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Service Scale and Level: How Origin–Destination Interactions Shape Intercity Travel Flows Within Mega-City Regions

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Abstract

As regional integration and high-speed transport networks advance, intercity travel flows within mega-city regions (MCRs) provide a lens for understanding regional functional division of labor and spatial organization. Concentrated high-intensity flows between core cities and major peripheral nodes suggest that explanations should move beyond distance constraints and single-end city attributes to origin–destination functional linkages. Consumer and producer services help connect these functional linkages with actual travel flows, yet existing studies have focused mainly on service scale and paid insufficient attention to service level, which reflects functional non-ubiquity and diversity. This study incorporates service type, scale, and level, and origin–destination relationships into a unified framework to identify key factors associated with intercity travel flows within MCRs. Focusing on the Yangtze River Delta, this study examines subdistrict/town-level flows from 15 peripheral cities to Shanghai's central urban area. Mobile phone signaling records measure flow intensity. Counts and complexity are used to measure service scale and level. Two XGBoost models are estimated: an origin–destination service model and a difference model. SHAP identifies contributions and directions, while two-dimensional ALE examines interactions between services at origins and destinations. Results show that both service scale and level are associated with intercity travel flows within MCRs, but their patterns differ by service type. Significant interaction effects exist between services at origins and destinations. These interactions mainly combine origin-scale foundations with destination-level-based attraction, with destination service level often showing threshold-like characteristics. This study extends the explanation of intercity travel flows to origin–destination functional linkages and service level.

Keywords: intercity travel flows; mega-city regions; functional linkages; service; level; scale

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1. Introduction

A mega-city region (MCR) is a regional urban network composed of multiple relatively independent cities and towns clustered around one or more core cities and linked by intensive flows of people and information [1]. As regional integration advances and high-speed transport infrastructure expands, travel times between cities decline. Intercity commuting, business travel, and service consumption become more frequent, generating stable intercity travel flows within MCRs [2,3]. Such long-distance travel reflects not only the movement of people across space but also increasingly close functional linkages between

cities [4]. Intercity travel flows therefore provide an important lens for understanding functional division of labor and regional spatial organization within MCRs.

However, intercity travel flows within MCRs do not increase evenly as transport conditions improve. Existing studies show that high-intensity intercity travel tends to concentrate between core cities and key peripheral nodes, rather than being evenly distributed across all city pairs [5,6]. Similar patterns have been observed in the London–South East England metropolitan region, the San Francisco Bay Area, and the Guangdong–Hong Kong–Macao Greater Bay Area, where stronger intercity linkages tend to form between core cities and key peripheral nodes [7–9]. This suggests that intercity travel flows are constrained by travel distance and accessibility but cannot be explained solely by distance decay or attributes of a single city. For MCRs, a more critical question is why some origin–destination city pairs can sustain high-intensity travel linkages, while other city pairs with similar transport conditions show weaker flows. This question calls for a shift from explanations based on attributes of a single city to those based on functional linkages between origin and destination cities. It also requires closer attention to intercity travel flows between core cities and peripheral cities within MCRs. Therefore, the influence of urban functional linkages on intercity travel flows should not be treated only as the separate effects of attributes of origin or destination cities. It is also necessary to examine whether joint effects and interaction effects exist between the two cities in an origin–destination pair.

Within MCRs, services provide an important lens for understanding how urban functional linkages are reflected in intercity travel flows. Consumer and producer services are important components of urban place functions. Hall and Pain [1] argue that spillovers of advanced producer services from core cities create functional nodes in nearby cities and varied linkages with the core, driving MCR formation. Producer services generate intercity business and commuting travel through industrial linkages and high-end employment [10,11]. Consumer services attract intercity service-seeking travel through public and commercial services [12,13]. Accordingly, urban place functions in the core city meet demand from peripheral cities, reflecting functional division of labor within the MCR and associated population flows from peripheral cities to the core city. From a functional perspective, examining the associations between different service types and intercity travel flows from peripheral cities to the core city can help clarify the underlying logic of functional linkages.

However, existing studies often analyze services primarily in terms of scale, typically using the number and density of service facilities. These indicators mainly capture the quantity and types of service provision, while paying relatively limited attention to the non-ubiquity of service–function combinations [14]. Intercity travel depends not only on the scale of destination services but also on whether the corresponding service functions are available locally. Service level, by contrast, emphasizes the diversity of service–function combinations and their spatial non-ubiquity. A higher service level indicates that an area concentrates more relatively non-ubiquitous service functions, which have greater irreplaceability for travelers who cannot access equivalent services locally, such as certain specialized public and commercial services and advanced producer services [15–17]. Distinguishing scale from level therefore helps explain why cities with similar service scales generate different intercity travel flows.

Existing research on intercity travel flows has three main limitations. First, most studies explain these flows through travel distance, accessibility, or the built environment, with limited attention to the functional linkages created by services. Second, studies of services tend to emphasize scale, leaving the role of service level in intercity attraction underexplored. Third, although the importance of origin and destination service attributes is increasingly recognized, the joint effects and interaction effects of services between

origins and destinations remain insufficiently examined. An analytical framework incorporating consumer and producer services, service scale and level, and origin–destination relationships is therefore needed to explain the intensity of intercity travel flows from peripheral cities to the core city within MCRs. This study focuses on the Yangtze River Delta, a major MCR in China. It uses mobile phone signaling data to measure intercity travel flow intensity from 15 peripheral cities to Shanghai's central urban area and applies machine learning methods to address the following research questions:

Q1: Within MCRs, how are the scale and level of different service types at origins and destinations associated with intercity travel flows from peripheral cities to the core city?

Q2: Within MCRs, do service attributes at origins and destinations interact in their associations with intercity travel flows from peripheral cities to the core city? If so, how do these interactions vary by service type, service scale and level, and the roles of origins and destinations?

By addressing these questions, this study interprets intercity travel flows as the spatial expression of functional linkages between origins and destinations within transport networks, with a particular focus on service attributes at both ends of an origin–destination pair. It also examines the sources of intercity attraction from the perspective of service level, thereby revealing how urban place functions are associated with intercity travel.

The remainder of this study is organized as follows. Section 2 reviews the literature and develops the research hypotheses. Section 3 describes the study area, research framework, data sources, preprocessing procedures, measures of intercity travel flows and service level, and modeling methods. Section 4 presents the results. Section 5 summarizes the main findings, discusses their implications and limitations, and identifies directions for future research.

2. Literature Review

2.1. Intercity Travel Flows and Services

Travel behavior is commonly explained in terms of the built environment and travel distance. Built-environment research often draws on the 5Ds framework, which relates residents' travel behavior to density, diversity, design, destination accessibility, and distance to transit [18]. Subsequent studies have extended this framework from intracity travel to regional mobility, with growing attention to urban spatial form and land use [19,20]. In parallel, studies of travel distance explain variation in travel linkages primarily through time costs and mode choice [21–23].

Within MCRs, however, intercity travel is not merely movement under distance impedance. It is also a spatial expression of functional linkages between cities. The MCR perspective emphasizes functional division of labor, complementarity, and regional activity linkages [24]. Diversified linkages between producer and consumer functions across cities generate sustained intercity travel demand for commuting, business, and service-seeking purposes [25,26]. Commuting travel refers to repeated trips between residences and workplaces under residence–employment separation. Business travel refers to trips for firm collaboration, meetings, and other producer-service activities [27]. Service-seeking travel refers to trips made to access public or commercial services [28]. Distance and the built environment help explain distance decay and locational preferences, but do not fully capture functional division of labor or linkages between origin and destination cities [29].

Services are an important driver of functional linkages within MCRs. Regional networks were initially shaped mainly by manufacturing, but service growth has become an important force in restructuring regional spatial organization. Services are therefore an important basis for understanding functional linkages within MCRs [30]. Producer services promote business travel and commuting through value–chain relations, headquarters–

branch networks, and high-end employment [11,14,31]. Consumer services meet daily living and consumption needs, influencing service-seeking travel through public and commercial services [28,32]. However, studies often treat services as aggregate industrial indicators [33,34], obscuring differences between consumer and producer services.

