, port–hinterland integration, and port–free-trade zone integration. Second, all quantitative indicators were standardized before weighting so that scale differences would not dominate the composite score. Third, AHP weights were applied within the hierarchical structure, which reduces the risk that a single correlated indicator mechanically determines the final index. Correlation among individual indicators is therefore treated as part of the multidimensional structure of port smartization rather than as a reason to remove theoretically important dimensions.

To examine the long-term evolution of port smartization between 2011 and 2021, descriptive statistical analysis was first conducted for the panel dataset covering the five sampled ports. The mean values of and variances in each indicator are reported in Table 4. The mean values reflect the average development level of each port during the observation period, while the variances capture the degree of fluctuation and stability over time. Together, these statistics provide an initial understanding of the differences in smart port development across the YRD.

Table 4. Statistical Data for Shanghai and Surrounding Areas, 2011–2021.

Ports	B1							
	C1		C2		C3		C4	
	Mean	Variance	Mean	Variance	Mean	Variance	Mean	Variance
Shanghai	0.49	0.00	11.86	0.07	3.87	0.15	3.77	0.07
Hangzhou	0.55	0.00	10.92	0.02	3.13	0.19	3.03	0.09
Ningbo–Zhoushan	0.61	0.00	9.98	0.00	3.47	0.09	3.76	0.08
Nantong	0.55	0.00	10.92	0.02	3.18	0.07	2.92	0.08
Taizhou	0.55	0.00	10.92	0.02	3.04	0.07	2.75	0.11
Ports	B2				B3			
	C5		C6		C7			
	Mean	Variance	Mean	Variance	Mean	Variance	Mean	Variance
Shanghai	13,451.64	11,400,000	1.79	0.35	73,706.64	6,016,175		
Hangzhou	11,563.55	6,280,821	0.71	0.11	5725.91	1,326,543		
Ningbo–Zhoushan	17,022.73	31,200,000	1.95	0.53	74,445	4,367,262		
Nantong	11,552.73	14,600,000	0.34	0.02	8067	1,487,363		
Taizhou	10,185.09	11,700,000	0.30	0.01	16,092.55	16,700,000		

The mean values reveal clear differences in development levels among the sampled ports. Ningbo–Zhoushan Port records the highest average values for R&D investment (C1), hinterland economic support (C5), external openness (C6), and cargo throughput (C7), indicating strong comprehensive competitiveness supported by its large operational scale, extensive hinterland economy, and international trade connectivity. By contrast, the Port of Shanghai performs particularly well in technology- and management-related indicators, including the proportion of R&D personnel (C2), equipment intelligence (C3), and intelligent management capability (C4). This suggests that Shanghai’s smart port development relies more heavily on technological innovation and advanced management systems. Meanwhile, Hangzhou Port, Nantong Port, and Taizhou Port show relatively similar levels of R&D investment and technical personnel input, although their performance in indicators related to economic scale, trade openness, and operational capacity remains noticeably lower than that of Shanghai and Ningbo–Zhoushan. This pattern reflects a clear hierarchical structure within the regional port system.

The variance results further reveal differences in development stability across indicators. The variances in R&D investment (C1) and R&D personnel proportion (C2) are relatively small for most ports, indicating that long-term investment in innovation and technical capability has remained comparatively stable over time. In contrast, hinterland per capita GDP (C5) shows much larger fluctuations, especially for Shanghai and Ningbo–Zhoushan, suggesting that regional economic conditions are more sensitive to macroeconomic cycles, policy adjustments, and external shocks. Cargo throughput (C7) also exhibits relatively high variance, reflecting the strong influence of international trade conditions and market demand on port operations. By comparison, the variances in equipment intelligence (C3) and intelligent management capability (C4) remain at moderate levels, implying that technological upgrading and digital transformation generally followed a gradual and relatively stable process during the study period.

Overall, the descriptive statistics indicate substantial differences in the level and development patterns of port smartization across major YRD ports. While internal innovation-related investment tends to remain stable, external economic conditions and operational performance fluctuate more significantly over time. These findings provide preliminary empirical support for the subsequent AHP evaluation and PVAR analysis of the dynamic relationship between port smartization and regional economic development.

