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Comparison of PCA and Fractal Analysis approaches in the evaluation of air-HSR intermodal network

Abstract: ***The importance of air transport and high-speed rail (HSR) in building comprehensive transportation systems has grown substantially in recent years. Evaluating the air-HSR intermodal network is essential in identifying the developmental hurdles and charting a course for its progress. This paper compares alternative methods for evaluating the performance of air-high-speed rail (HSR) intermodal networks, with a focus on developing a comprehensive index framework that considers multiple perspectives. Ten Chinese cities with viable air-HSR connectivity are assessed using principal component analysis (PCA) and Fractal Analysis. The study finds that while PCA provides a valuable high-level overview of air-HSR intermodal network integration by identifying major trends and key components, Fractal Analysis offers a complementary and more detailed evaluation by capturing local characteristics and complex spatial interactions. The combined use of PCA and Fractal Analysis ensures a comprehensive assessment, highlighting that Fractal Analysis is particularly effective for evaluating complex intermodal networks when spatial coherence and local variations are critical. The analysis provides decision-makers with a more balanced understanding of the intricate interrelationships between various aspects of the air-HSR intermodal network, which can inform policy decisions related to transportation infrastructure investment and development.***

Keywords— Air-High Speed Rail intermodal transport, Network Evaluation, Fractal Analysis, Principal Component Analysis

1. Introduction

Air transport and high-speed rail (HSR) have become increasingly important for the development of comprehensive transportation systems worldwide. Civil aviation and HSR exhibit complementary technical and economic characteristics, such as complementary market segmentation, range efficiency, transport network and operation resilience, making it important to promote intermodal transport between these modes to enhance integrated transport effectiveness and drive economic and social development (Albalate et al., 2015). In fact, Reiter et al. (2022) found that simple substitution of air services by HSR is not likely to deliver optimal connectivity and argue that multimodal integration is more desirable.

While some European countries have made progress in air-HSR integration, particularly in major hubs like Frankfurt and Paris Charles de Gaulle (Global Railway Review, 2021), significant challenges remain. These include the lack of HSR stations at many large airports and the fragmentation of national HSR networks, which complicates direct transfers and cross-border travel (EUROCONTROL, 2021). Despite these advancements, the lack of seamless intermodal connectivity and operational coordination continues to limit the full potential of air-HSR intermodal networks in Europe (Rail Signalling & Power, 2024).

However, this study specifically focuses on China, where air-HSR intermodal network has rapidly developed in recent years (Xia & Zhang, 2016). Although China started integrating air and HSR services later than Europe, the pace of development has been remarkable. For example, the Meilan Airport Station in Haikou became the first direct high-speed railway station at an airport in China at the end of 2010 (CNN, 2010), followed by the establishment of the first integrated air-HSR interchange hub at Shanghai Hongqiao Airport in 2012 (CNN, 2012).

Airlines and rail operators in China have increasingly recognised the complementary advantages of these transport modes and have introduced various intermodal products and services. For instance, China Eastern Airlines partnered with the railway's 12306 platform to offer integrated ticketing, allowing passengers to purchase both air and rail tickets on a single platform. By 2023, this service was available in 37 hub cities and at over 800 stations, offering conveniences such as pick-up, check-in, and seat selection through the 12306 platform (China Railway, 2024).

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Despite rapid development, the integration of air and HSR systems in China remains uneven. While cities like Shanghai and Chongqing have made significant strides—offering co-located terminals or direct HSR access—other major cities continue to face substantial integration challenges. For example, Beijing, Guangzhou, and Shenzhen demonstrate poor intermodal connectivity due to spatial mismatches and limited coordination between modes. In Guangzhou, Baiyun International Airport and Guangzhou South Railway Station are separated by approximately 50 km, resulting in long and inconvenient transfers. Beijing Capital International Airport lacks a direct HSR connection, forcing passengers to rely on slower ground transport. Even in Shenzhen, fragmented planning hinders seamless air-rail transfer. These spatial mismatches significantly reduce the attractiveness of intermodal travel and highlight the need for coordinated infrastructure development and operational alignment.

These spatial mismatches are compounded by deeper institutional and regulatory fragmentation. As Voltes-Dorta and Martín (2022) argue, connectivity in transport systems is not only a function of infrastructure, but also of enabling policies, coordination mechanisms, and user-oriented integration. Even in technically advanced hubs like Shanghai Hongqiao, the actual level of integration between air and HSR is limited due to the absence of unified scheduling, ticketing, and coordination frameworks (Givoni & Chen, 2017). This reflects a broader challenge in China, where the aviation and rail sectors are governed by separate institutions with competing mandates, leading to fragmentation in planning and operations.

Evaluating the integration between air transport and high-speed rail (HSR) is essential for improving intermodal connectivity and optimising multimodal transport networks. Numerous studies have explored the accessibility of transport modes across China. Cao et al. (2013) quantified the impact of China's HSR network on accessibility using travel time, contour, and potential accessibility measures. Their results highlight that accessibility gains are unevenly distributed, with eastern and central regions benefiting most due to their central network positions and high population densities. Sun et al. (2021) developed a high-resolution, grid-cell-based framework to evaluate the land-side accessibility of Chinese airports and HSR stations. They found that HSR stations are generally more accessible than airports, especially due to their proximity to city centres. Moreover, airports dominate in less populated areas, while HSR has stronger coverage in urbanised eastern regions. This insight is vital for intermodal planning, as it confirms the competitive geography between these two systems. In addition, Voltes-Dorta and Martín (2022) provided a broader discussion on how accessibility and connectivity are measured in air transport networks. They emphasise the importance of integrating both land-side and air-side accessibility dimensions to understand the full picture of airport performance, which is equally applicable to the joint evaluation of air-HSR systems.

Building upon these foundational studies, this paper seeks to move beyond isolated analyses of accessibility by adopting a multi-dimensional evaluation of air-HSR intermodal network integration. While past studies have focused on individual transport modes or comparative accessibility, this research employs Principal Component Analysis (PCA) and Fractal Analysis to assess both service capacity and spatial structure in ten representative Chinese cities. In doing so, the paper offers a comparative and systematic method for evaluating the integration of air and HSR networks, addressing both quantitative connectivity and local quality characteristics.

2. LITERATURE REVIEW

To provide a comprehensive understanding of the current research landscape, the literature review is structured into two main aspects: problems in air-HSR integration and evaluation methods used to assess these challenges. This structure first identifies the key issues that hinder efficient air-HSR integration and then examines the methodologies employed to evaluate intermodal network.

2.1 Challenges in Air-HSR Integration

While the potential benefits of air-HSR integration are clear, its implementation has faced significant challenges globally. The following section identifies key problems that limit the practice of air-HSR integration. These categories are informed not only by operational reviews but also by empirical

passenger surveys and systematic literature assessments (Sun et al., 2024; Román & Martín, 2014), which reveal consistent passenger concerns around accessibility, coordination, and convenience.

2.1.1 Lack of Infrastructure and Planning Integration

One of the most critical issues in air-HSR integration is the lack of infrastructure designed for integrated operations. In many cases, air and rail systems have been developed independently, with little consideration for intermodal connectivity during the planning phases (Lu et al., 2024). This has led to operational redundancies and poor connections between airports and HSR stations, particularly in terms of geographical proximity, which in turn hampers efficient transfers. Survey studies have indicated that passengers prioritise proximity and ease of transfer when choosing intermodal options. Román and Martín (2014) found that accessibility and direct connectivity significantly influence passenger satisfaction in air-HSR integration. When HSR stations are located far from airports, passengers perceive the transfer process as inconvenient and are less likely to choose intermodal travel. Sun et al. (2024) also highlight that infrastructure fragmentation remains one of the most cited barriers to seamless integration in the literature. For example, while Shanghai Hongqiao Airport successfully integrates both services in a single hub, most other airports in China do not have direct connections to the HSR network, resulting in fragmented systems (Givoni & Chen, 2018).

Globally, similar challenges have been observed. Even in Europe, where air-HSR systems are more established, integrated hubs are relatively few, and expansion of such systems remains limited due to infrastructural constraints (European Court of Auditors, 2015). These infrastructural limitations often make it difficult to achieve seamless intermodal transport, with passengers experiencing significant time delays or the inconvenience of multiple transfers.

2.1.2 Insufficient Coordination of Schedules

Another significant challenge in air-HSR integration is the insufficient coordination of schedules between air and rail services. While ticketing integration has been relatively successful in China and other regions, the lack of coordinated scheduling remains a major bottleneck (Delahaye et al., 2022). Air transport and HSR services often operate on different timelines, with limited alignment between arrival and departure times, reducing the effectiveness of intermodal transfers. In many cases, passengers miss connecting flights or trains due to poor timetable synchronisation, which ultimately discourages the use of intermodal options (Scozzaro et al., 2023). According to Román and Martín (2014), passengers value seamless and well-coordinated schedules when using intermodal transport. A lack of alignment between flight and train schedules often leads to long waiting times, missed connections, and dissatisfaction, significantly reducing the appeal of air-HSR integration. Sun et al. (2024) reinforce this by identifying schedule mismatch as one of the most cited passenger complaints. Additionally, D'Alfonso et al. (2016) emphasise that integrating schedules not only improves passenger convenience but also reduces operational inefficiencies, contributing to better utilisation of both air and rail services.