2.2. Intercity Travel Flows, Service Scale, and Service Level

Service scale and service level are two complementary attributes of service provision. Existing studies often explain intercity travel in terms of service scale, using indicators such as the number of firms, employment, and economic output in producer services [30], as well as the number and density of consumer-service facilities and POIs [33,35]. For long-distance intercity travel, however, the decision to travel to another city depends not only on the scale of destination services but also on whether the corresponding service functions are available at the origin or in surrounding areas [32]. Service level is therefore an important complementary dimension. In this study, service level does not refer to administrative rank or facility grade but emphasizes the diversity of service–function combinations and their spatial non-ubiquity. More non-ubiquitous service functions are distributed across fewer places and therefore have greater irreplaceability for travelers who cannot access equivalent services locally. Among public and commercial services, tourism and leisure services, and knowledge-intensive producer services such as finance, law, consulting, and information services, more specialized service functions often exhibit stronger spatial non-ubiquity. Because such functions are less widely available in surrounding areas, they may be associated with stronger intercity attraction [17,36].

Research on economic complexity provides a useful approach to measuring service level. Economic complexity theory was initially developed to identify national productive capabilities through the recursive relationship between diversity and ubiquity. Products that fewer countries can export competitively, and countries that competitively export more such products, tend to have higher complexity [37]. Recent studies have extended complexity methods to spatial units such as cities and neighborhoods to characterize the diversity and non-ubiquity of industrial structures, facility composition, and service provision [15,38,39]. Applying complexity methods to services does not equate complexity with functional scarcity. Instead, it identifies whether an area concentrates a diverse combination of relatively non-ubiquitous service functions, thereby providing a measure of the service level defined above.

Both service scale and service level may affect intercity travel flows, but through different pathways. Existing studies have devoted more attention to scale than to level and rarely examine the two as parallel dimensions within a unified framework. As a result, their distinct and joint roles in shaping intercity travel flows remain unclear.

2.3. Intercity Travel Flows and the Joint Effects Between Origins and Destinations

Intercity travel flows are shaped by both origin and destination cities, but the two cities operate through different pathways. Spatial complementarity theory argues that flows often arise from functional supply–demand differences between two places. Origin cities provide potential demand, whereas destination cities provide opportunities; actual flows are more likely to emerge when the two match [40]. Push–pull theory also distinguishes the generative role of origin cities from the attractive role of destination cities [41]. Existing empirical studies have long emphasized destination cities, especially the inflow effects and hinterland extent of core cities, central urban areas, and major employment nodes. These studies highlight the attraction of concentrated functional supply at destinations for intercity travel [13,42]. By contrast, attributes of origin cities, such as population size, economic level, and housing conditions, are often included only as control variables. Their

role in generating flows has received relatively limited attention [43]. However, functional differences in origin cities can also shape the direction of flows [44]. Using large-scale flow data, studies based on spatial interaction frameworks have examined attributes of origin and destination cities in greater detail. They find that variables in the two cities do not operate symmetrically. Employment density, firm agglomeration, and commercial functions mainly affect destination attraction, whereas education level, housing conditions, consumer services, and transport accessibility mainly affect origin generation [19,45]. The same type of variable may also differ in direction and strength when located in the origin or destination city [46–48]. These findings suggest that intercity travel flows cannot be explained by the attributes of only one city. Their determinants therefore need to be examined within an origin–destination city framework.

More importantly, intercity travel flows are not simple additive outcomes of the effects of origin and destination cities. They are spatial interactions embedded in specific origin–destination city combinations. Analyses of origin–destination matrix types, flow hierarchies, and network structures show that flows are not evenly distributed across all city pairs. Instead, they concentrate in particular origin–destination city combinations [5,49,50]. When shifting from flow-structure identification to mechanism explanation, existing studies usually go beyond the separate attributes of origin and destination cities in two ways. The first approach uses difference or ratio indicators to capture relative differences between two places, such as wage gaps, housing–employment mismatch, and job–housing balance [51–53]. The second approach uses interaction terms, moderation models, or non-parametric joint-effect methods to test interaction effects among variables. Previous findings show that distance decay in travel flows varies by land-use type in origin and destination cities. The effects of built-environment variables in both cities are also moderated by employment supply, residential demand, and commuting distance. This indicates conditional effects among the determinants of travel flows [45,47]. Although existing studies recognize the importance of attributes of origin and destination cities and their relative differences, they pay limited attention to the joint effects of service functions between the two cities. The interaction effects between producer services and consumer services in origin and destination cities remain especially underexplored.

Based on this review, this study proposes three hypotheses:

H1. *Within MCRs, services are significantly associated with intercity travel flows from peripheral cities to the core city, but consumer and producer services exhibit different patterns of association.*

H2. *Service scale and service level are associated with intercity travel flows from peripheral cities to the core city in different ways. Scale is more likely to reflect basic support at both origins and destinations, whereas level is more likely to reflect destination-oriented attraction. Service scale is expected to have positive associations at both origins and destinations, whereas service level may have stronger associations when measured at destinations or as differences between destinations and origins.*

H3. *Within MCRs, the associations of service attributes in origin–destination pairs are not simply the additive effects of origins and destinations. Interaction effects may exist, and these effects may vary by service type, service scale or level, and the roles of origins and destinations. A unified framework that incorporates consumer and producer services, service scale and level, and both origins and destinations is therefore necessary for explaining intercity travel flows within MCRs from the perspective of functional linkages.*

3. Data and Methods

3.1. Study Area and Data Sources

This study focuses on the Yangtze River Delta MCR, covering 16 cities within the region. The 16 cities in this study include Shanghai, Nanjing, Wuxi, Changzhou, Suzhou, Nantong, Yangzhou, Zhenjiang, and Taizhou in Jiangsu Province; and Hangzhou, Ningbo, Jiaxing, Huzhou, Shaoxing, Zhoushan, and Taizhou in Zhejiang Province. This area is among the most closely connected parts of the Yangtze River Delta and has particularly active intercity mobility. It covers approximately 111,100 km^2, has a resident population of about 122.84 million, and recorded a gross regional product of approximately CNY 23.79 trillion. The analysis focuses on intercity travel flows from 15 cities to the central urban area of Shanghai (the central urban area of Shanghai refers to the subdistrict/town units within Shanghai's Inner Ring Road). It does not distinguish among specific travel purposes, such as commuting, business, or service-seeking travel, but measures the overall intercity travel flow intensity of these peripheral-to-core intercity travel flows. Descriptive comparisons show that the producer-service scale at Shanghai destinations is substantially larger than at peripheral origins, with mean and median values being approximately 177% and 616% higher, respectively; consumer-service scale is similar in mean terms, while its median is approximately 100% higher at Shanghai destinations. In terms of spatial scale, this study uses subdistricts and towns, the basic administrative level of urban governance in China, as the units of analysis. This scale balances data availability with spatial precision and helps identify intra-urban differences in functional distribution and travel linkages. The analysis includes 1219 origin subdistrict/town units distributed across 15 peripheral cities and 132 destination subdistrict/town units located within Shanghai's central urban area. The average area of these units is approximately 76.22 km^2 (Figure 1).