4.3. Regional Economic Evaluation Data

To examine the relationship between port intelligent transformation and regional economic development, this study employs PCA and PVAR model using regional economic indicators as the core analytical variables. Regional economic development is measured using three indicators: local GDP, the proportion of GDP generated by the tertiary sector, and waterway freight turnover. These variables represent regional economic scale, industrial structure, and logistics activity intensity, respectively, and together provide a multidimensional description of regional economic performance. The data for Shanghai were obtained from the Shanghai Statistical Yearbook [48].

The economic statistics of the sampled cities from 2011 to 2021 are summarized in Table 5. The descriptive statistical results reveal several notable characteristics of regional economic development in the YRD.

From the perspective of mean values, clear regional disparities can be observed among the sampled cities. Shanghai records the highest average values across all three indicators, reflecting its dominant position in economic scale, service-sector concentration, and logistics capacity. This finding is consistent with Shanghai’s role as an international shipping center and a major economic growth pole within the YRD region. Hangzhou and

Ningbo–Zhoushan form the second tier of regional development, although their economic structures differ substantially. Hangzhou shows relatively high values in both GDP and the share of the tertiary sector, indicating a stronger service-oriented economic structure. In contrast, Ningbo–Zhoushan exhibits waterway freight turnover levels close to those of Shanghai, highlighting the important role of port logistics and maritime trade in supporting regional economic growth. Nantong and Taizhou, by comparison, report relatively lower average values across most indicators, suggesting comparatively weaker economic scale and logistics capacity within the regional system.

Table 5. Regional Economic Statistics for Various Cities, 2011–2021.

Ports	GDP		Share of the Tertiary Sector in GDP		Waterway Freight Volume	
	Mean	Variance	Mean	Variance	Mean	Variance
Shanghai	30,515.06	61,400,000	68.12	27.17	22,836.27	46,500,000
Hangzhou	12,073.52	13,500,000	45.18	6.21	5693.27	1,266,431
Ningbo–Zhoushan	11,477.29	7,402,186	52.45	12.13	21,200.18	47,800,000
Nantong	7327.74	5,265,804	44.25	9.17	8068	1,488,655
Taizhou	4143.9	1,434,777	41.85	4.66	4753	831,700

The variance results further reflect differences in development stability across cities and indicators. Local GDP and waterway freight turnover exhibit relatively large variances for most cities, indicating that regional economic activity and port-related logistics operations are strongly influenced by macroeconomic conditions, international trade fluctuations, and external shocks. This suggests that regional economic growth and logistics performance contain substantial dynamic volatility over time. By contrast, the variance in the tertiary industry share remains comparatively small across the sample, implying that regional industrial structures are relatively stable during the observation period. In other words, while economic output and logistics activities fluctuate considerably, the overall service-oriented development pattern of the sampled cities changes more gradually.

Overall, the descriptive statistics indicate that port intelligent transformation takes place within a regional economic environment characterized by significant heterogeneity and dynamic change. Differences in economic scale, industrial structure, and logistics activity among cities provide an important background for understanding the uneven development of port smartization across the YRD region. At the same time, the volatility observed in economic and logistics indicators further supports the use of dynamic econometric methods in subsequent analysis. These characteristics justify the application of PCA for dimensionality reduction and the PVAR framework for examining the dynamic relationship between port smartization and regional economic development.

5. Results and Discussions

5.1. Analysis and Evaluation of Port Intelligence

The results of the AHP-based weighting process are presented in Tables 6–10. Table 6 reports the statistical characteristics of expert evaluations for both the criterion and indicator levels, and the arithmetic mean is adopted to construct the pairwise comparison matrices. Based on these values, the judgment matrices for the criterion level (Table 7) and the indicator level (Table 8) are established. The resulting weights, obtained through AHP, are summarized in Table 9, while the overall ranking weights are presented in Table 10.

Table 6 further reveals the distribution of expert judgments across different indicator pairs. For some comparisons, expert opinions are relatively consistent. For example, the scores for C1–C2 show a narrow range (0.25–3) and low variance (0.72), with a mean value close to 1, indicating a high level of agreement regarding the comparable importance of

research investment and research personnel. In contrast, other indicator pairs exhibit greater variability. The comparison between C3 and C4 shows a wide range of scores (0.14–8) and a high variance (7.62), suggesting substantial disagreement among experts regarding the relative importance of equipment intelligence and management capability. Similar dispersion patterns are observed for C1–C4 and C2–C4, reflecting heterogeneity in expert perceptions of technical priorities.