This problem is exacerbated by the complexities of operating within different regulatory and organisational frameworks (Voltes-Dorta & Martín, 2022). Airlines and HSR operators often operate independently, with limited cooperation in schedule planning (Li et al., 2018). This is particularly problematic in countries like China, where both modes of transport experience high passenger volumes and infrastructure capacity constraints. Without better coordination of schedules, the full potential of air-HSR integration remains unrealised.

2.1.3 Complexity of Integrating Operational Models

The operational models for air and HSR systems are fundamentally different, making integration challenging. Air transport generally focuses on long-haul, point-to-point services, while HSR operates on a hub-and-spoke model designed for medium-distance routes. Integrating these distinct models requires complex adjustments, such as reallocating routes, frequencies, and capacity between the two modes to avoid redundancies and inefficiencies (Jiang et al., 2021).

Surveys on passenger preferences indicate that travellers expect a streamlined transition between air and rail services. However, D'Alfonso et al. (2016) highlight that the absence of harmonised operational models often leads to fragmented services, causing confusion among passengers and

leading to underutilisation of intermodal opportunities. Sun et al. (2017) also argue that lack of coordination at the strategic level between operators hinders the development of coherent air-HSR services and disincentivises both operators and passengers from embracing integrated travel. As a result, many intermodal services fail to maximise their operational efficiency, leading to underutilisation of capacity and increased operational costs.

2.1.4 Passenger Experience Challenges

Passenger awareness and experience also pose challenges to the adoption of air-HSR integration. Many passengers remain unaware of intermodal options, or they perceive them as too complex or inconvenient compared to direct flights (Duarte Costa, 2012). This perception can be attributed to the lack of visible marketing of intermodal services and the absence of clear information on how to navigate the air-HSR transfer process. Román and Martín (2014) emphasise that clear communication, consistent ticketing systems, and coordinated service information significantly influence passengers' willingness to choose intermodal travel. Their survey revealed that inadequate information about intermodal services often leads to low adoption rates, even when integrated transport options are available. Additionally, inconsistent standards for services such as baggage handling can further discourage passengers from choosing intermodal options (Li et al., 2018). Sun et al. (2024) also highlight the lack of standardised passenger interfaces and poor branding of intermodal products as key factors affecting adoption.

A survey conducted at Shijiazhuang Zhengding International Airport in 2019 identified key factors influencing traveller satisfaction with air-HSR integration services, including transfer time, real-time information availability, arrival punctuality, and ticket prices (Jiang et al., 2022). The study found that transfer time is negatively correlated with satisfaction; travellers tend to prefer services with shorter transfer times, even if the total travel time remains the same. Furthermore, passengers are more tolerant of the travel time of airlines than that of HSR, indicating a need for improved scheduling and information dissemination to enhance the passenger experience.

2.2 Evaluation methods in transport studies

2.2.1 Evaluation methods for air-HSR intermodal network

The evaluation of air-HSR intermodal networks has been approached from various perspectives and methods. Current studies have focused on various aspects such as cost-benefit analysis (Jorge & Rus, 2004), location selection problem (Dai et al., 2022; Zhang et al., 2022), accessibility (Ma et al., 2023), and passenger satisfaction (Yuan et al., 2021). The evaluation methods vary from cost-benefit analysis (Jorge & Rus, 2004), performance indicator measurement (Rajendran (2022), to mathematical models (Yuan et al., 2021) and machine learning (Ren et al., 2023).

Discrete choice experiments are commonly used to assess passenger preferences in air-HSR intermodal services. For instance, Román and Martín (2014) estimated willingness-to-pay for service attributes, highlighting the importance of schedule coordination in reducing connecting time. Brida et al. (2017) combined discrete choice models with cluster analysis to investigate how different market segments affect the transition to HSR for the second leg of multimodal trips.

Studies such as Wandelt and Sun (2022) used scenario analysis to evaluate the benefits and limitations of air-HSR intermodal networks in terms of time and fare, specifically focusing on the Lufthansa Express Rail (LER) in Germany. Liu et al. (2021) applied cost-benefit analysis to assess supply chain sensitivity following the High Speed 2 project in the UK. Optimisation models, such as those proposed by Lu et al. (2025), focused on spatial and temporal coordination to reduce emissions and operational costs by optimising route allocation and connection frequency between air and HSR networks.

The integration of metropolitan HSR stations with local urban transport systems has also been studied, with research emphasising the importance of ticketing coordination and passenger wayfinding (Wang et al., 2020). Moreover, Xu (2018) evaluated air-HSR facilitation in China using AHP and entropy weight methods, focusing on infrastructure and service capacity.

Accessibility assessment remains a crucial area, with Ma et al. (2023) evaluating the combined high-speed rail and air transport network in China using Average Travel Time (ATT), Weighted Average Travel Time (WATT), and Potential Accessibility (PA). Qi and Kwon (2021) employed centrality metrics to assess urban connectivity within China's expanding air and HSR networks.

Yuan et al. (2021) employed the Finite Mixture Partial Least Squares (FIMIX-PLS) method to explore passenger satisfaction with air-HSR integration services, revealing heterogeneity in user preferences. Ren et al. (2013) used a machine learning framework to analyse the non-linear and interactive effects on passengers' choices of air-HSR intermodal travel.

Timetable coordination models have also been developed to improve intermodal connectivity. For example, Ke et al. (2020) formulated a multi-objective optimisation model to synchronise air and HSR timetables, focusing on maximising synchronisation coverage while minimising transfer penalties. Wang et al. (2021) proposed a model to enhance connectivity by optimising HSR schedules, achieving a 40.2% increase in intermodal connections.

These authors have emphasised the importance of considering various factors, including infrastructure, service capacity, and passenger preferences, in evaluating air-HSR intermodal network. Lu et al. (2024) proposed a new evaluation method with Fractal Analysis that considers multiple perspectives of the integrated network. However, existing literature has not cross-checked evaluation methods with traditional approaches, leading to the potential to validate the scientific soundness of the results.

2.2.2 Evaluation methods in transport studies

Previous studies on transport assessment have utilised several methods, each with its own strengths and weaknesses, depending on the specific research question and data available (Wang, 2014). A wide range of methodologies have been applied, including Multi-Criteria Decision Making (MCDM) methods such as Analytic Hierarchy Process (AHP), Entropy Weight Method (EWM), Grey Relational Analysis (GRA), Fuzzy Comprehensive Evaluation (FCE), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), as well as Data Envelopment Analysis (DEA) (Taherdoost & Madanchian, 2023). While these methods have proven effective in various contexts, their applicability to air-HSR integration evaluation is limited due to the unique challenges posed by complex intermodal networks.

AHP is a structured technique used for decision-making, particularly in resource allocation and strategic planning within transport studies (Vaidya & Kumar, 2006). For example, Awasthi and Chauhan (2011) used AHP combined with Dempster-Shafer theory to assess the impact of transport measures on urban sustainability. However, AHP relies on pairwise comparisons and subjective judgments, which can introduce bias. It is less effective in handling large datasets with numerous variables and complex relationships inherent in air-HSR intermodal networks.

Entropy Weight Method (EWM) assigns weights based on the entropy value, which measures uncertainty or diversity of information (Shannon, 1948). It has been used for performance evaluation and environmental assessments (Wang & Lee, 2009). While EWM objectively determines weights, it fails to capture the interactions and dependencies between variables, which is crucial when dealing with multi-dimensional, spatially diverse networks.

Grey Relational Analysis (GRA) addresses systems with incomplete or uncertain information by measuring the degree of similarity between sequences (Deng, 1982). Zhang (2022) applied a modified GRA-TOPSIS method to locate international multimodal logistics hubs. Despite its effectiveness in handling uncertainty, GRA primarily deals with linear relationships and may not capture the non-linear dynamics typical of complex transport networks.

Fuzzy Comprehensive Evaluation (FCE) incorporates fuzzy logic to manage uncertainty and subjectivity (Zadeh, 1965). Niu (2020) used FCE for maritime transport costing, demonstrating its ability to handle vague information. However, FCE becomes complex and less interpretable when applied to large datasets, and its reliance on subjective input can affect consistency in evaluating intermodal connectivity.

TOPSIS ranks alternatives by calculating the distance to an ideal solution (Hwang & Yoon, 1981). Although useful for ranking transport alternatives, it can oversimplify the complex relationships within air-HSR intermodal networks, as it primarily focuses on distance measures rather than the underlying network dynamics.

DEA evaluates the efficiency of decision-making units (DMUs) using multiple inputs and outputs (Charnes et al., 1978). González et al. (2021) applied DEA to evaluate the efficiency of multimodal public transport. However, DEA is limited when dealing with qualitative factors and complex interactions between modes, making it less suitable for assessing the intricate structure of air-HSR intermodal networks where spatial hierarchy and intermodal interactions are crucial.

Both PCA and Fractal Analysis have been widely used in transport evaluation due to their distinct analytical strengths. For example, PCA has been applied in traffic flow analysis to identify the principal components of traffic patterns and to reduce the dimensionality of large traffic datasets (Adler & Golany, 2001). This makes PCA particularly valuable for identifying overarching trends and extracting dominant factors from complex, multi-dimensional datasets. However, PCA primarily captures linear correlations and may lead to information loss when reducing dimensionality, especially when non-linear interactions or complex interdependencies exist. This limitation can be significant when assessing the multi-faceted nature of intermodal transport integration, where non-linear relationships between variables may be critical.