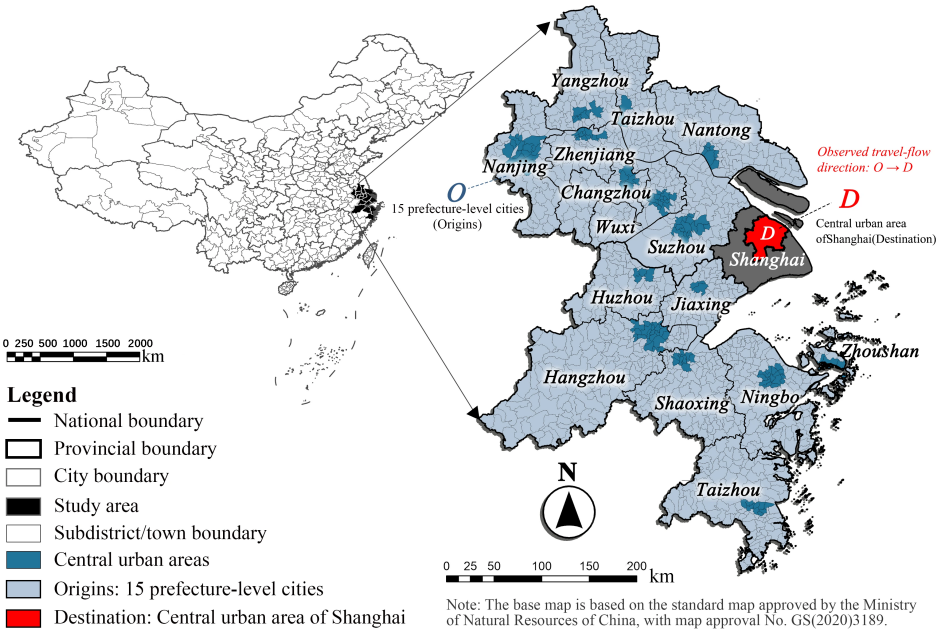


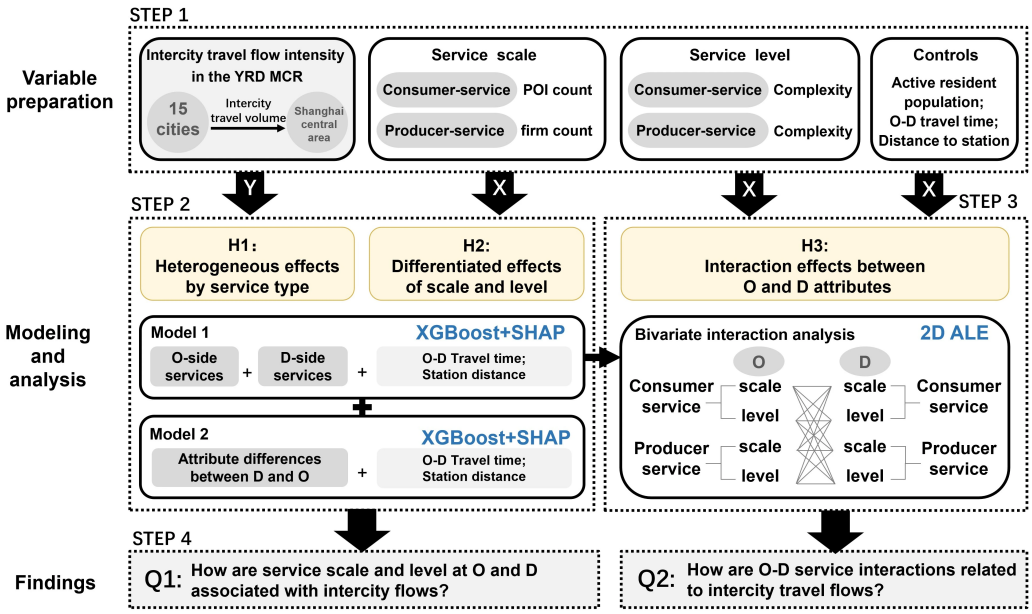
Figure 1. Study area.

Based on this spatial framework, this study integrates three types of data: intercity travel flows, urban place functions, and transport data. First, intercity travel flow data are derived from mobile phone signaling records covering 30 days in June 2024. June was selected as a relatively regular travel period outside major extended holiday and winter/summer vacation periods, thereby reducing the influence of atypical peak travel. The large sample, broad spatial coverage, and continuous passive recording of mobile phone

signaling data enable consistent identification of residence–destination linkages across the study area, making them well suited to the subdistrict/town-level analysis in this study. The records were preprocessed by the data provider and include residence and destination grids, as well as the number of intercity person-trips. Residence locations are represented by geohash6 grids, whereas destinations within Shanghai are represented by geohash7 grids. Second, urban place function data include active resident populations, consumer services, and producer services. Active resident population data come from the same source as the intercity travel flow records. Consumer-service data are obtained from 2024 point of interest (POI) records and mainly cover public and commercial service facilities. Producer-service data are derived from 2024 firm records, including firms registered in the Yangtze River Delta MCR as of 2024. Third, transport accessibility data include two components. Origin–destination travel times were obtained from the route-planning application programming interface (API) provided by Baidu Maps. Spatial data on conventional railway, high-speed railway, and intercity railway passenger stations are derived from 2022 remote-sensing imagery and are used to calculate distances to railway stations. Together, these datasets provide the basis for variable measurement and empirical analysis.

3.2. Research Framework

To examine how different service types are associated with intercity travel flow intensity and whether interaction effects exist between the two ends of origin–destination pairs, this study first constructs key variables, including flow intensity, service scale, and service level. It then examines factors associated with intercity travel flows in the Yangtze River Delta MCR through two model specifications for service-related variables: an origin–destination model and a difference model based on differences between attributes at destinations and origins. It further conducts origin–destination interaction analysis to examine the joint effects of service variables (Figure 2).



Note: O denotes origin and D denotes destination. Difference variables are calculated as destination values minus origin values.Y represents the dependent variable, and X represents the independent variable.

Figure 2. Research framework.

Following the hypotheses in Section 2, the modeling strategy has three components. For H1, consumer and producer services are included separately to compare their effects. For H2, service scale and level at origins and destinations are included to represent the quantity of service provision and the diversity and non-ubiquity of service functions,

respectively, and a difference model examines the corresponding difference variables. For H3, origin–destination service interaction analysis identifies interaction effects between service functions at the two ends.

Finally, the results of Models 1 and 2 are combined to summarize how different services and their scale and level are associated with intercity travel flow intensity, thereby answering Research Question 1. Origin–destination interaction analysis is then used to determine whether service functions at the two ends produce interaction effects, thereby answering Research Question 2.

3.3. Data Processing

Mobile phone signaling records are used to measure the active resident population. First, each user's candidate residence is identified as the grid cell with the longest cumulative dwell time between 21:00 and 7:00 the next day. Second, dates with at least one hour of nighttime dwell time at this location are retained, and the location is identified as the user's residence if it appears on at least 50% of the days in the month. Users with identified residences are then aggregated to subdistrict/town units. The average active resident population is 28,500, accounting for about 33.83% of the permanent population recorded in the Seventh National Population Census. To further assess its spatial validity, the signaling-derived active resident population was matched with the census permanent population for 1127 subdistrict/town units and showed significant positive correlations (Pearson's $r = 0.423$; Spearman's $\rho = 0.499$; both $p < 0.001$). These results indicate that the signaling-derived population captures meaningful spatial variation in resident population size while not implying full demographic representativeness.

POIs are used to measure the scale of consumer services. The data are first cleaned by removing categories with unclear functional meanings, such as names and addresses, road facilities, and indoor facilities. The remaining records are reclassified according to the subcategories of China's national standard, Industrial Classification for National Economic Activities (GB/T 4754-2017) [54]. This study uses it to select and classify consumer-service POIs and producer-service firm records. They are grouped into 13 major categories and 139 subcategories, including catering, tourism, medical services, and retail services. A total of 2.9072 million POIs are retained. POI counts are then aggregated by subdistrict/town to represent consumer-service scale.

Firm records are used to measure the scale of producer services. First, only firms in normal operation are retained, and micro-firms are excluded. Second, five industrial sections and 20 major industries (including railway transport; road transport; water transport; air transport; pipeline transport; multimodal transport and transport agencies; loading, unloading, handling and storage; postal services; telecommunications, radio and television, and satellite transmission services; internet and related services; software and information technology services; monetary and financial services; capital market services; insurance; other financial services; leasing; business services; research and experimental development; professional technical services; and technology promotion and application services) are selected based on the Industrial Classification for National Economic Activities. A total of 619,400 firm records are retained. Small, medium-sized, and large firms are assigned weights of 1, 2, and 3, respectively, and the weighted firm count is aggregated by subdistrict/town as an operational measure of producer-service scale [55].

Station data are used to measure the distance to railway stations. Based on the locations of conventional railway, high-speed railway, and intercity railway passenger stations, the distance from each subdistrict/town center to the nearest station is calculated.

The Baidu Maps route-planning API is used to measure origin–destination travel time. Origin–destination pairs are constructed using subdistrict/town centers, and the API is

used to estimate the shortest travel time across multiple feasible options. This indicator captures the shortest integrated travel time returned by the API across combinations of walking, driving, bus, metro, railway, and air travel (Figure 3).