Tables 7 and 8 present the constructed judgment matrices at the criterion and indicator levels, respectively. Table 7 illustrates the relative importance of the three dimensions (B1–B3), where B1 consistently exhibits higher values, indicating that internal operational intelligence is generally regarded as the most critical component of port intelligence. Table 8 focuses on the sub-indicators under B1, capturing the relative importance of technological and management-related factors. Together, these matrices provide the basis for weight calculation and satisfy the fundamental requirements of the AHP framework.

Table 6. Expert Rating Scale.

Layers	Indicators	Minimum Value	Maximum Value	Mean	Variance
Policy Layer	B1–B2	0.14	4	1.89	1.55
	B1–B3	0.13	7	5.04	1.87
	B2–B3	0.14	3	0.78	0.66
Metrics Layer	C1–C2	0.25	3	0.72	1.06
	C1–C3	0.14	3	0.94	0.83
	C1–C4	0.14	6	4.05	1.73
	C2–C3	0.12	4	1.87	1.33
	C2–C4	0.2	5	3.39	1.97
	C3–C4	0.14	8	7.62	2.89
	C5–C6	0.14	5	2.63	1.86
	C5–C7	0.14	3	1.03	0.97
	C6–C7	0.13	3	1.04	1.15

Table 7. Decision Matrix for the Guideline Layer.

Indicator Item	B1	B2	B3
B1	1.000	1.563	1.852
B2	0.640	1.000	0.658
B3	0.540	1.520	1.000

Table 8. Indicator-Level Decision Matrix.

	B1			
	C1	C2	C3	C4
C1	1.000	1.064	0.826	1.724
C2	0.940	1.000	1.333	2.000
C3	1.210	0.750	1.000	2.857
C4	0.580	0.500	0.350	1.000
	B3			
	C6		C7	
C6	1.000		0.714	
C7	1.400		1.000	

Table 9. Results of the AHP Analysis.

Item	Feature Vectors	Weight	Largest Eigenvalue	CI Value	CR Value
Policy Layer					
B1	1.369	45.6359%	3.039	0.019	0.037
B2	0.726	24.1991%			
B3	0.905	30.1649%			
B1 Indicator Layer					
C1	1.052	26.3003%	4.503	0.018	0.020
C2	1.197	29.9369%			
C3	1.213	30.3127%			
C4	0.538	13.4501%			
B3 Metrics Layer					
C6	0.833	41.6667%	2.000	0.000	0.000
C7	1.167	58.3333%			

Table 10. Overall Weighting of Evaluation Indicators for Smart Ports.

Indicator Item	Weight	Sort
Smart Port Operations B1	0.456	
C1 R&D Investment	0.120	6
C2 Percentage of R&D Personnel	0.136	4
C3 Level of Equipment Intelligence	0.139	3
C4 Level of Smart Management	0.061	7
Smart Port–Hinterland Integration B2	0.243	
C5 Per Capita GDP in the Hinterland	0.243	1
Smart Port–Free-Trade Zone Integration B3	0.301	
C6 Per Capita Import/Export Value	0.126	5
C7 Cargo Throughput	0.175	2

The consistency test results are reported in Table 9. The consistency ratio (CR) is 0.037 for the criterion layer, 0.020 for the B1 indicator layer, and 0.000 for the B3 metrics layer. All reported CR values are below the acceptable threshold of 0.10, indicating that the constructed judgment matrices satisfy the consistency requirement. These results confirm that the expert-based pairwise comparisons are internally consistent and that the derived AHP weights are reliable for subsequent analysis.

To assess whether the main conclusions depend excessively on the AHP-derived weights, the results were interpreted together with the consistency test, expert-judgment dispersion, and cross-port indicator patterns. The CR values below 0.10 indicate internally consistent judgment matrices, while the descriptive results show that the leading ports, especially Shanghai and Ningbo–Zhoushan, perform strongly across multiple dimensions rather than relying on a single highly weighted indicator. Therefore, moderate changes in individual weights are unlikely to overturn the main tiered pattern of port intelligence development. Nevertheless, future studies could further test robustness by applying alternative weighting schemes when more complete objective indicator data become available.