Fractal Analysis, on the other hand, has been used to evaluate road networks and transportation systems by analysing connectivity and complexity, providing insights into efficiency and sustainability (Benguigui, 2016; Kim et al., 2007). It is particularly effective in examining non-linear relationships and spatial hierarchies within transport networks, making it valuable for capturing underlying complexities and dynamic interdependencies. However, its application may be limited when the data exhibit low spatial variability or uniform patterns, as the method's focus on fractal characteristics may not adequately reflect less complex or homogeneous structures. Additionally, interpreting fractal dimensions can be challenging, particularly in cases where the network lacks clear hierarchical patterns.

Despite the availability of other established methods such as MCDM approaches, DEA, and Network Efficiency Models, PCA and Fractal Analysis were specifically chosen for this study due to their distinct yet complementary capabilities. MCDM methods like AHP and TOPSIS are often limited by their reliance on subjective weight assignments, which may introduce bias when assessing complex intermodal networks. DEA, while useful for efficiency evaluation, primarily focuses on input-output relationships and does not account for spatial hierarchy or non-linear interactions, which are critical in air-HSR intermodal network. Network Efficiency Models, though effective for assessing performance, may not fully capture the intricate connectivity patterns and spatial dependencies inherent in intermodal transport systems.

In contrast, PCA objectively reduces the complexity of multi-dimensional data without requiring pre-defined weights (Jolliffe & Cadima, 2016), making it particularly effective for identifying high-level determinants of air-HSR intermodal network. Fractal Analysis, by examining the self-similarity and spatial irregularities within the network, addresses the non-linear and hierarchical nature of intermodal connectivity that other methods may overlook. The choice of these methods reflects a balanced approach that leverages PCA's ability to detect dominant components and Fractal Analysis's capacity to uncover underlying structural complexities.

Nonetheless, it is essential to acknowledge the trade-offs involved. PCA's limitation in handling non-linear correlations and Fractal Analysis's challenges with homogeneous data require careful interpretation of the results. By employing both methods, this study aims to capitalise on their complementary strengths while mitigating individual limitations.

Despite the extensive use of PCA and Fractal Analysis in transport evaluation, existing studies have not systematically compared their outcomes in the context of air-HSR intermodal networks. This lack of comparative validation raises questions about the robustness and applicability of these methods in assessing intermodal transport integration. To address this gap, this study conducts a systematic comparison of PCA and Fractal Analysis to evaluate their respective strengths and limitations in

assessing air-HSR intermodal network integration. The study seeks to answer the following research question: How do the results of traditional PCA-based evaluation compare with those of Fractal Analysis in assessing air-HSR intermodal network? Through this comparative approach, the study aims to shed light on the most critical factors affecting intermodal potential, such as capacity limitations, transfer efficiency, and network connectivity, ultimately guiding future strategies for improving air-HSR intermodal network in China.

3. METHODOLOGY

The methodology of this paper focuses on employing two evaluation techniques—Principal Component Analysis (PCA) and Fractal Analysis—to assess the intermodal potential of air-HSR intermodal networks in ten Chinese cities where both transportation modes coexist.

3.1 PCA method

The first method used for assessing air-HSR intermodal network integration is principal component analysis (PCA). This method involves transforming multiple indicators into a smaller number of key and uncorrelated indicators, referred to as principal components, which capture typically the majority of the original indicators' information (Jolliffe & Cadima, 2016).

The air-HSR intermodal networks are ranked according to the scores of their principal components, with those with higher scores being considered better than those with lower scores. The main steps of the principal component analysis are as follows:

Assuming there are n targets containing p indicators to be assessed, x_{ij} is the value of the j-th indicator of the i-th target. The original data matrix is given as $\mathrm{X} = \left(\mathrm{x_{ij}}\right)_{\mathrm{n\times p}}$.

(1) Data Standardisation

Data is standardised by subtracting the mean of each column from each observation and dividing by the standard deviation of that column. This ensures that each variable is on the same scale and that none of the variables dominate the analysis.

$$x_{ij}^{*} = \frac{1}{s_j}\left(x_{ij} - \overline{x_{\imath j}}\right) \qquad (1.1)$$

Where $\overline{x_{\imath j}} = \frac{1}{n}\sum_{i=1}^{n} x_{ij}$, $s_j = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(x_{ij} - \overline{x_j}\right)^2}$

(2) Correlation coefficient matrix

By calculating the correlation coefficient between each indicator, a p x p correlation coefficient matrix R is obtained, where p is the number of indicators. Then, the covariance matrix is calculated as:

$$\mathrm{Covariance(x,y)} = \Sigma\left[(\mathrm{xi} - \bar{\mathrm{x}})(\mathrm{yi} - \bar{\mathrm{y}})\right] / (p-1) \qquad (1.2)$$

Where xi is the ith observation of variable x, $\bar{\mathrm{x}}$ is the mean of x, yi is the ith observation of variable y, $\bar{\mathrm{y}}$ is the mean of y.

Then, the correlation coefficient matrix is determined using:

$$\mathrm{Correlation(x,y)} = \mathrm{Covariance(x,y)} / (\sigma_x \times \sigma_y) \qquad (1.3)$$

Where Covariance(x,y) is the covariance between variables x and y, σ x is the standard deviation of x, and σ y is the standard deviation of y.

(3) Eigenvalues, eigenvectors, contribution rates and cumulative contribution rates of the correlation coefficient matrix

The p eigenvalues and corresponding eigenvectors of the correlation matrix R are obtained by decomposing its eigenvalues. Then, the contribution rate corresponding to each eigenvalue, and the cumulative contribution rate of the first k eigenvalues, where k is the number of selected principal components, are determined.

Let the p eigenvalues of R $\lambda_1 \geq \lambda_2 \geq, \ldots \lambda_p$, then the contribution of λ_k is:

$$a_k = \frac{\lambda_k}{\sum_{i=1}^{p} \lambda_i} \qquad (1.4)$$

The cumulative contribution of the first m eigenvalues is $\sum_{i=1}^{m} \frac{\lambda_i}{\sum_{j=1}^{p} \lambda_j}$. When the cumulative contribution rate of the first m eigenvalues is larger than a certain number (90% has been selected in this calculation), then the number of principal components is determined. The choice of a 90% cumulative contribution rate in PCA is often considered sufficient for retaining the principal components that explain a significant portion of the variance in the data (Minitab, 2023).

(4) Linear combination formula of the principal components

The feature vectors corresponding to the first k eigenvalues are selected and weighted according to their contribution rates to obtain the linear combination formula of each principal component:

$$Y_{ik} = \sum_{j=1}^{p} l_{kj}\, x_{ij}^{*} (k = 1,2, \ldots, p; i = 1,2, \ldots, n) \qquad (1.5)$$

(5) Principal component scores of the evaluated targets

The original data of the evaluated object is standardised and brought into the linear combination formula of principal components to obtain the score of each object on each principal component. The relative ranking of the evaluated targets is obtained by ranking them according to the magnitude of the principal component scores.

3.2 Fractal Analysis

The second method used for assessing air-HSR intermodal network integration is Fractal Analysis. The intermodal integration assessment model proposed in this paper is based on the network-covering algorithm and fuzzy sets fractal dimensional models, and is processed in three steps: data standardisation, de-correlation, and fractal dimension calculation, capturing the spatial distribution and relationships among indicators, as described in our previous work for assessing air-HSR intermodal network integration (Lu et al., 2024).

(1) Standardisation

Assessing air-HSR intermodal network integration involves indicators with different units, making direct comparisons challenging. To ensure comparability, a two-step normalisation process is applied:

1) Min-Max Normalisation: Each indicator is rescaled between 0 and 100 using the following formula:

If the indicator value is positively correlated with integration:

$$\acute{a}_{ij} = \frac{a_{ij}}{a_{maxj}} \times 100 \qquad (1.6)$$

If the indicator value is negatively correlated with integration:

$$\acute{a}_{ij} = \frac{a_{ij}}{a_{minj}} \times 100 \qquad (1.7)$$

Where $a_{maxj}\ and\ a_{minj}$ represent the maximum and minimum values of indicator j.

2) Z-Score Standardisation: The normalised values are further standardised to ensure comparability across indicators using:

$$b_{ij} = \frac{á_{ij} - \bar{á_j}}{s_j} \quad (1.8)$$

where

$\bar{á_j} = \frac{1}{k}\sum_{i=1}^{k} á_{ij}$ (1.9) is the mean of the unstandardised indicator j,

and

$s_j = \sqrt{\frac{1}{k-1}\sum_{i=1}^{k}\left(á_{ij} - \bar{á_j}\right)^2}$ (1.10) is the standard deviation.

This process ensures that all indicators are expressed on a comparable scale without introducing negative values, making them suitable for further analysis, including logarithmic transformations in fractal analysis.

(2) De-correlation

Despite standardisation, correlations may still exist between the secondary indicators. To address this, a transformation is applied to obtain a set of uncorrelated indicators.