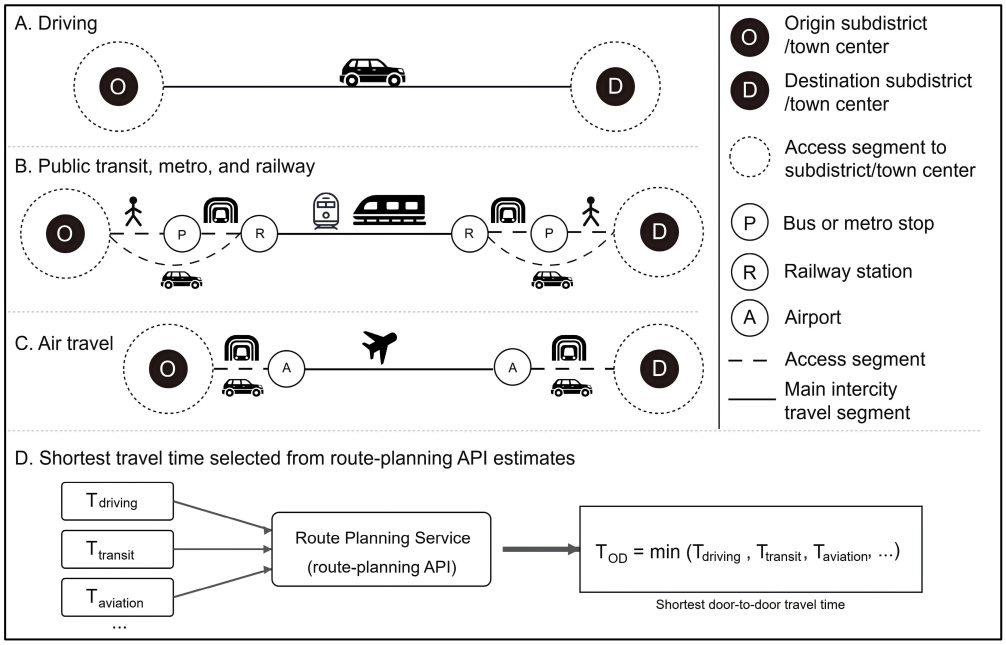


Figure 3. Intercity origin–destination travel time calculation using the Baidu Maps route-planning API.

3.4. Research Methods

3.4.1. Measuring Intercity Travel Flow Intensity

The intercity travel flow intensity used in this study is derived from the underlying mobile phone signaling data through the following steps.

First, user origins are identified. The residence identified above is used as the origin of travel flows, and users without a stable residence are excluded.

Second, travel destinations are identified from grid-level stay records. A trip is defined as intercity travel when the residence and destination are located in different prefecture-level cities. For intercity trips entering Shanghai, destinations are represented by geohash7 grids. An individual stay at a destination grid is retained as a valid stay when its duration reaches 15 min. Multiple valid stays by the same user at the same destination grid on the same day are then merged, and their valid stay durations are accumulated. Subsequently, the five destination grids with the longest valid stay durations are retained for each user-day, and each residence–destination grid record is counted as one person-trip. Therefore, when a user has multiple valid destination grids on the same day, multiple person-trip records may be generated, reflecting valid activity stops at different destinations associated with an intercity journey.

The 15 min threshold was determined through the processing of comparable mobile phone signaling datasets over previous years, taking into account the 5G network environment, grid resolution, and user mobility characteristics. Under the denser base-station coverage of 5G networks, more frequent handovers and potential signal drift may distribute the stay records of a single activity episode across adjacent grids, thereby shortening the continuous stay duration recorded within an individual grid. At the same time, at this relatively fine spatial scale, low-speed movement or stays lasting 15 min or longer provide a reasonable criterion for identifying stays with meaningful activity. Therefore, a higher

threshold may omit valid short-duration activities, whereas a lower threshold may increase the likelihood of identifying short stops or pass-through locations as destinations.

Third, residence and destination grids are mapped to subdistrict/town units. The center of the residential subdistrict/town is used as the origin, and the center of the destination subdistrict/town is used as the destination. Finally, person-trips are aggregated by date, origin subdistrict/town, and destination subdistrict/town to generate a subdistrict/town-level intercity origin–destination flow table. The cumulative number of person-trips for each origin–destination pair represents the intercity travel flow intensity. This process yields 111,093 intercity origin–destination flows and 6,786,344 intercity person-trips in total (Figure 4). Accordingly, the model explains variation in intercity travel flow intensity among observed flows rather than the formation of all potential intercity linkages. The detailed processing workflow is provided in Supplementary Material S1 and Figures S1 and S2.

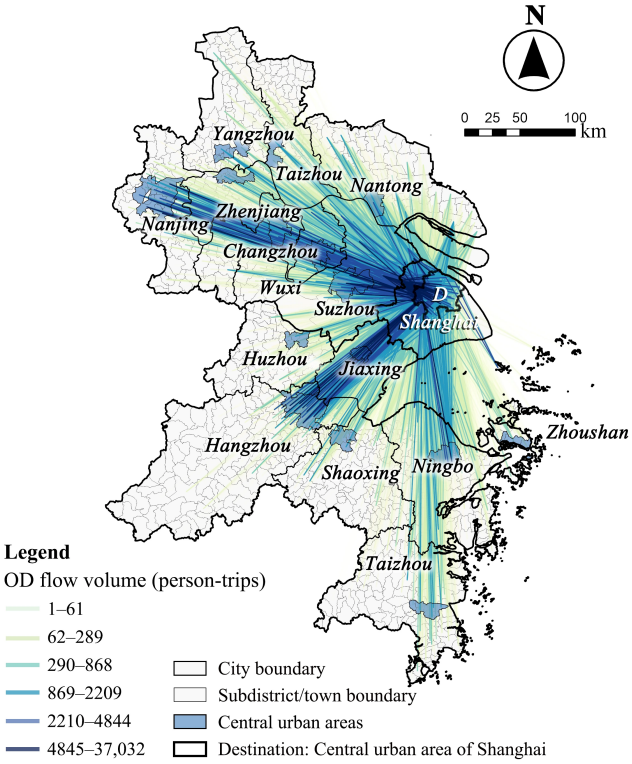


Figure 4. Spatial distribution of intercity travel flows. Note: flow classes are determined using the head/tail breaks method.

3.4.2. Quantifying Service Level

This study introduces complexity indicators from evolutionary economic geography [37,56] to measure the service level of consumer and producer services, respectively.

Consumer-service and producer-service complexity use different spatial reference systems, reflecting the spatial characteristics of the two service types and the measurement purposes of this study. For consumer services, the analysis focuses on relative differences in service–function combinations among subdistricts/towns within the MCR; therefore, the non-ubiquity of service types within the MCR is used as the reference. For producer services, the Yangtze River Delta MCR itself has a high level of producer-service development and a strong concentration of advanced producer services. Measuring complexity solely on the basis of industry non-ubiquity within the region may weaken the identification of some producer-service industries that exhibit relatively high complexity at the national scale. We therefore introduce national producer-service industry complexity as

the industry-level reference. Accordingly, both complexity indicators are used to represent service level, but their values do not constitute a common absolute scale and are more appropriately interpreted as relative service-level indicators within their respective service types. Subsequent analyses compare the associations and relative contributions of the two service levels to intercity travel flows rather than directly comparing the absolute values of the two complexity measures.

(1) Consumer-service complexity

Consumer-service complexity is calculated from POIs using the region-industry iterative method adopted in traditional complexity indicators [57].

Step 1 constructs a subdistrict/town–industry matrix based on consumer-service types and calculates the revealed comparative advantage of each subdistrict/town for each consumer-service type. The formula is as follows:

$$RCA_{ia}^{L} = \frac{x_{ia}^{L} / \sum_{a} x_{ia}^{L}}{\sum_{i} x_{ia}^{L} / \sum_{i} \sum_{a} x_{ia}^{L}} \tag{1}$$

where RCA_{ia}^{L} is the revealed comparative advantage of subdistrict/town i in consumer-service type a; x_{ia}^{L} is the number of POIs of consumer-service type a in subdistrict/town i; $\sum_{a} x_{ia}^{L}$ is the total number of consumer-service POIs in subdistrict/town i; $\sum_{i} x_{ia}^{L}$ is the total number of POIs of consumer-service type a in the study area; and $\sum_{i} \sum_{a} x_{ia}^{L}$ is the total number of consumer-service POIs in the study area.

Step 2 uses the revealed comparative advantage to identify the relative advantage of each subdistrict/town for each consumer-service type and converts the results into a binary matrix:

$$M_{ia}^{L} = \begin{cases} 1, & RCA_{ia}^{L} \geq 1 \\ 0, & RCA_{ia}^{L} < 1 \end{cases} \tag{2}$$

where M_{ia}^{L} is the binary matrix for subdistrict/town units and consumer-service types. $M_{ia}^{L} = 1$ indicates that subdistrict/town i has a relative advantage in consumer-service type a, while $M_{ia}^{L} = 0$ indicates no relative advantage.