Based on the derived weights, an evaluation matrix is constructed for each port. Indicator values are normalized using a max-scaling approach, where the maximum value is set to 1. The weighted standardized matrix is then obtained by multiplying the normalized values by their corresponding weights (Tables 10 and 11). The overall port intelligence level is calculated as the weighted sum of all indicators (Table 12).

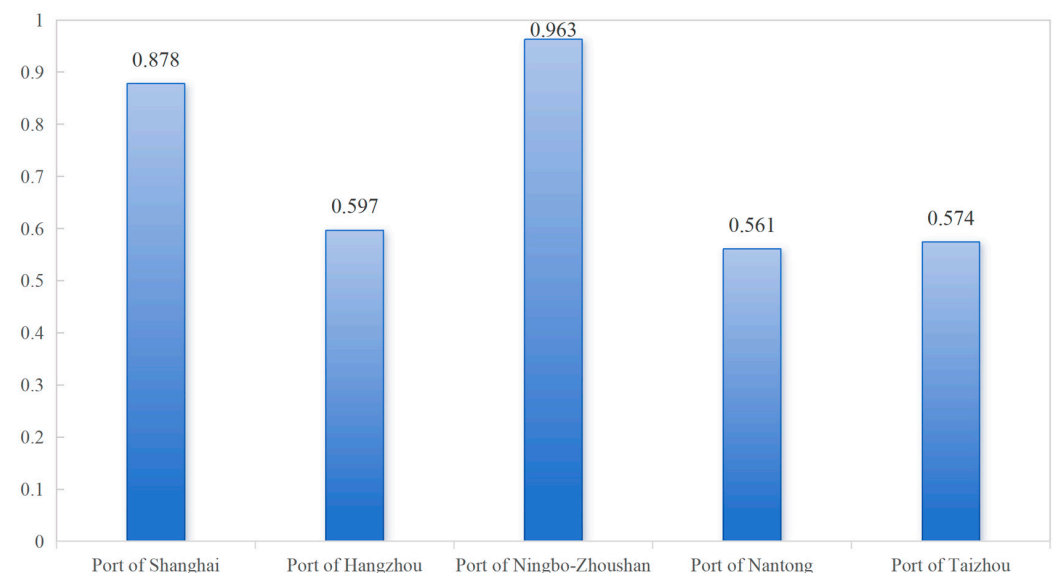
Table 11. Evaluation Matrix for Shanghai and Surrounding Areas in 2021.

Ports	B1				B2	B3	
	C1	C2	C3	C4	C5	C6	C7
Shanghai	0.74	1.00	1.00	1.00	0.74	0.85	0.98
Hangzhou	0.87	0.91	0.84	0.84	0.63	0.31	0.09
Ningbo–Zhoushan	1.00	0.82	0.88	0.97	1.00	1.00	1.00
Nantong	0.87	0.91	0.8	0.79	0.60	0.15	0.11
Taizhou	0.87	0.91	0.77	0.76	0.56	0.13	0.32

Table 12. Weighted Normalization Matrix.

Ports	B1				B2	B3	
	C1	C2	C3	C4	C5	C6	C7
Shanghai	0.08	0.14	0.14	0.061	0.179	0.107	0.171
Hangzhou	0.10	0.12	0.12	0.05	0.153	0.039	0.015
Ningbo–Zhoushan	0.12	0.11	0.13	0.059	0.243	0.126	0.175
Nantong	0.10	0.12	0.11	0.048	0.146	0.018	0.019
Taizhou	0.10	0.12	0.1	0.046	0.136	0.016	0.056

Figure 3 illustrates the port intelligence levels across major ports in 2021. Ningbo–Zhoushan Port exhibits the highest score, approaching 1, indicating the most advanced level of intelligent development. Shanghai Port follows closely, with a score of approximately 0.9. In contrast, Hangzhou, Nantong, and Taizhou ports display similar and comparatively lower levels (around 0.6), suggesting a moderate stage of intelligent transformation. Overall, a clear hierarchy is observed, with leading ports significantly outperforming regional counterparts.