1) Forming the Normalised Indicator Matrix:
The standardised indicators form a matrix B where:

$$B = (b_{ij}) \quad (1.11)$$

2) Computing the Covariance Matrix:
The covariance matrix M of B is calculated as:

$$M_{n\times n} = \begin{bmatrix} \mathrm{cov}(B_1, B_1) & \dots & \mathrm{cov}(B_1, B_n) \\ \vdots & \ddots & \vdots \\ \mathrm{cov}(B_n, B_1) & \dots & \mathrm{cov}(B_n, B_n) \end{bmatrix} \quad (1.12)$$

where the covariance between indicators B_m and B_n is:

$$\mathrm{cov}(B_m, B_n) = \frac{\sum_{k=1}^{m}(B_{ik} - \overline{B_i})(B_{jk} - \overline{B_j})}{n-1} \quad (1.13)$$

3) Transforming the Indicators:
A transformation matrix P is used to derive a new set of indicators C, where:

$$C_{ij} = BP \quad (1.14)$$

The transformed indicators in C are now uncorrelated while preserving the information of the original indicators. This de-correlation process ensures that the indicators used in further analysis are independent.

(3) Fractal dimensions

The main outcome of a Fractal Analysis is to calculate the fractal dimension. To understand the fractal dimension of a given complex network, one can consider a sphere of radius r with the origin in the centre of the N-dimensional space, encompassing all points when r equals the maximum distance, R, from any point to the centre. Adjustments are made to ensure all distances are positive, enabling the encapsulation of all points within the sphere at r=R. The fractal dimension is then derived from the relationship between the logarithms of the cumulative distribution of points. Suppose $C(r)$ is a cumulative distribution function that reflects the distribution of indicator points in space, then $\ln C(r)$ and $\ln r$ are linearly related, and the fractal dimension D is the slope of $\ln C(r)$-$\ln r$ curve:

$$D = \frac{d(\ln C(r))}{d(\ln r)} \quad (1.15)$$

This dimension is an indicator of the network's ability to occupy and use space efficiently, and a higher value corresponds to a better overall score for the indicators. Therefore, measuring the fractal

dimension is an effective way to evaluate the air-HSR intermodal network's capacity to use space and accommodate complex forms in a geometrically efficient manner.

4. Data Collection

4.1 Data collection

The assessment framework for evaluating air-HSR intermodal network is structured around three primary criteria: service capability, network connectivity, and transfer potential (Lu et al., 2024). These criteria were chosen to capture the complex interactions and interdependencies within intermodal networks, with each criterion supported by carefully selected secondary indicators (see Table 1).

Service capability reflects the infrastructure and operational capacity of airports and HSR stations. Indicators such as daily delivery capacity, HSR speed, and airport on-time performance were selected to account for mode-specific characteristics. For example, airports are evaluated using passenger volumes due to capacity constraints observed at major Chinese airports, while HSR stations are assessed based on track availability and daily maximum passenger capacity due to the lack of official passenger volume data.

Network connectivity assesses the extent and complementarity of access provided by each mode. Indicators such as the number of destinations, service frequency, and catchment area coverage reflect the unique priorities of air and rail passengers. For instance, airports emphasise global connectivity through destination variety, while HSR prioritises frequent services to support seamless transfers.

Transfer potential captures the ease and value of intermodal connections, using indicators like transfer opportunities and ground transportation modes. Together, these 16 secondary indicators form a comprehensive framework that is consistent with established intermodal network evaluation practices while being tailored to the operational realities and data availability in China.

Table 1. Definition of indicators and sources

Primary indicators	Secondary indicators	Definition	Reflection and Source
Service capability	Airport size	The annual number of passengers departing and arriving at the airport by air	Reflects the capacity of the airport to provide air services. Source: IATA (2019)
	Airport OTP	The percentage of flights that arrive and depart from an airport within a specified time frame, typically within 15 minutes of their scheduled arrival or departure time.	On-time performance, reflecting airport and airline operating efficiency and quality. Source: OAG (2022)
	HSR station size	The number of tracks available at the HSR station is used a proxy for its capacity as it relates to the number of trains it can receive in a given period of time.	The corresponding closest pair of HSR station-airport is chosen according to the distance by the fastest mode of surface transport. Source: China Statistical Yearbook (2021)
	HSR daily delivery capacity	Maximum number of passengers can be transported by high-speed rail in a single day	Reflects the capacity of the train station to provide HSR services. Source: China Academy of Railway Sciences (2022)
	HSR Maximum speed	The upper limit of operating speed for the lines using the HSR station (km/h)	Reflects the expected quality of HSR services. Source: China Statistical Yearbook (2021)
	Proportion of transfer passengers at the airport	Transfer passengers as a percentage of total passengers.	Reflects airport transfer capacity and hub status. Source: IATA (2019)
	Proportion of international passengers at the airport	The proportion of international passengers to total passengers.	Reflects the structure of international and domestic routes and the level of international connections at the airport. Source: IATA (2019)

Primary indicators	Secondary indicators	Definition	Reflection and Source
Network connectivity	Destinations available at the airport	Number of total different destination (cities)	Reflects the connectivity of domestic and international air networks. Source: IATA (2019)
	Number of flights per day at the airport	Total number of flights in 2019/365 days	Reflects the service quality of the air network in terms of opportunities to travel by air. Source: IATA (2019)
	Distribution of flights (at the airport) throughout the day	Average time distribution (B) of flights to each destination in a day, seven days a week: $\mathrm{B}=\frac{1}{\mathrm{n}}\sum_{c=1}^{n}(\frac{1}{7}\sum_{j=1}^{7}\mu\lambda)$ Where n is the total number of destinations (c); *j* is the day of the week; *μ* denotes the availability of flights to the same destination in 4 segments of the day (00:00-05:59,06:00-11:59,12:00-17:59,18:00-23:59), i.e., if flights to a city *c* appear in 3 segments of the day, then *μ*=3/4; *λ* is the flight distribution considering 30 mins interval time segments (i.e., if the flights to a city *c* appear in 3 intervals, then *λ*=3/48) (Abdelghany et al., 2008; Lu et al., 2024)	Reflects the distribution of flights to a particular destination throughout different time periods of the day. Source: OAG (2019)
	Number of stops on the HSR routes	The number of stations reachable within 800 km (about 3 hours) of the HSR station	Reflect the catchment opportunities for the HSR station. Source: 12306 China Railway (2019)
	Headway between HSR services	Average time duration (in minutes) between high-speed train arrivals at the HSR station during the day, by dividing the number of minutes in a day by the average number of trains arriving at the HSR station each day.	Reflects the availability of train connections throughout the day. 2019 data is used as some trains suspended operation due to the response to the Covid-19 pandemic. Source: 12306 China Railway (2019)
	Network overlapping	Coincidence coefficient between subnetworks: D=2*|AA∩BB|/(|A|+|B|)	0 ≤D≤1. D= 0 means that the markets accessible by air and rail are completely differentiated. D=1 means both networks provide access to the same markets. The larger the value of D, the higher the degree of overlapping. Sources: 12306 China Railway (2019); IATA (2019)
Transfer convenience	Transfer opportunities	H * F Number of trains (H) arriving within a 2 – 4 hours time window, times the number of flights (F) departing within the same time window	Reflects the connection opportunities between flights and HSR trains 2019 data. Source: OAG (2019); 12306 China Railway (2019)
	Transfer modal choice	Number of ground transportation options between the airport and HSR station	Reflects the selection available between subway, airport shuttle, car, bus and other ground transportation options. Source: Gaode Map (2022)
	Transfer efficiency	The reciprocal of the average travel time from the HSR station to the airport using the fastest mode available. I.e., the average number of transfers that passengers could complete per hour	Reflects the quality of the transfer alternatives between the airport and HSR station. Source: Gaode Map (2022)

The selection of the ten Chinese cities for this study followed a structured, two-tiered approach to ensure both analytical clarity and representativeness across different scales of air-HSR intermodal development. First, six cities were chosen based on their status as hosts of the busiest airports in China

by total passenger traffic in 2019, as reported by the Civil Aviation Administration of China (CAAC, 2020). These include Beijing Capital, Shanghai Pudong, Guangzhou Baiyun, Chengdu Shuangliu, Shenzhen, and Kunming. These airports represent China's primary national and international air transport hubs, and their inclusion provides a baseline for understanding intermodal integration at the highest capacity levels. To complement this group and avoid over-representing megacities, four additional cities were selected from those with airports ranked between 10th and 20th nationally in 2019. This includes Zhengzhou (12th), Wuhan (14th), Changsha (15th), and Haikou (17th), which serve as representative regional hubs. These cities offer insight into air-HSR intermodal performance at a more localised level and allow for comparison with the largest hubs.

For each selected city, the closest HSR station to the airport was chosen rather than the largest station, to reflect realistic passenger transfer patterns. Our analysis showed that the nearest HSR station was, on average, 18.3 km from the airport, whereas the largest station was significantly farther, averaging 38.9 km. As longer distances reduce the feasibility of seamless intermodal connections, this criterion ensured a more practical evaluation of air-HSR intermodal network.

In cases where a city had multiple airports (Beijing, Shanghai, Chengdu), the primary international airport in operation at the time of data collection was selected—namely, Beijing Capital International Airport, Shanghai Pudong International Airport, and Chengdu Shuangliu International Airport. This choice was made because newer airports, such as Beijing Daxing and Chengdu Tianfu, had only become operational during the Covid and had not yet established full intermodal connectivity.