Step 3 calculates subdistrict/town diversity and service-type ubiquity from the binary matrix. Subdistrict/town diversity refers to the number of consumer-service types in which a subdistrict/town has a relative advantage. Service-type ubiquity refers to the number of subdistricts/towns with a relative advantage in a given consumer-service type:

$$k_{i,0}^{L} = \sum_{a} M_{ia}^{L} \tag{3}$$

where $k_{i,0}^{L}$ is the consumer-service diversity of subdistrict/town i, indicating the number of consumer-service types in which subdistrict/town i has a relative advantage.

$$k_{a,0}^{L} = \sum_{i} M_{ia}^{L} \tag{4}$$

where $k_{a,0}^{L}$ is the spatial ubiquity of consumer-service type a, indicating the number of subdistricts/towns with a relative advantage in that type.

Step 4 uses the recursive relationship in economic complexity to calculate complexity at both the subdistrict/town and service-type levels. This method assumes that the complexity of a subdistrict/town depends on the complexity of the service types in which it has advantages, while the complexity of a service type depends on the complexity of the subdistricts/towns that have advantages in that type:

$$k_{i,N}^{L} = \frac{1}{k_{i,0}^{L}} \sum_{a} M_{ia}^{L} k_{a,N-1}^{L} \tag{5}$$

where $k_{i,N}^{L}$ is the Nth-order consumer-service complexity of subdistrict/town i; $k_{i,0}^{L}$ is the consumer-service diversity of subdistrict/town i; M_{ia}^{L} indicates whether subdistrict/town i has a relative advantage in consumer-service type a; and $k_{a,N-1}^{L}$ is the complexity of consumer-service type a in the previous iteration.

$$k_{a,N}^{L} = \frac{1}{k_{a,0}^{L}} \sum_{i} M_{ia}^{L} k_{i,N-1}^{L} \tag{6}$$

where $k_{a,N}^{L}$ is the Nth-order complexity of consumer-service type a; $k_{a,0}^{L}$ is the spatial ubiquity of consumer-service type a; M_{ia}^{L} indicates whether subdistrict/town i has a relative advantage in consumer-service type a; and $k_{i,N-1}^{L}$ is the consumer-service complexity of subdistrict/town i in the previous iteration.

Step 5 converts the recursive relationship into a subdistrict/town-level complexity matrix and extracts the consumer-service economic complexity index from the non-trivial eigenvector of this matrix. Specifically, the matrix is expressed as:

$$S_{ij}^{L} = \sum_{a} \frac{M_{ia}^{L} M_{ja}^{L}}{k_{i,0}^{L} k_{a,0}^{L}} \tag{7}$$

where S_{ij}^{L} represents the strength of association between subdistrict/town i and subdistrict/town j in their consumer-service relative-advantage structures.

Finally, the second eigenvector of matrix S^{L} is extracted as the consumer-service economic complexity index of each subdistrict/town:

$$S^{L}\mathbf{v}_{2}^{L} = \lambda_{2}^{L}\mathbf{v}_{2}^{L} \tag{8}$$

$$ECI_{i}^{L} = v_{2,i}^{L} \tag{9}$$

where $\mathbf{v}_{2}^{L}$ is the second eigenvector corresponding to matrix S^{L}; $v_{2,i}^{L}$ is the value of subdistrict/town i on this eigenvector; and ECI_{i}^{L} denotes the consumer-service economic complexity index of subdistrict/town i. Because the first eigenvector mainly corresponds to the trivial structure of the bipartite network, the second eigenvector better captures relative differences in the diversity–non-ubiquity structure across subdistricts/towns. To maintain a consistent interpretation, this study adjusts the sign of $\mathbf{v}_{2}^{L}$ so that a higher ECI_{i}^{L} value indicates that a subdistrict/town has more combinations of relatively non-ubiquitous consumer-service types. A higher value therefore indicates a higher consumer-service level.

Additional details on the construction of consumer-service complexity are provided in Supplementary Material S2.

(2) Producer-service complexity

National producer-service industry complexity (PCI) is used to calculate producer-service complexity (ECI) for subdistrict/town units within the Yangtze River Delta MCR.

Step 1 calculates producer-service industry complexity at the national scale. The economic complexity method is also applied to prefecture-level cities nationwide. Specifically, a national prefecture-level city–industry matrix is constructed using population census data on employment by industry, and the industry-side complexity index, PCI, is calculated. A higher PCI indicates that a producer-service industry is more likely to appear in cities with richer producer-service structures and more complex functions, and that its spatial distribution is less ubiquitous. This indicator is then used to calculate producer-service complexity ECI_{i}^{P} for subdistricts/towns in the Yangtze River Delta MCR.

Step 2 calculates producer-service ECI for subdistricts/towns in the Yangtze River Delta MCR. First, following Formulas (1) and (2), a subdistrict/town–industry matrix is constructed from producer-service firm records. The revealed comparative advantage of each subdistrict/town for each producer-service type is calculated and converted into a binary matrix. Producer-service complexity is then calculated using national producer-service industry complexity PCI_a^P, the subdistrict/town producer-service advantage matrix M_{ia}^P, and the regional share of each subdistrict/town in the corresponding industry:

$$ECI_{i,raw}^P = \frac{1}{k_i^P} \sum_a M_{ia}^P \left(\frac{x_{ia}^P}{\sum_i x_{ia}^P} \right) PCI_a^P \tag{10}$$

where $ECI_{i,raw}^P$ is the producer-service complexity of subdistrict/town i; PCI_a^P is the national industry complexity of producer-service type a; M_{ia}^P indicates whether subdistrict/town i has a relative advantage in producer-service type a; x_{ia}^P is the number of firms of producer-service type a in subdistrict/town i, or the scale-weighted firm count; $\sum_i x_{ia}^P$ is the total number of firms of producer-service type a in the Yangtze River Delta MCR; $x_{ia}^P / \sum_i x_{ia}^P$ represents the regional share of subdistrict/town i in that producer-service type; and k_i^P is the number of producer-service types in which subdistrict/town i has a relative advantage.

3.4.3. Model Design

(1) Dependent variable

The dependent variable is the volume of subdistrict/town-level intercity origin–destination travel flows from 15 cities to the central urban area of Shanghai within the MCR, measured in person-trips. Person-trips are first constructed from valid residence–destination grid activity records and are then aggregated to the subdistrict/town level. The indicator therefore reflects the intensity of destination activity person-trips associated with intercity travel between subdistrict/town units.

(2) Independent variables

The independent variables are also constructed at the subdistrict/town scale and include baseline explanatory variables, service variables, and transport variables (Table 1). The baseline variables are the active resident populations at origins and destinations. In addition to controlling for population size, these variables also help account for differences in signaling-sample exposure across subdistrict/town units, reducing the extent to which larger observed intercity travel flows simply reflect larger detected resident populations. Service variables include consumer services and producer services, each divided into scale and level attributes. Consumer-service and producer-service scales are measured by the count of consumer-service POIs and the weighted count of producer-service firms, respectively. These count-based measures are intended to capture the total amount of service supply and functional activities within each subdistrict/town unit, rather than service concentration relative to land area or population. Service level is measured by complexity indicators. Transport variables include origin–destination travel time and the distance from origins and destinations to conventional railway and high-speed railway stations.

(3) Model design

First, negative binomial regression is used as a conventional parametric benchmark for count data. The full process and results of the negative binomial regression are presented in Supplementary Material S3. The results show that the model variables do not suffer from severe multicollinearity, and all service variables are statistically significant in this regression. McFadden's pseudo-R^2 is used only as a within-model fit statistic for the negative binomial regression and is not directly compared with the predictive R^2 of XGBoost. XGBoost is adopted as the primary analytical model because it can capture nonlinear relationships and interaction effects among variables.

Table 1. Model design.

Type	Model 1 Origin and Destination	Model 2 Difference Between Destination and Origin
Baseline explanatory variable	Active resident population	Difference in active resident population
Consumer-service scale	Count	Difference in count
Consumer-service level	Complexity	Difference in complexity
Producer-service scale	Count	Difference in count
Producer-service level	Complexity	Difference in complexity
Transport variable 1	Distance to the nearest railway station at the origin	
Transport variable 2	Distance to the nearest railway station at the destination	
Transport variable 3	Travel time	

To identify how service scale, service level, and differences between attributes at destinations and origins are associated with intercity travel flow intensity, this study constructs two models. Model 1 is an origin–destination model. It incorporates service scale and service level at both origins and destinations, together with transport and baseline variables, to examine the separate contributions of services at the two ends. Model 2 is a difference model, in which each difference variable is calculated as the destination value minus the origin value to examine how relative advantages between destinations and origins are associated with intercity travel flows.