**Figure 3.** Smart Infrastructure of Ports in 2021.

The temporal evolution of port intelligence from 2011 to 2021 is presented in Table 13 and Figure 4. Overall, all ports exhibit a clear upward trend, reflecting continuous progress in intelligent transformation. Shanghai Port shows the most notable improvement, with its index increasing from 0.688 in 2011 to 0.878 in 2021. Ningbo–Zhoushan Port also demonstrates substantial growth, rising from 0.671 to 0.963, achieving the highest overall level. Although Hangzhou, Nantong, and Taizhou ports experience more moderate increases, their indices also display steady growth over time. These results indicate that while dis-

parities persist across ports, the overall trajectory is characterized by sustained and stable development, highlighting the progressive advancement of port intelligence in the region.

Table 13. Smart City Development in 2011–2021.

Port	Min	Max	Mean	Var
Shanghai	0.688	0.878	0.795	0.004
Hangzhou	0.478	0.587	0.533	0.002
Ningbo–Zhoushan	0.671	0.963	0.837	0.009
Nantong	0.458	0.561	0.506	0.001
Taizhou	0.469	0.574	0.522	0.001

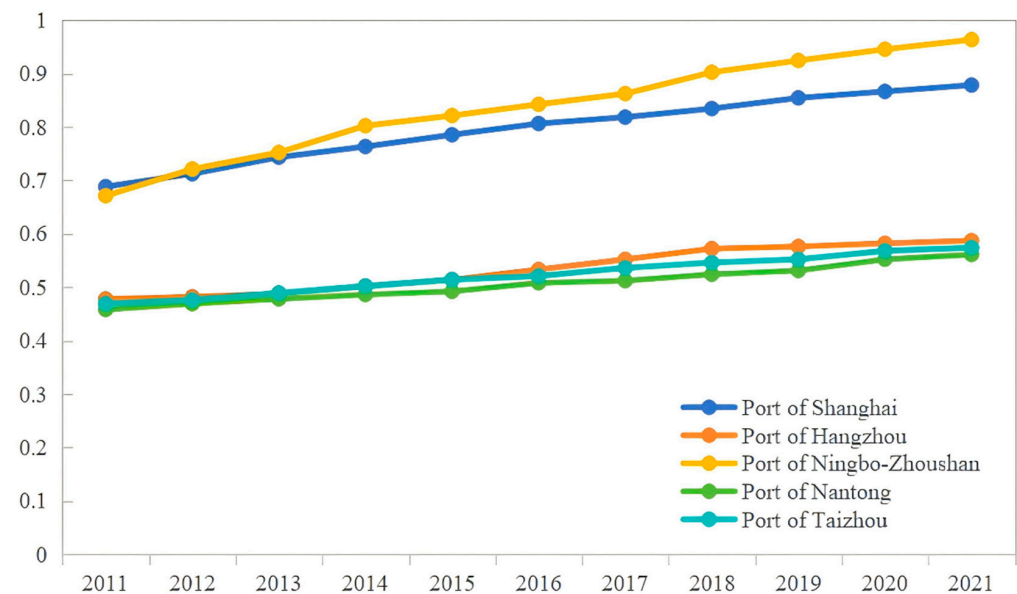


Figure 4. Smart technology adoption in Ports from 2011 to 2021.

5.2. Analysis of Regional Economic Conditions

The suitability of the data for principal component analysis was first evaluated using the KMO measure and Bartlett's test of sphericity. The KMO value is 0.703, exceeding the commonly accepted threshold of 0.6, indicating adequate sampling adequacy. In addition, Bartlett's test is statistically significant ($p < 0.05$), confirming that the variables are sufficiently correlated to justify the application of PCA.

The PCA results are presented in Table 14. Three principal components are extracted, all with eigenvalues greater than 1. These components explain 88.561%, 9.277%, and 2.163% of the total variance, respectively, with a cumulative variance contribution of 100%. This indicates that the selected components capture nearly all the information contained in the original indicators and can effectively represent regional economic characteristics.

Table 14. Principal Component Characteristics.