Table 2. Values of indicators for 10 Chinese cities

Primary indicators	Secondary indicators	PEK-Beijing North Railway Station	PVG-Shanghai Railway Station	CAN-Guangzhou North Railway Station	SZX-Shenzhen Airport North Station	KMG-Kunming South Railway Station	CTU-Shuangliu Airport Station	CGO-Xinzheng Airport High Speed Railway Station	CSX - Changsha South Railway Station	WUH - Hankou Station	HAK - Meilan Station
Service capability	Airport size (in 10 thousand passengers)	10001	7615	7338	5293	4808	5586	2913	2691	2715	2422
	Airport On-time performance	81%	83%	85%	88%	89%	83%	71%	75%	76%	65%
	HSR station size (in tracks)	11	15	16	2	30	6	4	28	4	4
	HSR daily delivery capacity (in 10 thousand passengers)	3.2	64.8	1.0	16.5	2.6	13.6	6.7	6.5	6.3	6.2
	HSR Maximum speed (km/h)	160	250	300	200	300	300	323	300	250	229
	Proportion of transfer passengers at the airport (in 2019)	0.11	0.12	0.12	0.02	0.07	0.03	0.01	0.01	0.03	0.01
	Proportion of international passengers at the airport (in 2019)	0.24	0.51	0.26	0.32	0.09	0.10	0.05	0.09	0.10	0.04
Network connectivity	Number of destinations available at the airport (in 2019)	228	208	166	132	136	146	75	88	81	84
	Number of flights per day at the airport (in 2019)	1628	1402	1346	1014	978	1005	593	538	557	451
	Distribution of flights (at the airport) along the day (in 2019)	0.08	0.09	0.08	0.06	0.05	0.05	0.04	0.03	0.03	0.04
	Number of stops on the HSR routes (within 800 km)	10	16	19	15	17	20	9	10	28	13
	Headway between HSR services (in hours)	1.00	0.28	0.63	2.40	0.44	0.66	0.23	0.05	0.66	0.30
	Network overlapping (in 2019)	0.03	0.04	0.03	0.00	0.18	0.07	0.02	0.35	0.13	0.00
Transfer convenience	Transfer opportunities	290	986	378	82	860	132	76	1512	80	330
	Transfer modal choice	3	3	5	1	3	1	4	5	3	2
	Transfer efficiency	0.67	0.77	2	3	1	4	5	2	2	5

5. RESULTS

5.1 PCA results

The principal component analysis was conducted using IBM SPSS Statistics (18.0.1.1) and the results are presented in Table 3-7. The correlation coefficient matrix in Table 3 displays the correlation between the variables representing the indicators in the assessment framework. In Table 4, it is evident that HSR Daily Delivery Capacity has the highest information extracted from the original variables, capturing 98.9% of the original information, while HSR Maximum Speed has the least, extracting 74.8%. Nevertheless, the overall loss rate of extracted information was relatively low. Table 5 shows that the top five principal components collectively explain 91.3% of the variance in the original 16 indicators. Selecting the top five principal components ensures that the retained components represent substantial variance while minimising the inclusion of trivial components. The rigorous application of both the Scree Test and Parallel Analysis demonstrates a methodologically sound approach, addressing potential concerns regarding the arbitrariness of component selection and reinforcing the robustness of our findings (Cattell, 1966; Horn, 1965).

From Table 6, with the absolute value of the coefficients representing the contributing factors, it can be observed that the first principal component (PC1) has the largest coefficients for indicators Number of Destinations at the airport, Number of Flights per Day at the Airport and Distribution of Flights along the day. The positive coefficient for Number of Destinations at the Airport suggests that airports serving a greater number of destinations contribute positively to this principal component. This indicates that PC1 is associated with a higher level of network reach and connectivity provided by the airport. The positive coefficient for Number of Flights per Day at the Airport implies that an increase in the number of daily flights enhances the score on PC1. This reflects the frequency and availability of air travel options, which is a critical factor for connectivity and convenience. The positive coefficient for Distribution of Flights along the Day indicates that a more evenly distributed schedule of flights throughout the day also contributes positively to PC1. This ensures that passengers have flexible travel options and can find suitable flight times, thereby improving the overall service quality and accessibility. Therefore, PC1 can be interpreted as a component representing Airport Service Capacity and Connectivity. As can be seen in Table 7, Shanghai, Beijing and Guangzhou perform well in this dimension, while Zhengzhou and Haikou perform relatively poorly, with weak airport service capacity and connectivity.

The second principal component (PC2) has the largest coefficients for indicators HSR Station size, Transfer Opportunities, and Network overlapping. The positive coefficients for HSR Station Size and Transfer Opportunities implies that PC2 is associated with larger HSR stations and higher transfer opportunities, which typically enhance the accessibility and connectivity of the intermodal network. Conversely, the negative contribution of Network Overlapping indicates that reduced redundancy within the network is associated with higher scores on PC2. Therefore, PC2 captures the trade-off between maximising station size and transfer options while minimising network overlap, and can be interpreted as a component representing Intermodal Network Connectivity. As can be seen in Table 7, Changsha, Kunming and Shanghai perform well in this dimension, while Shenzhen and Haikou perform relatively poorly, with weak intermodal connectivity.

In the third principal component (PC3), the largest coefficients extracted are for Headway Between HSR services, Transfer Efficiency and Number of Stops on the HSR Routes. The positive coefficient for Headway Between HSR Services implies that PC3 is related to high frequent HSR services and scheduling efficiency. The positive coefficient for Transfer Efficiency indicates that higher transfer efficiency (smooth and quick transfers) also contributes positively to PC3. The negative coefficient for Number of Stops on the HSR Routes suggests that more direct and faster HSR services are valued in this component, reducing travel time and increasing efficiency. Hence, PC3 can be interpreted as a component representing Intermodal Transfer Efficiency. As can be seen in Table 7, Haikou, Zhengzhou and Changsha perform well in this dimension, while Wuhan and Kunming perform relatively poorly, with low intermodal transfer efficiency.

The fourth principal component has (PC4) the largest coefficients for indicators HSR Daily Delivery Capacity, Proportion of International Passengers at the Airport and Number of Stops on the HSR Routes. The positive coefficient for HSR Daily Delivery Capacity suggests that a higher daily delivery capacity of HSR services contributes positively to this principal component. The positive coefficient for Proportion of International Passengers at the Airport highlights the international connectivity and the role of the airport as a hub for international travel, showing the importance of accommodating international passengers in the network. The positive coefficient for Number of Stops on the HSR Routes implies a greater number of stops increases the accessibility of the HSR network, making it easier for passengers to reach various destinations. Therefore, PC4 can be interpreted as a measure of Capacity and Connectivity for International and Regional Integration. As can be seen in Table 7, Shanghai, Wuhan and Shenzhen perform well in this dimension, while Beiijng and Guangzhou perform relatively poorly, with low capacity and connectivity for international and regional integration.

Lastly, the fifth principal component (PC5) has the largest coefficients for indicators Number of Stops on the HSR Routes, HSR Maximum Speed and Headway Between HSR Services. A greater number of stops increases the network's accessibility. Higher maximum speeds reflect the network's ability to provide fast travel options, reducing overall journey times. Shorter headways indicate more frequent services and improve the convenience and flexibility of the HSR network. Therefore, PC5 can be interpreted as a measure of Operational Efficiency and Accessibility. As can be seen in Table 7, Guangzhou, Zhengzhou and Wuhan perform well in this dimension, while Shenzhen and Beijing perform relatively poorly, with low operational efficiency and accessibility.

Table 3. Correlation matrix (Z score) of the indicators

Secondary indicators	Airport size	Airport On-time performance	HSR station size	HSR daily delivery capacity	HSR Maximum speed	Proportion of transfer passengers at the airport	Proportion of international passengers at the airport	Number of destinations available at the airport	Number of flights per day at the airport	Distribution of flights along the day	Number of stops on the HSR routes	Headway between HSR services	Network overlapping	Transfer opportunities	Transfer modal choice	Transfer efficiency
Airport size	1.00	-0.21	-0.08	0.37	-0.05	-0.46	-0.39	-0.45	-0.39	-0.42	0.10	0.58	-0.40	0.26	0.44	0.28
Airport On-time performance	-0.21	1.00	0.32	0.32	0.53	0.86	0.68	0.87	0.89	0.89	0.09	0.03	0.24	0.16	0.27	-0.73
HSR station size	-0.08	0.32	1.00	-0.03	0.18	0.25	0.76	0.39	0.30	0.48	0.05	0.05	0.18	0.28	-0.18	-0.24
HSR daily delivery capacity	0.37	0.32	-0.03	1.00	0.33	0.09	0.01	0.16	0.14	0.05	-0.17	0.43	-0.74	0.86	0.56	-0.60
HSR Maximum speed	-0.05	0.53	0.18	0.33	1.00	0.59	0.53	0.60	0.67	0.55	0.28	-0.50	0.00	0.07	-0.16	-0.61
Proportion of transfer passengers at the airport	-0.46	0.86	0.25	0.09	0.59	1.00	0.69	0.98	0.99	0.92	-0.09	-0.29	0.37	-0.04	-0.04	-0.61
Proportion of international passengers at the airport	-0.39	0.68	0.76	0.01	0.53	0.69	1.00	0.74	0.73	0.84	0.03	-0.35	0.33	0.15	-0.07	-0.55
Number of destinations available at the airport	-0.45	0.87	0.39	0.16	0.60	0.98	0.74	1.00	0.98	0.93	-0.08	-0.22	0.31	0.08	-0.08	-0.66
Number of flights per day at the airport	-0.39	0.89	0.30	0.14	0.67	0.99	0.73	0.98	1.00	0.94	-0.04	-0.30	0.36	-0.01	-0.02	-0.64
Distribution of flights along the day	-0.42	0.89	0.48	0.05	0.55	0.92	0.84	0.93	0.94	1.00	-0.07	-0.26	0.52	-0.01	-0.07	-0.53
Number of stops on the HSR routes	0.10	0.09	0.05	-0.17	0.28	-0.09	0.03	-0.08	-0.04	-0.07	1.00	-0.11	0.01	-0.30	-0.22	-0.17
Headway between HSR services	0.58	0.03	0.05	0.43	-0.50	-0.29	-0.35	-0.22	-0.30	-0.26	-0.11	1.00	-0.41	0.49	0.57	0.04
Network overlapping	-0.40	0.24	0.18	-0.74	0.00	0.37	0.33	0.31	0.36	0.52	0.01	-0.41	1.00	-0.76	-0.46	0.33
Transfer opportunities	0.26	0.16	0.28	0.86	0.07	-0.04	0.15	0.08	-0.01	-0.01	-0.30	0.49	-0.76	1.00	0.50	-0.48
Transfer modal choice	0.44	0.27	-0.18	0.56	-0.16	-0.04	-0.07	-0.08	-0.02	-0.07	-0.22	0.57	-0.46	0.50	1.00	-0.29
Transfer efficiency	0.28	-0.73	-0.24	-0.60	-0.61	-0.61	-0.55	-0.66	-0.64	-0.53	-0.17	0.04	0.33	-0.48	-0.29	1.00