Because service scale and service level are included jointly in the main models, we further estimate supplementary XGBoost specifications in which the two dimensions are entered separately, while retaining the same baseline and transport variables. These analyses are used to examine the stability of the main predictive relationships; detailed results are reported in Supplementary Material S5.

Because origin variables, destination variables, and difference variables all help explain intercity travel flows, the two models should be interpreted jointly. Four possible patterns can be identified. When all three types of variables make positive contributions, the pattern is interpreted as a "destination-advantage positive effect pattern". When origin and destination variables make positive contributions, but difference variables make negative contributions, the pattern is interpreted as an "origin–destination joint-positive effect pattern". When origin variables make a negative contribution, but destination variables and difference variables make positive contributions, the pattern is interpreted as a "destination-positive effect pattern". When origin variables make a positive contribution, but destination variables and difference variables make negative contributions, the pattern is interpreted as an "origin-positive effect pattern".

3.4.4. Modeling and Interpretation

(1) Model selection

This study uses the XGBoost regression model [58] to examine the relationships between service variables and intercity travel flows. Compared with traditional linear models, XGBoost is better suited to large samples and can capture nonlinear relationships and interaction effects among variables.

During model training, the dataset is first divided into training and validation sets. Random search is then used to determine the optimal parameters. To assess potential information leakage arising from records sharing the same origin-side attributes, an additional origin-grouped validation is conducted. Approximately 20% of origin subdistrict/town units, together with all their associated origin–destination records, are held out as the test set, ensuring that the same origin does not appear in both the training and test sets [59]. The random seed is set to 2026 to ensure reproducibility. The XGBoost hyperparameter settings are reported in Supplementary Material S4.

(2) Interpretation methods

This study uses the gain indicator in XGBoost to measure global variable importance. Gain reflects the average contribution of a variable to reducing model loss during tree splitting. A higher value indicates greater importance for model prediction. SHAP [60] is then used to interpret variable effects. SHAP decomposes the contribution of each variable to model predictions at the sample level, allowing the relative influence of each variable on intercity travel flow intensity to be assessed. SHAP dependence plots are also used to identify the direction and marginal effects of variables as their values change, supporting interpretation of the empirical results.

Based on the single-variable analysis, this study uses two-dimensional accumulated local effects (ALE) analysis [61] to examine interaction effects between origin–destination service variables. Two-dimensional ALE characterizes the joint effect surface of two variables after controlling for other independent variables, thereby identifying differences in flow-intensity responses across different origin–destination service combinations.

To avoid relying only on visual interpretation of the two-dimensional ALE plots, an interaction-strength indicator is introduced to verify interaction effects between origin–destination functional variables quantitatively. Friedman's H [62] measures the proportion of a two-variable joint effect that cannot be explained by the two single-variable main effects. A larger H value indicates a stronger interaction. The formula is as follows:

$$H_{jk} = \sqrt{\frac{Var\left[f_{jk}(x_j, x_k) - f_j(x_j) - f_k(x_k)\right]}{Var\left[f_{jk}(x_j, x_k)\right]}} \tag{11}$$

where H_{jk} is Friedman's H statistic for variables j and k; $f_{jk}(x_j, x_k)$ is the two-variable joint effect; $f_j(x_j)$ and $f_k(x_k)$ are the single-variable main effects; and $Var[\cdot]$ denotes the variance over the grid of variable values.

Given the observational and cross-sectional nature of the data, these model interpretation results are used to characterize predictive relationships and interaction patterns rather than causal effects.

4. Results

4.1. Effects of Service Scale and Level by Service Type

4.1.1. XGBoost Model Performance

To evaluate model fit and generalization for intercity travel flows, this study reports the RMSE, MAE, and R^2 of XGBoost under the original random split and the additional origin-grouped validation (Table 2). Predictive performance decreases under the stricter origin-grouped validation, indicating that random splitting provides a relatively optimistic assessment of model generalization. Nevertheless, both models retain positive out-of-sample R^2 for origins that are completely excluded from model training. The XGBoost results are therefore used to analyze the relative contributions, effect directions, and origin–destination interaction effects of different service variables.

Table 2. Performance of XGBoost models under random and origin-grouped validation.

Model	Validation Strategy	RMSE	MAE	R^2
Model 1	Original random split	135.50	18.55	0.750
Model 1	Origin-grouped test	140.01	26.68	0.634
Model 2	Original random split	155.18	26.00	0.680
Model 2	Origin-grouped test	167.28	30.43	0.478

4.1.2. Relative Contribution Ranking of Independent Variables

Based on XGBoost Gain, this study compares the contribution of each variable in Model 1 to predicting intercity travel flow intensity (Figure 5). Service-related variables make substantial contributions. First, after controlling for active resident population and other variables, service-scale variables retain high gains, indicating contributions not fully captured by signaling-based population exposure. Second, several service variables contribute more than origin–destination travel time, suggesting greater relative importance than the travel time impedance variable in the model. Third, consumer services contribute more than producer services overall, and consumer-service scale contributes more than consumer-service level. Producer services show pronounced origin–destination asymmetry: origin scale and destination level make greater contributions. H1 is supported.

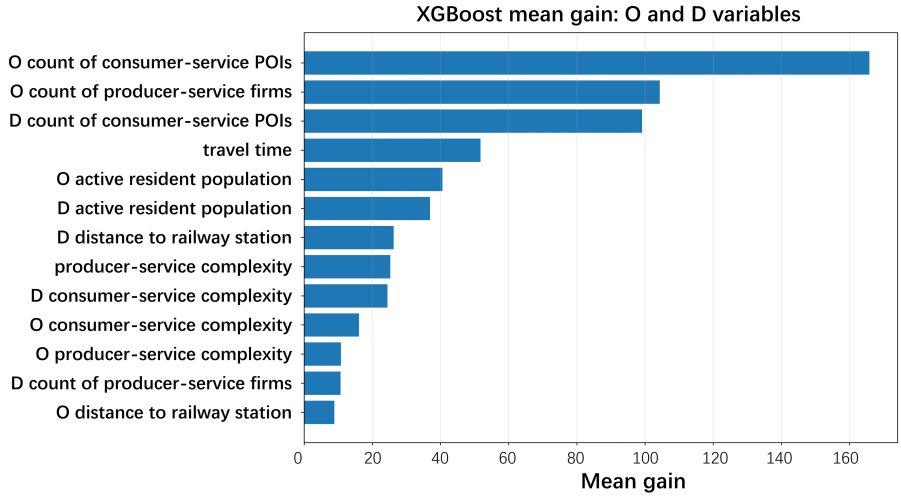


Figure 5. Gain-based importance of explanatory variables in the O–D model.

4.1.3. Direction of Independent-Variable Effects

To improve the interpretability of the XGBoost models, this study uses SHAP to identify the direction of each variable's effect in Models 1 and 2. The results show that both consumer and producer services are important, but their effects differ across origin variables, destination variables, and difference variables (Figure 6).

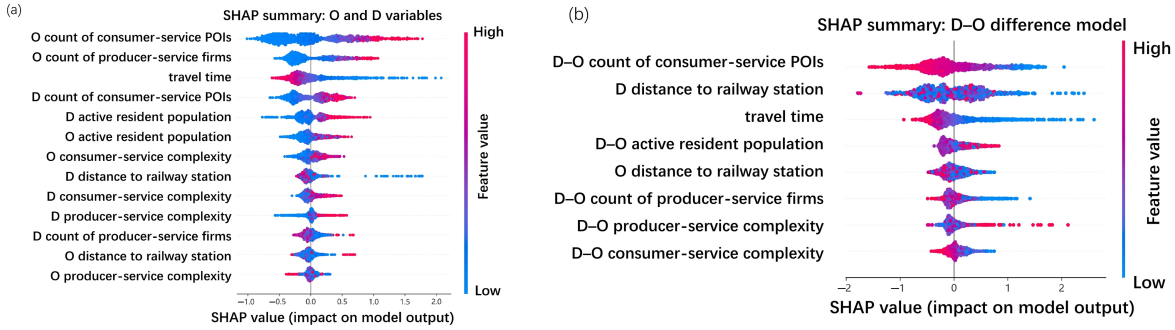


Figure 6. SHAP summary plots of explanatory variables: (**a**) origin–destination model; (**b**) difference model based on differences in attributes between destinations and origins.