Number	Eigenvalue	R-Squared (%)	Cumulative (%)
1	2.657	88.561	88.561
2	1.278	9.277	97.837
3	1.065	2.163	100.00

Based on the proportion of variance explained, weights are assigned to each indicator. GDP carries the largest weight (0.8856), followed by the share of the tertiary sector (0.0928) and waterway freight turnover (0.0216). This result indicates that regional economic

scale, as measured by GDP, dominates the composite index, while structural and logistics-related factors play relatively smaller roles. The composite scores of regional economic development for each city are reported in Table 15.

Table 15. Scores for Urban Economic Development.

City	Min	Max	Mean
Shanghai	18,031.26	38,991.47	27,523.88
Hangzhou	6476.45	16,329.78	10,819.71
Ningbo–Zhoushan	8251.81	15,773.28	10,627.35
Nantong	3796.94	9959.51	6668.043
Taizhou	2221.01	5474.19	3776.605

Figure 5 illustrates the evolution of regional economic development across major port cities in the YRD from 2011 to 2021. Shanghai consistently ranks first, with its composite score increasing from 18,031.26 in 2011 to 38,991.47 in 2021, indicating both a large economic scale and rapid growth. Ningbo–Zhoushan follows as the second tier, with its score rising from 8251.81 to 15,773.28 over the same period, demonstrating steady expansion supported by its strong port-oriented economy. Hangzhou exhibits a comparable growth trajectory, with its index increasing from 6476.45 to 16,329.78, and gradually narrowing the gap with Ningbo–Zhoushan, reflecting the increasing importance of service-oriented and digital economic activities. Nantong and Taizhou, starting from relatively lower bases, also show substantial growth, with their scores rising from 3796.94 and 2221.01 to 9959.51 and 5474.19, respectively. Although their absolute levels remain lower, the growth rates indicate an ongoing process of economic integration and industrial upgrading. From a comparative perspective, Shanghai, Hangzhou, and Ningbo–Zhoushan form a leading group, while Nantong and Taizhou constitute a secondary tier. Overall, all cities exhibit a clear upward trend, highlighting sustained regional economic expansion and providing a basis for subsequent analysis of the interaction between port intelligence and economic development.

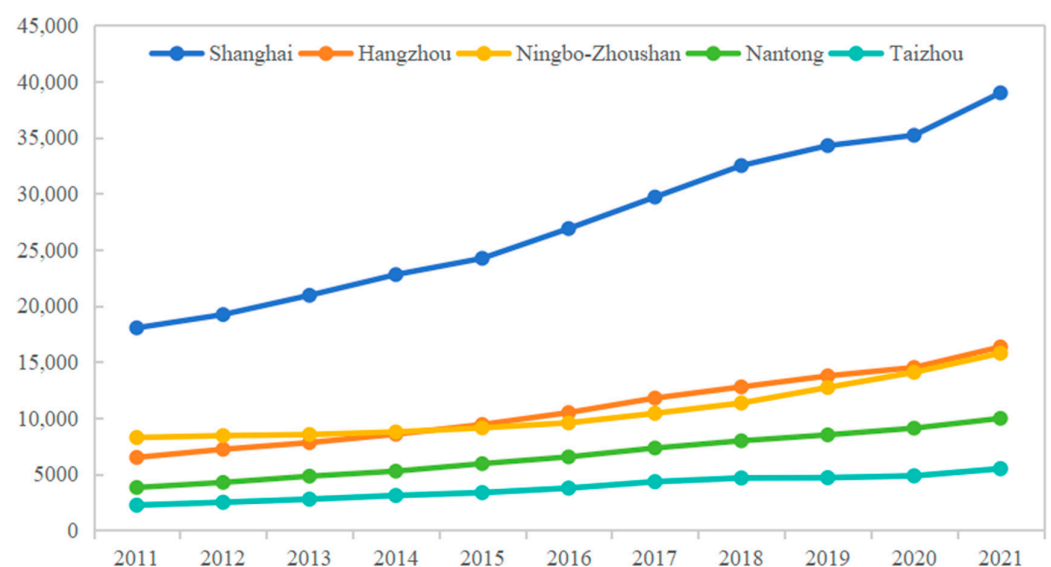


Figure 5. Score of Urban Economic Development Levels in 2011–2021.