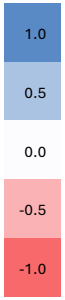


Table 4. Extraction of Variance from Common Factors

Indicator	Extracted	Indicator	Extracted
HSR daily delivery capacity	0.989	HSR station size	0.936
Number of flights per day at the airport	0.979	Proportion of international passengers at the airport	0.916
Distribution of flights along the day	0.978	Headway between HSR services	0.88
Transfer opportunities	0.978	Number of stops on the HSR routes	0.874
Proportion of transfer passengers at the airport	0.974	Transfer efficiency	0.873
Airport size	0.967	Airport On-time performance	0.848
Number of destinations available at the airport	0.952	Transfer modal choice	0.768
Network overlapping	0.946	HSR Maximum speed	0.748

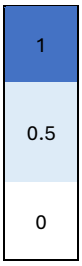
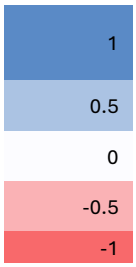


Table 5. Explained Variance and Cumulative Variance by Principal Components

Components	Original Eigenvalue		
	Total	Explained Variance (%)	Cumulative Variance (%)
1	6.852	42.826	42.826
2	3.877	24.233	67.058
3	1.482	9.262	76.321
4	1.275	7.966	84.287
5	1.121	7.007	91.294
6	.700	4.372	95.666
7	.462	2.890	98.556
8	.159	.995	99.552
9	.072	.448	100.000
10	7.547E-016	4.717E-015	100.000
11	4.639E-016	2.899E-015	100.000
12	1.387E-016	8.669E-016	100.000
13	1.073E-016	6.704E-016	100.000
14	-9.990E-018	-6.244E-017	100.000
15	-1.632E-016	-1.020E-015	100.000
16	-2.959E-016	-1.849E-015	100.000

Table 6. PCA Component Coefficient

Principal Component	1	2	3	4	5
HSR Maximum speed	-0.069	0.124	-0.032	0.157	0.449
Proportion of transfer passengers at the airport	0.129	0.067	0.062	-0.071	0.293
HSR daily delivery capacity	0.067	0.012	0.186	0.651	-0.097
HSR station size	0.019	0.24	-0.113	-0.085	-0.103
Airport On-time performance	0.1	0.027	-0.409	0.009	-0.001
Airport size	0.138	-0.007	0.055	-0.196	0.06
Proportion of international passengers at the airport	0.125	-0.006	0.073	0.311	-0.107
Number of destinations available at the airport	0.141	0.011	0.065	-0.083	0.005
Number of flights per day at the airport	0.141	0.003	0.019	-0.145	0.086
Distribution of flights along the day	0.14	-0.017	0.142	0.007	0.085
Number of stops on the HSR routes	0.004	-0.042	-0.455	0.289	0.452
Headway between HSR services	-0.05	0.165	0.294	0.098	0.342
Network overlapping	0.051	-0.206	0.228	-0.008	0.24
Transfer opportunities	0.007	0.23	0.062	0.16	-0.319
Transfer modal choice	-0.012	0.191	0.167	-0.201	0.258
Transfer efficiency	-0.102	-0.135	0.212	0.03	0.092



To calculate the composite score of the principal components, the proportion of the eigenvalues corresponding to each principal component to the sum of the total eigenvalues was used as the weight, as shown in the following equation:

$$\text{Total score} = \frac{1}{91.294}(42.826 \cdot \text{PC}_1 + 24.233 \cdot \text{PC}_2 + 9.262 \cdot \text{PC}_3 + 7.966 \cdot \text{PC}_4 + 7.007 \cdot \text{PC}_5) \quad (3.1)$$

Table 7. PCA Results and Ranking

City (airport – HSR station)	PC1	PC2	PC3	PC4	PC5	Score	Rank
Shanghai (PVG - Shanghai)	0.84	0.47	0.26	0.75	0.69	0.66	1
Guangzhou (CAN - Guangzhou North)	0.59	0.42	-0.02	-0.10	1.31	0.48	2
Beijing (PEK - Beijing North)	0.79	0.21	0.18	-0.43	0.60	0.45	3
Kunming (KMG - Kunming South)	0.34	0.61	-0.43	0.04	0.70	0.34	4
Changsha (CSX - Changsha South)	-0.04	0.88	0.30	0.21	0.61	0.31	5
Shenzhen (SZX- Shenzhen Airport North)	0.42	-0.23	0.02	0.32	0.59	0.21	6
Chengdu (CTU - Shuangliu Airport)	0.24	0.04	-0.24	0.31	0.85	0.19	7

City (airport – HSR station)	PC1	PC2	PC3	PC4	PC5	Score	Rank
Wuhan (WUH – Hankou)	0.04	0.12	-0.45	0.35	0.92	0.11	8
Zhengzhou (CGO - Xinzheng Airport)	-0.08	0.09	0.41	0.09	0.93	0.11	9
Haikou (HAK – Meilan)	-0.05	-0.17	0.46	0.19	0.67	0.05	10

5.2 Fractal results

The proposed model for conducting Fractal Analysis was implemented using MATLAB. To calculate the fractal dimension, which is typically non-integer, data is plotted on logarithmic scales. The fractal dimension is determined by computing the slope on a log-log plot against primary indicators. Each city's overall dimension is then calculated from the secondary indicators. The complexity of the fractal object across various scales is shown by the logarithm of the number of spheres (Log M(r)) required for coverage, while Log r indicates the sphere sizes at different scales.

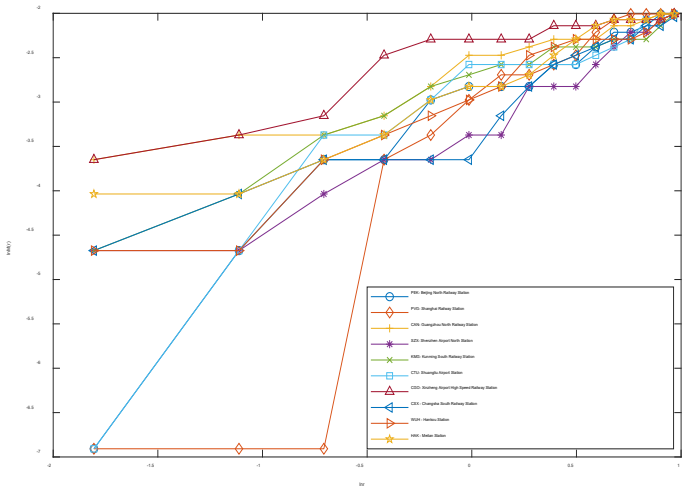


Figure 1. Results for the Fractal Analysis

The overall results of the Fractal Analysis generated another ranking, to determine the level of integration between air and HSR networks in different cities. This ranking can be seen in Table 8. Shanghai, Beijing, and Chengdu emerged as the top three cities. Shanghai ranks first overall, driven by its exceptional transfer potential and strong network connectivity, despite lower service capability due to airport on-time performance and HSR speed. Beijing secures the second position primarily because of its extensive network connectivity, though its service capability and transfer potential are average. Chengdu ranks third, showcasing excellent network connectivity, but needs to improve air transfer passenger attraction and air-HSR intermodal network connection optimisation.

In terms of service capability, Kunming, Shenzhen, and Guangzhou lead. Kunming excels due to its top airport on-time performance, large HSR station, and high-speed trains. Shenzhen and Guangzhou follow, attributed to their high on-time performance, significant international passenger percentages, and robust HSR capacities. These findings suggest that integrated service capability is influenced not only by the scale of the infrastructure but also by performance metrics like punctuality and speed.

Regarding network connectivity, Chengdu, Shanghai, and Beijing are the top performers. Chengdu benefits from numerous HSR stops, indicating a large catchment area. Shanghai's success is due to the highest distribution of flights throughout the day and short HSR headways, while Beijing's connectivity is boosted by numerous destinations and high flight frequency, coupled with low destination overlap.