First, consumer services generally follow an origin–destination joint-positive effect pattern. The SHAP value distributions show positive effects for the count of consumer-service POIs and consumer-service complexity at both the origin and the destination, but negative effects for the corresponding difference variables. In other words, stronger intercity travel flows are more likely when consumer services are strong at both ends in

terms of both scale and level and when the differences between the two places are relatively small. Consumer services therefore operate mainly through joint strengthening of service scale and service level at the origin and destination.

Second, producer services generally follow both an origin-scale positive effect pattern and a destination-level positive effect pattern. The SHAP value distributions show positive effects for the origin count of producer-service firms and destination producer-service complexity. In the difference model, the two corresponding difference variables show opposite effects: the difference in the count of producer-service firms is negative, whereas the difference in producer-service complexity is positive. Producer services therefore do not show synchronized increases in scale and level at both ends. Instead, they show a differentiated combination of origin-scale effects and destination-level effects.

Finally, among the transport variables, origin–destination travel time shows a relatively stable negative effect on intercity travel flows, indicating that distance remains an important constraint. By contrast, origin and destination distances to railway stations do not show the same stable directional patterns in the two SHAP plots as the service variables.

Taken together, model performance, variable-contribution rankings, and effect-direction analysis show that both service scale and service level are important factors associated with intercity travel flows. The observed patterns also differ clearly between the two ends, but the patterns vary markedly by service type. Consumer services exhibit joint strengthening of scale and level at both the origin and destination. Producer services show a differentiated combination of origin scale and destination level (Figure 7). H2 is therefore broadly supported, and the differentiated roles of service scale and level at origins and destinations, as emphasized in Research Question 1, are preliminarily identified.

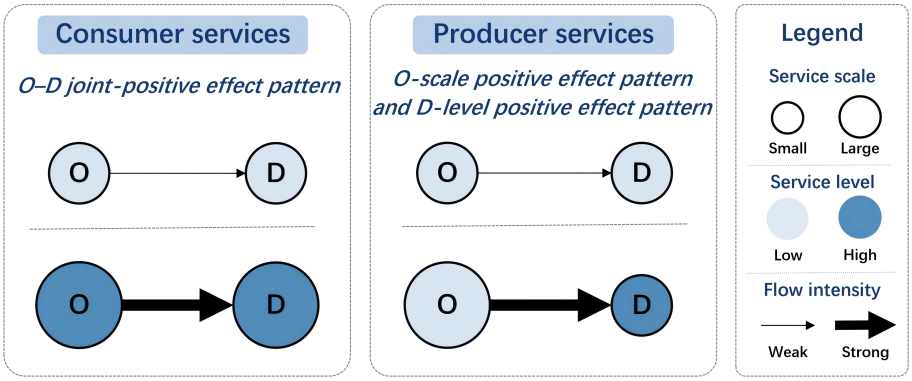


Figure 7. Schematic diagram of the effects of service scale and level at the origin and destination on intercity travel flows.

Supplementary analyses further examine the stability of these predictive relationships when service scale and service level are entered separately. Across four supplementary XGBoost specifications, the corresponding service indicators retain the same overall SHAP directions, although some differences in importance ranking remain. Detailed results are reported in Supplementary Material S5.

4.2. Interaction Effects of Origin and Destination Services

Building on the identified effects of service scale and service level in Section 4.1, this study further examines whether interaction effects exist between service variables at the two ends of origin–destination pairs beyond the simple addition of single-end effects. It also examines how origins and destinations differ in these interaction effects. Quantitative interaction indicators and two-dimensional ALE plots are combined to analyze the existence, forms, and dominant structures of origin–destination service interaction effects.

4.2.1. Interaction Term Setting

Based on the preceding results, variables with substantial contributions and relatively clear directional patterns are selected for interaction analysis. This improves the focus and interpretability of the analysis. Specifically, the origin variables included in the interaction analysis are the count of consumer-service POIs, consumer-service complexity, and the count of producer-service firms, while the destination variables are the count of consumer-service POIs, consumer-service complexity, and producer-service complexity. Origin producer-service complexity and the destination count of producer-service firms are not included in the two-dimensional interaction combinations because of their relatively low global importance and unstable directional patterns. In total, nine origin–destination service-variable interaction combinations are constructed and tested.

4.2.2. Overall Test of Interaction Effects

The overall test shows that all nine origin–destination service combinations have detectable non-additive effects (Table 3). Specifically, Friedman's H values for all combinations are greater than zero and range from 0.13 to 0.29, indicating non-additive components in the two-dimensional effect surfaces. The effects of service variables at the two ends therefore cannot be understood simply as independent additions of single-end effects. Interaction effects are therefore generally detectable. However, the presence of interaction effects does not necessarily imply stable enhancement effects. Their specific forms still need to be identified using two-dimensional ALE plots.

Table 3. Interaction test for origin–destination service-variable combinations.

Combination	Origin-Side Variable	Destination-Side Variable	Friedman's H	Identified Interaction Pattern
1	The count of consumer-service POIs	Consumer-service complexity	0.16	Interaction enhancement pattern
2	The count of producer-service firms	Consumer-service complexity	0.22	Interaction enhancement pattern
3	The count of consumer-service POIs	The count of consumer-service POIs	0.29	Destination threshold pattern
4	The count of producer-service firms	The count of consumer-service POIs	0.24	Destination threshold pattern
5	The count of consumer-service POIs	Producer-service complexity	0.17	Destination threshold pattern
6	The count of producer-service firms	Producer-service complexity	0.21	Destination threshold pattern
7	Consumer-service complexity	Consumer-service complexity	0.21	Origin threshold pattern
8	Consumer-service complexity	Producer-service complexity	0.19	Non-enhancing interaction pattern
9	Consumer-service complexity	The count of consumer-service POIs	0.13	Non-enhancing interaction pattern

4.2.3. Identification of Interaction Forms

Based on the two-dimensional ALE plots, the nine interaction combinations can be further grouped into four morphological types: the "interaction enhancement pattern", the "destination threshold pattern", the "origin threshold pattern", and the "non-enhancing interaction pattern". Here, the threshold patterns refer to morphological changes identified from the two-dimensional ALE surfaces rather than statistically estimated cutoff values.

Combinations 1 and 2 show an interaction enhancement pattern. As both origin and destination variables increase, the two-dimensional ALE surface continues to rise. This interaction reflects the joint strengthening of intercity travel flows by variables at both ends. Although this type includes only a few combinations, it directly captures the joint effect that occurs when variables at both the origin and destination increase together.

Combinations 3–6 exhibit a destination threshold pattern. When the destination variable remains low, increases in the origin variable contribute little to intercity travel flows. The two-dimensional ALE surface rises markedly as the destination variable enters a relatively high-value range, indicating that the positive contribution of the origin variable becomes more pronounced once the destination variable enters a relatively high-value range. This pattern suggests that higher destination values provide a condition under which the joint effect becomes more pronounced.

Combination 7 exhibits an origin threshold pattern. In this pattern, the destination variable produces a relatively gradual response, whereas the two-dimensional ALE surface rises markedly as the origin variable enters a relatively high-value range. Compared with the destination threshold pattern, this structure is less prevalent among the interaction enhancement combinations.

In addition, although the non-enhancing interaction pattern shows detectable non-additivity in the quantitative tests, its two-dimensional ALE plots do not reveal a stable high–high enhancement zone. This type is represented by two combinations: origin consumer-service level with destination producer-service level, and origin consumer-service level with destination consumer-service scale. Because their plot patterns do not indicate a stable enhancing interaction, they are not included in the subsequent focused discussion of interaction enhancement structures.