5.3. Dynamic Relationship Between Port Intelligence and Regional Economic Development

To avoid spurious regression, panel unit root tests were first conducted using the Augmented Dickey–Fuller (ADF) method (Table 16). The results indicate that the original series is non-stationary, as the test statistic (−1.557) does not exceed the critical values and

the p -value (0.505) is greater than 0.10. After first-order differencing, the series becomes stationary ($p = 0.072 < 0.10$), suggesting that the variables are integrated of order one, $I(1)$, and suitable for subsequent PVAR analysis.

Table 16. Unit Root Test Table.

Order of the Difference	t	p	Threshold		
			1%	5%	10%
0	−1.557	0.505	−3.593	−2.932	−2.604
1	−2.712	0.072	−3.593	−2.932	−2.604

The optimal lag order was determined based on standard information criteria, including the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), as reported in Table 17. The results suggest that a lag order of 1 is appropriate for model estimation. Model stability was further assessed using the characteristic root test. As illustrated in the AR eigenvalue plot (Figure 6), all characteristic roots lie within the unit circle, indicating that the PVAR model is stable and suitable for dynamic relationship analysis.

Table 17. Ordering Results.

Order	AIC	BIC	FPE	HQIC
	13.269	13.350	579,104.485	13.299
1	11.350	11.591	84,974.522	11.440
2	11.493	11.895	98,247.173	11.643
3	11.661	12.223	116,544.072	11.870
4	11.818	12.541	137,151.015	12.087
5	11.984	12.867	163,429.666	12.313
6	12.145	13.189	194,629.739	12.534
7	12.279	13.483	226,839.165	12.728
8	12.413	13.778	266,143.286	12.922

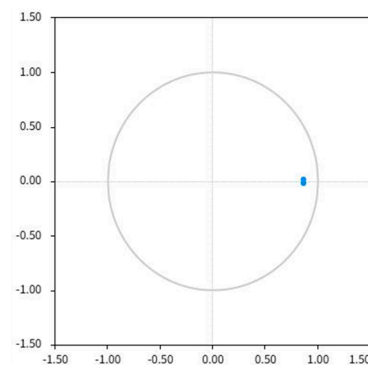


Figure 6. AR Root Test.

Based on the estimation results reported in Table 18, port intelligence and regional economic development exhibit significant dynamic associations. The coefficients of lagged variables indicate that improvements in port intelligence are positively related to subsequent increases in regional economic development levels. This finding is consistent with the expectation that intelligent transformation enhances operational efficiency, reduces logistics costs, and improves resource allocation efficiency, thereby facilitating regional economic activities and trade connectivity.

Table 18. VAR Model Results.

Vars	Shanghai		Hangzhou		Ningbo–Zhoushan		Nantong		Taizhou	
	Coef	Std	Coef	Std	Coef	Std	Coef	Std	Coef	Std
GDP	0.38	0.47	1.72	0.87	0.87	0.28	0.87	0.37	0.66	0.29
VAR	0.24	0.36	−1.07	1.09	0.27	0.33	0.08	0.41	−0.76	0.31
Sq	0.9852		0.9926		0.9983		0.9960		0.9837	
p val	0.165		0.085		0.00		0.063		0.00	

At the same time, the results also suggest the existence of feedback relationships, whereby higher levels of regional economic development are associated with further improvements in port intelligence. Economic expansion provides stronger financial capacity, technological support, and market demand for intelligent port upgrading, while more advanced port systems further strengthen regional logistics efficiency and industrial integration. These findings indicate a mutually reinforcing relationship between port intelligent transformation and regional economic development.

Although impulse response functions (IRFs) are not explicitly estimated in this study, the lagged structure of the PVAR model and the observed temporal trends provide qualitative insights into the dynamic adjustment process. Specifically, the economic response to improvements in port intelligence is unlikely to occur instantaneously. In the short term, the effect may remain relatively moderate due to the time required for intelligent technologies and infrastructure investments to be fully integrated into port operations. Over the medium term, the positive effects become more apparent as improvements in logistics coordination, operational efficiency, and trade facilitation gradually accumulate. In the longer term, the response tends to stabilize, suggesting that the interaction between port systems and regional economies follows a process of gradual adjustment and dynamic equilibrium.