For transfer potential, Shanghai, Guangzhou, and Changsha rank highest. Shanghai's extensive connection opportunities and ground transfer options contribute to its top rating, despite inefficiencies in intermodal transfers. Guangzhou excels in providing a wide range of ground transfer alternatives, while Changsha demonstrates strong connection opportunities and ground transport choices. These aspects underline the importance of both connectivity and transfer efficiency in determining overall network integration performance.

Table 8. Ranking according to the fractal dimension

Rank	City (airport – HSR station)	Service capability	Network connectivity	Transfer convenience	Overall
1	Shanghai (PVG - Shanghai)	1.019	3.141	6.622	2.163
2	Beijing (PEK - Beijing North)	0.699	3.071	0.743	1.521
3	Chengdu (CTU - Shuangliu Airport)	0.885	3.320	0.891	1.463
4	Shenzhen (SZX- Shenzhen Airport North)	3.492	0.963	0.891	1.076
5	Wuhan (WUH – Hankou)	0.954	3.068	1.061	1.062
6	Changsha (CSX - Changsha South)	1.088	0.991	6.514	0.992
7	Kunming (KMG - Kunming South)	3.549	0.567	0.392	0.906
8	Haikou (HAK – Meilan)	1.019	1.016	1.061	0.886
9	Guangzhou (CAN - Guangzhou North)	1.145	0.673	6.622	0.668
10	Zhengzhou (CGO - Xinzheng Airport)	0.574	0.580	0.392	0.615

6. Comparison and Discussion

6.1 Result comparison

The comparison of rankings derived from PCA and Fractal Analysis for evaluating the air-HSR intermodal network integration performance of ten Chinese cities was conducted using the WS Coefficient method (Sałabun & Urbaniak, 2020). The WS Coefficient provides a measure of the similarity between the two rankings, with higher values indicating a closer alignment. As shown in Table 9, our analysis revealed that Shanghai achieved a perfect WS Coefficient of 1.000, indicating identical rankings by both PCA and Fractal Analysis. This suggests a robust consensus on Shanghai's leading position in the air-HSR intermodal network integration. Changsha, Shenzhen, Wuhan, Zhengzhou and Haikou also exhibited high WS Coefficients, above 0.99, highlighting a strong agreement between the two methodologies regarding their performance.

However, some cities displayed more substantial differences. For instance, Chengdu ranked 7th in PCA but 3rd in Fractal Analysis, resulting in a comparatively lower WS Coefficient. This divergence highlights how the two methods capture different aspects of network integration. Chengdu benefits from excellent HSR network connectivity, with a high number of stops within an 800 km radius, contributing to its strong performance in Fractal Analysis. Yet, its moderate airport capacity, relatively limited intermodal transfer infrastructure, and weaker performance in key PCA components such as intermodal efficiency and transfer opportunities resulted in a lower PCA score. This case exemplifies how Fractal Analysis captures spatial reach and local accessibility more effectively, while PCA gives greater weight to system-wide operational metrics.

A similar discrepancy is observed in Guangzhou, which had a WS Coefficient of 0.781. Guangzhou performed well in indicators heavily weighted in PCA—such as number of flights per day, destination count, and temporal flight distribution—but scored poorly in Fractal-related indicators like headway

between HSR services and network overlap. These quality-related variables, while marginal in PCA, significantly reduced Guangzhou's Fractal Analysis score.

Beijing secured the third spot in PCA and the second spot in Fractal Analysis, reflecting a similarity in the favourable indicators contributing to the first principal component in both analyses. Overall, the WS Coefficient results demonstrate the consistency and reliability of the PCA and Fractal Analysis in most cases, while also identifying specific instances—like Chengdu and Guangzhou—where the methods diverge, underscoring their complementary value in revealing different dimensions of intermodal performance.

Table 9. WS Coefficient for PCA and Fractal results

City (airport – HSR station)	PCA Rank	Fractal Rank	WS Coefficient
Shanghai (PVG - Shanghai)	1	1	1.0000
Guangzhou (CAN - Guangzhou North)	2	9	0.7813
Beijing (PEK - Beijing North)	3	2	0.9821
Kunming (KMG - Kunming South)	4	7	0.9688
Changsha (CSX - Changsha South)	5	6	0.9938
Shenzhen (SZX- Shenzhen Airport North)	6	4	0.9922
Chengdu (CTU - Shuangliu Airport)	7	3	0.9896
Wuhan (WUH – Hankou)	8	5	0.9941
Zhengzhou (CGO - Xinzheng Airport)	9	10	0.9980
Haikou (HAK – Meilan)	10	8	0.9998

The integration of PCA and Fractal Analysis results allows for a more comprehensive evaluation of air-HSR intermodal network. PCA primarily captures the quantitative aspects of connectivity and service capability, focusing on factors like airport size, frequency of flights, and number of destinations. In contrast, Fractal Analysis emphasises spatial patterns and the hierarchical structure of the network, reflecting transfer potential and the spatial coherence of the intermodal system. Combining insights from both methods allows to identify how the two perspectives complement each other and where they diverge.

6.1.1 Service Capability

For service capability, PCA highlights Shanghai, Beijing, and Guangzhou as the top performers in terms of service capability, mainly driven by their large airport sizes, high on-time performance, and substantial HSR speed. Specifically, Shanghai stands out with its significant airport size and strong punctuality, while Beijing benefits from the largest airport size and a moderate on-time performance. Guangzhou also excels due to its robust international connectivity.

However, Fractal Analysis results indicate a slightly different perspective. Kunming and Shenzhen outperform other cities in service capability due to their exceptional HSR speeds and high on-time performance. In contrast, Beijing, despite its high volume of air traffic, ranks lower in fractal dimension for service capability. This discrepancy arises because Fractal Analysis not only considers the size and frequency of services but also their spatial coherence and how well they are integrated within the network.

The integrated analysis suggests that while PCA effectively captures high-volume service capacity, it does not fully reflect spatial efficiency and operational integration, which are better captured by Fractal Analysis. Cities like Shanghai, which rank high in both analyses, demonstrate that achieving high service capability requires not just capacity but also spatial alignment of services. On the other hand, Beijing's lower fractal score highlights the gap between quantitative capacity and practical intermodal integration.

6.1.2 Network Connectivity

In terms of network connectivity, PCA ranks Shanghai, Beijing, and Guangzhou at the top, primarily due to their extensive number of destinations and high number of daily flights. These cities are identified as major hubs with significant air traffic and broad network coverage.

Fractal Analysis, however, places Chengdu, Shanghai, and Beijing as the most connected cities, emphasising spatial network density and coordination rather than just the number of routes. For instance, Chengdu's high fractal connectivity score reflects its numerous HSR stops and short headway between HSR services, indicating frequent and spatially consistent connections.

The combination of PCA and Fractal Analysis suggests that achieving optimal network connectivity requires both quantitative breadth and spatial coherence. Cities like Shanghai, which consistently rank high in both analyses, exemplify well-balanced connectivity, while Guangzhou, which shows high PCA scores but lower fractal scores, indicates potential inefficiencies in spatial integration despite high flight frequency.

6.1.3 Transfer Convenience

PCA identifies Shanghai, Guangzhou, and Changsha as leading in transfer convenience, highlighting factors such as high transfer efficiency and numerous ground transport options. Shanghai's high score is driven by its extensive ground transfer opportunities and efficient intermodal transfer rates.

Fractal Analysis ranks Shanghai, Guangzhou, and Changsha highly as well, but places a stronger emphasis on spatial coherence between transfer points. In cities like Guangzhou, the high transfer convenience in fractal analysis is influenced by multiple ground transport choices and frequent HSR connections, which ensure reliable and consistent transfer opportunities.

The integrated results reveal that high transfer convenience arises from not only having numerous transport options but also ensuring spatial proximity and alignment between air and HSR networks. While PCA captures the volume of transfer services, Fractal Analysis emphasises their spatial integration, making both perspectives essential for a comprehensive evaluation.

6.2 Analysis for discrepancy and complementary

Upon careful reflection on the comparative analysis, it is evident that PCA and Fractal Analysis each offer distinct yet complementary perspectives on evaluating air-HSR intermodal networks. Despite some similarities in their application to air-HSR intermodal network, it is important to clarify that neither Fractal Analysis nor PCA can be categorically deemed superior. While Fractal Analysis is particularly valuable for capturing local characteristics and variations in the network, PCA excels in identifying overall network connectivity and intermodal service capabilities. This difference underscores the importance of using both methods to achieve a holistic assessment.

From the above analysis, PCA places significant emphasis on quantitative connectivity and service scale, with indicators such as the Number of Destinations at the airport, the Number of Stops on the HSR Routes, and the HSR Station Size receiving considerable weight. These indicators are crucial for understanding the scale and reach of the network. However, PCA tends to overlook quality-related indicators, such as Airport On-time Performance and Transfer Modal Choices. These factors are often underrepresented in the top five principal components identified by PCA, highlighting a limitation in capturing qualitative aspects of network performance.

Quality-related factors are critical for a comprehensive understanding of air-HSR intermodal network integration, as they directly impact passenger experience and operational efficiency. Fortunately, Fractal Analysis captures these features effectively through its Service Capability and Transfer Potential primary indicators, which incorporate local characteristics and variations. This implies that while PCA might overemphasise quantitative metrics, Fractal Analysis provides a more nuanced perspective by capturing the subtleties of local service quality and transfer efficiency.