Overall, the empirical findings suggest that port intelligent transformation is closely associated with regional economic development and plays a supportive role in promoting coordinated regional growth. These results provide empirical support for policy efforts aimed at strengthening the integrated development of smart ports, hinterland economies, and regional logistics systems.

To further strengthen the plausibility of the interpretation, the preliminary findings were reviewed through qualitative external feedback. After the AHP, PCA, and PVAR results were obtained, the main patterns—including the leading position of Shanghai and Ningbo–Zhoushan, the tiered structure among the five ports, and the mutually reinforcing relationship between port intelligence and regional economic development—were discussed with external specialists familiar with smart-port development, port logistics, and regional transport planning. Their feedback generally supported the interpretation that intelligent upgrading affects regional development through operational efficiency, logistics coordination, and hinterland connectivity. This feedback was used as a qualitative validation step to refine the discussion of the results, although it was not treated as an additional statistical test.

Compared with studies that mainly evaluate smart ports through internal digital readiness or operational automation, the findings of this study highlight the regional-system dimension of the Smart Ports concept. The YRD results show that leading ports such as Shanghai and Ningbo–Zhoushan benefit not only from advanced equipment and management systems but also from stronger hinterland economic support, trade openness, and cluster-level logistics connections. This helps explain why differences among ports are associated with both technological capacity and regional economic structure. This study therefore extends the Smart Ports concept from a port-internal digitalization perspective to a broader framework in which intelligent ports function as networked nodes linking operations, sustainability, port clusters, and regional economic development.

6. Conclusions

This paper examines the relationship between port smartization and regional economic development in the YRD. Using panel data from 2011 to 2021, it combines AHP, PCA, and PVAR methods to build an integrated analytical framework for evaluating port smartization and its association with regional economic performance. Drawing on port ecosystem theory, port–city interaction theory, and regional growth pole theory, this study develops a multi-dimensional evaluation system covering port operations, port–hinterland integration, and port–free-trade zone integration.

The results show a steady increase in the level of port smartization across all sampled ports during the study period, with Shanghai and Ningbo–Zhoushan remaining the regional leaders. Regional economic indicators also display a clear upward trend, although development gaps among cities remain evident. The empirical results further suggest a stable dynamic relationship between port smartization and regional economic development. In particular, improvements in intelligent technologies, equipment, and management systems appear to strengthen port efficiency, improve logistics connectivity, and support closer economic integration between ports and their hinterland economies.

This study contributes to the existing literature in three ways. First, it provides empirical evidence linking port smartization with regional economic development. Second, it proposes a comprehensive evaluation framework that captures multiple dimensions of port intelligence and regional integration. Third, by combining multi-criteria evaluation methods with dynamic econometric analysis, it offers a practical analytical approach for future research on smart ports and regional development.

From a practical perspective, the findings indicate that smart-port development should be coordinated across port operations, regional policy, and logistics infrastructure. Port administrations should prioritize intelligent scheduling systems, automated equipment upgrading, shore-power coordination, and integrated data platforms to improve operational efficiency while reducing environmental pressure. Regional authorities should link smart-port policies with hinterland industrial upgrading, digital infrastructure investment, and coordinated land–sea transport planning so that port intelligence can generate broader regional spillovers. Logistics infrastructure operators should focus on interoperable information systems, multimodal transport connections, and real-time cargo-flow monitoring to strengthen logistics resilience and support more efficient port–hinterland interaction.

Several limitations should also be acknowledged. The empirical analysis is based on five representative YRD port–city units in one of the most economically developed regions in China; therefore, the findings should be interpreted as evidence from a regional port cluster centered on Shanghai and Ningbo–Zhoushan rather than as universal conclusions for all port types, especially smaller inland ports, feeder ports, or less developed port systems. In addition, this study mainly examines macro-level relationships between port smartization and regional economic development, while the underlying transmission mechanisms through firms, industries, logistics networks, and technological adoption are not explored in sufficient detail. Future research could extend the framework to different regions and port taxonomies, including hub ports, feeder ports, inland river ports, and small and medium-sized regional ports, and use more disaggregated data to compare how the dynamic relationship differs across port types and development stages.

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