When dealing with numerous indicators and large datasets, PCA may inadvertently give disproportionate attention to quantitative measures while neglecting qualitative aspects. This issue is particularly relevant for major Chinese cities, where qualitative indicators, such as On-time Performance and Transfer Options, vary significantly between locations. In practice, these quality-related factors are often more critical for passenger satisfaction and network efficiency than purely quantitative metrics like the number of connections and station size. As a result, the overemphasis on quantitative indicators in PCA may lead to an incomplete evaluation of intermodal efficiency.

It is essential to recognise that China's strategic focus has historically been on expanding infrastructure by building larger airports and HSR stations and increasing connectivity. While these efforts have significantly improved the network's scale and reach, they may have inadvertently overshadowed qualitative aspects such as air service punctuality and the diversity of ground transfer modes. Fractal Analysis effectively identifies these gaps, providing a more precise indication of areas needing improvement.

Therefore, the integrated use of both PCA and Fractal Analysis allows for a more balanced evaluation. While PCA captures high-level service capacity and connectivity, Fractal Analysis highlights spatial coherence and local service quality. This complementary approach ensures that both quantitative expansion and qualitative improvement are considered in developing more efficient air-HSR intermodal networks.

7. Policy recommendation

Improving the air-HSR intermodal network in China requires targeted policy interventions that address the specific challenges identified through the PCA and Fractal Analysis. These analyses provide a comprehensive understanding of the strengths and weaknesses across service capability, network connectivity, and transfer potential in different cities. By tailoring strategies to the unique conditions of each city, policymakers can foster a more efficient and balanced air-HSR intermodal network. The following recommendations include both evidence-backed practices from existing literature and new policy strategies developed in this study based on the empirical results.

7.1 Strengthen Air-HSR Intermodal Complementarity

A fundamental challenge in developing an effective air-HSR intermodal network is the tendency to view the two modes as separate rather than as interconnected components of a cohesive transport system. The analyses indicate that cities with strong HSR connectivity, such as Shanghai, tend to perform well in network integration, while cities like Zhengzhou and Haikou, with limited air service capacity and operational efficiency, face challenges in achieving balanced intermodal connectivity.

To maximise the potential of the intermodal network, strategic planning should clearly position air travel for long-haul routes and HSR for short- to medium-haul distances, leveraging each mode's strengths (D'Alfonso et al., 2016). Creating dedicated HSR feeder services to major airports can reduce the dependency on short-haul flights, thus improving the overall network efficiency. Passenger preferences are significantly influenced by the availability of seamless and efficient transfers between air and HSR (Román & Martín, 2014). Currently, passengers in China often purchase air and HSR tickets separately and manage transfers independently due to the lack of integrated ticketing products. To enhance the intermodal network, policy interventions should focus on establishing joint ticketing systems, fostering cooperation between airlines and HSR operators. Developing integrated booking platforms would not only streamline the passenger experience but also facilitate data collection on intermodal travel patterns, providing valuable insights for improving network efficiency.

In addition to technical and operational coordination, stronger regulatory instruments could also play a transformative role in clarifying the functional boundaries between modes. For instance, implementing a ban or restriction on short-haul flights for routes where HSR offers competitive travel times—such as journeys under two hours—could significantly reduce redundancy and environmental impact (European Commission, 2021; D'Alfonso et al., 2016). Such policies have been piloted in European contexts (e.g. France), and applying similar thresholds in China would help reallocate short-distance demand from air to rail. Cities like Chengdu, Changsha, and Wuhan, which exhibit strong HSR spatial accessibility in Fractal Analysis, are well-positioned to absorb short-haul air demand under this framework. This would

not only enhance sustainability but also free up airport slots for long-haul and international services. By establishing clear modal roles, these policies support a more coherent planning approach and allow for prioritised infrastructure investment aligned with distance-based modal logic.

A major barrier to effective air-HSR complementarity is the regulatory and institutional fragmentation between aviation and railway sectors, leading to disconnected planning and operational inefficiencies (Voltes-Dorta & Martín, 2022). Establishing a centralised intermodal task force can facilitate collaboration between regulators, operators, and infrastructure planners. This task force should aim to develop a unified intermodal transport strategy that mandates schedule coordination, integrated ticketing, and pricing alignment between air and HSR services (Román & Martín, 2014).

While the concept of air-HSR complementarity and the regulatory suggestion of banning short-haul flights under two hours have been proposed in the European context (D'Alfonso et al., 2016), their application in the Chinese context—especially in cities such as Chengdu, Wuhan, and Zhengzhou—is a novel recommendation emerging from this study's empirical analysis. Our findings suggest that these cities, due to their strong HSR connectivity and moderate aviation dependency, would be ideal candidates for piloting such regulatory interventions.

7.2 Enhance Network Service Capability and Efficiency

Service capability is a key factor in building an efficient air-HSR intermodal network. The findings indicate that cities such as Zhengzhou and Haikou, identified as underperformers in both PCA and Fractal Analysis, require targeted improvements in both airport and HSR service quality. In contrast, cities like Shenzhen and Shanghai, which demonstrate higher on-time performance (OTP) and more extensive destination networks, exhibit better network performance.

Improving operational efficiency requires policies that encourage joint scheduling and real-time coordination between airlines and HSR operators. Governments should incentivise the adoption of real-time information systems and integrated scheduling platforms to enhance transfer efficiency and reduce delays (Román & Martín, 2014). This approach is particularly important in cities where recurrent delays, such as Zhengzhou and Changsha, negatively impact the intermodal network's reliability. Advanced air traffic management systems and enhanced HSR punctuality measures should be prioritised in these areas to improve service capability and network resilience.

Although the importance of real-time coordination and OTP improvements has been widely recognised in existing literature, this study contributes a novel aspect by linking these operational gaps to specific city profiles identified through dual-method performance discrepancies. For instance, Changsha shows weaker OTP but relatively strong HSR network coverage—indicating where targeted aviation-side improvements can yield better intermodal outcomes.

7.3 Promote Seamless Intermodal Connectivity

Seamless connectivity between air and HSR is essential for establishing a cohesive intermodal network. A key issue identified through Fractal Analysis is the physical and operational separation between airports and HSR stations, particularly in cities like Beijing and Guangzhou, where long distances between hubs hinder efficient transfers (Cao et al., 2013).

To enhance intermodal connectivity, investments should focus on integrated transport hubs where air and HSR services are either co-located or efficiently linked through ground transportation solutions. In cities where infrastructure constraints exist, implementing dedicated shuttle services, express buses, or rail links between airports and HSR stations can significantly reduce transfer times and improve passenger convenience.

Improving schedule synchronisation between flights and trains is crucial to minimising transfer delays. As Román and Martín (2014) emphasise, reducing connection times through integrated scheduling significantly enhances passenger satisfaction and willingness to pay. Currently, airlines and HSR operators in China typically plan schedules independently, leading to long waiting times and missed connections. Incentives such as regulatory support, revenue-sharing models, and joint ticketing agreements could encourage airlines and HSR operators to align schedules. Implementing real-time

information systems will also help passengers access accurate schedule updates, fostering a more integrated travel experience.

This study extends existing connectivity proposals by identifying how cities with low Fractal scores—but relatively strong PCA components (e.g., Guangzhou, Kunming)—would benefit most from infrastructure upgrades and ground access enhancements. These city-level insights represent a refinement of prior generic strategies, grounded in integrated performance assessment.

8. Conclusion

The paper addresses the need for a comprehensive evaluation of the air-HSR intermodal network by integrating Fractal Analysis with Principal Component Analysis (PCA). Rather than positioning one method as superior, the study demonstrates how PCA complements Fractal Analysis by providing statistical validation of its geometric insights. The alignment between fractal dimensions and principal components confirms the robustness of the findings, ensuring that the complex spatial patterns identified by Fractal Analysis are statistically significant.

PCA offers a valuable high-level overview by identifying major trends and dominant components, effectively reducing dimensionality. However, it may overlook qualitative aspects and local variations that are crucial for passenger experience and operational efficiency. In contrast, Fractal Analysis captures non-linear relationships and spatial hierarchies, offering deeper insights into the intricate dynamics of air-HSR intermodal networks. By combining both methods, the study achieves a balanced and comprehensive assessment, leveraging the strengths of PCA for quantitative analysis and Fractal Analysis for capturing local characteristics and spatial coherence.

The policy recommendations derived from this dual-method approach emphasise enhanced service capability, improved seamless intermodal connectivity and strengthened network resilience. By adopting these methods, decision-makers can develop more informed and effective strategies to enhance the integration and performance of air-HSR intermodal networks, ultimately leading to improved connectivity, efficiency, and passenger experience.

Moving forward, our study aims to enhance the air-HSR intermodal transport network evaluation index system by delving deeper into relevant characteristic indicators. This will broaden the evaluation content and make it more comprehensive. Additionally, we will explore the viability of incorporating alternative evaluation methods to offer a wider range of perspectives and recommendations for comprehensive evaluation and policy formulation. Meanwhile, it is important to acknowledge certain limitations in this study. The analysis is based on a sample of ten cities, selected to represent a mix of international and regional hubs. While this selection facilitates meaningful comparisons, it may not fully capture the diversity of air-HSR intermodal networks across China, particularly in cities with extreme variations in key indicators such as flight frequency, network connectivity, and HSR service availability. Future research could expand the sample size to include cities with more distinct air-HSR characteristics to enhance generalisability.

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