4.2.4. Summary of Interaction Structures

After excluding the two combinations classified as the non-enhancing interaction pattern, the remaining seven interaction enhancement combinations reveal a clearer dominant structure (Figure 8). First, in terms of pattern distribution, the destination threshold pattern accounts for the largest share among interaction enhancement combinations, covering four combinations. In these combinations, destination producer-service level and destination consumer-service scale show clear threshold characteristics. At the same time, the two combinations classified as the interaction enhancement pattern also show, to varying degrees, that the positive contribution becomes markedly stronger as destination consumer-service level increases into a relatively high-value range. Therefore, the destination threshold pattern can be regarded as the dominant structure in origin–destination service interaction enhancement combinations. Second, in terms of variable distribution, among the seven interaction enhancement combinations, the origin variables that play major roles are more concentrated in consumer-service scale and producer-service scale, rather than in service-level variables. By contrast, destination variables are more concentrated in the consumer-service level and producer-service level. Within interaction enhancement combinations, origin variables tend to operate through the scale dimension, whereas destination variables tend to operate through the level dimension.

Overall, the interaction analysis in Section 4.2 shows that interaction effects between services at the two ends of origin–destination pairs are generally detectable, but their forms differ across combinations. Hypothesis 3 is therefore supported. Among interaction enhancement combinations, the destination threshold pattern is the most common. Meanwhile, origin variables are more concentrated in the scale dimension, whereas destination variables are more concentrated in the level dimension. This indicates that the joint effects

of origin–destination services do not simply involve symmetric amplification across the two ends, but instead exhibit clear structural differences (Figure 9).

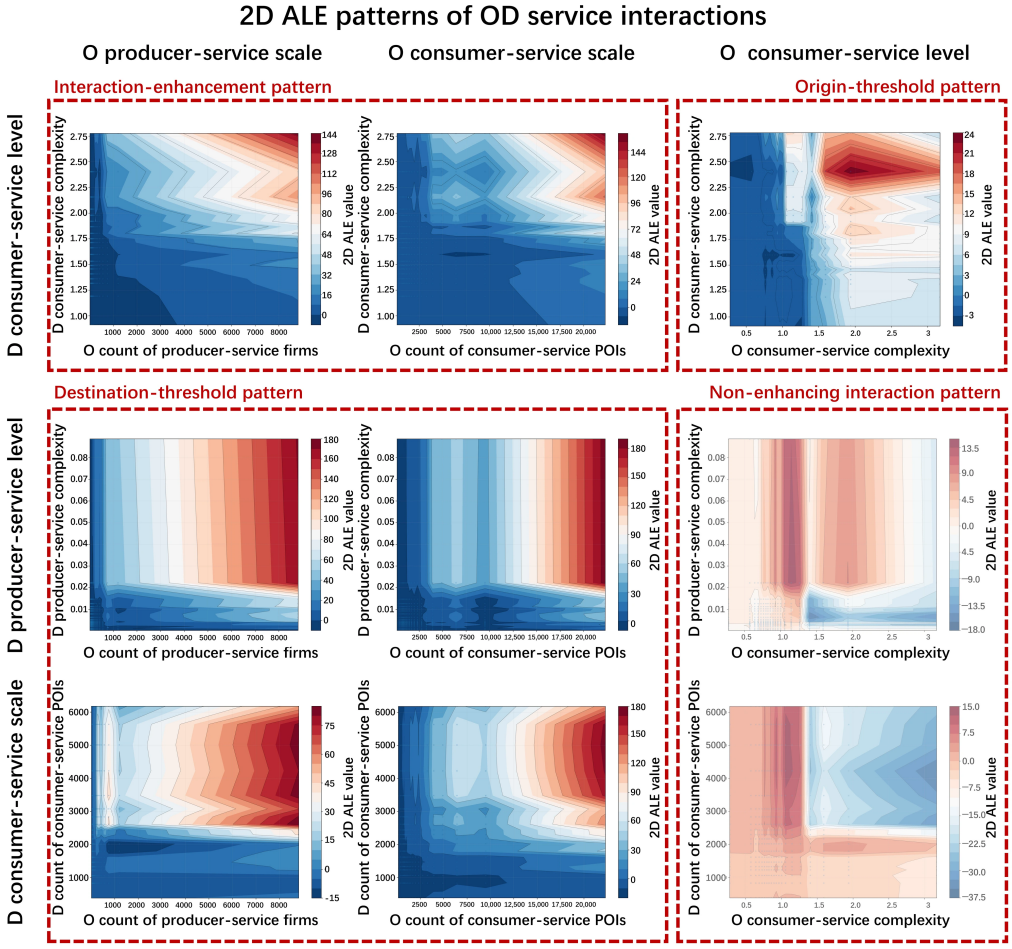


Figure 8. Two-dimensional ALE plots of origin–destination service-variable combinations.

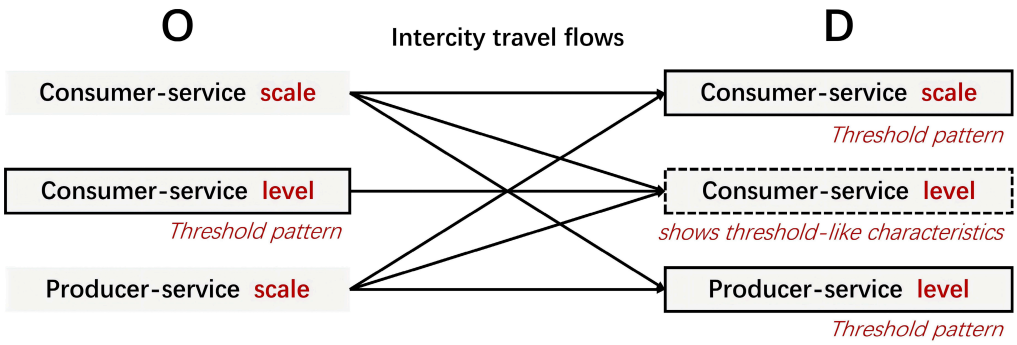


Figure 9. Schematic diagram of origin–destination service interaction effects. Note: Solid boxes indicate clearer positive or threshold-like effects; the dashed box indicates a weaker or less stable effect pattern.

4.2.5. Similarities Between Interaction Combinations and Travel Logic

Within MCRs, intercity travel mainly includes commuting, business, and service-seeking purposes. Different purposes often correspond to different functional linkages between origin and destination cities. From this perspective, the interaction enhancement combinations identified in this study can be broadly linked to the functional linkage logic associated with these three travel purposes.

Intercity commuting is related to the linkage between origin consumer functions and destination producer functions. Its travel logic may therefore correspond to the destination threshold pattern in the interaction between origin consumer-service scale and destination producer-service level. The results show that as destination producer-service level enters a relatively high-value range, the positive association between origin consumer-service scale and intercity travel flows becomes more pronounced.

Intercity business travel is related to the linkage between origin and destination producer functions. Its travel logic may therefore correspond to the destination threshold pattern in the interaction between origin producer-service scale and destination producer-service level. The origin producer-service–destination consumer-service combination does not strictly correspond to the functional linkage between origin and destination producer functions. Because a user-day may include multiple retained destination grids after valid-stay screening and aggregation, business travel may involve destination consumer services such as hotels and restaurants. These services, however, are more likely to play a supporting role in business travel, and this combination is therefore not classified as a business travel type. The results show that as destination producer-service level enters a relatively high-value range, the positive association between origin producer-service scale and intercity travel flows becomes more pronounced.

Intercity service-seeking travel is related to the linkage between origin and destination consumer functions. Its travel logic may therefore correspond to three interaction patterns between origin and destination consumer services: the interaction enhancement pattern, the destination threshold pattern, and the origin threshold pattern. The combination of origin consumer-service scale and destination consumer-service level shows an interaction enhancement pattern. Intercity travel flows continue to increase as origin consumer-service scale and destination consumer-service level rise together. By contrast, the combination of origin consumer-service scale and destination consumer-service scale shows a destination threshold pattern. The positive association between origin consumer-service scale becomes more pronounced as destination consumer-service scale enters a relatively high-value range. In addition, the combination of origin consumer-service level and destination consumer-service level shows an origin threshold pattern. The association with destination consumer-service level becomes more evident as origin consumer-service level enters a relatively high-value range.

The interaction results associated with different travel logic are discussed in detail in Section 5.2.

5. Conclusions and Discussion

5.1. Conclusions

Using subdistrict/town-level mobile phone signaling data for the Yangtze River Delta MCR, this study examines how service scale and level at the two ends of origin–destination pairs are associated with intercity travel flows toward the core city. Flow intensity is associated not only with transport distance but also with the scale, level, and combined effects of consumer and producer services. Scale reflects service supply, activity agglomeration, and potential demand, whereas level reflects the diversity and non-ubiquity of service functions captured by complexity. The two dimensions are not interchangeable and play distinct roles in functional linkages between subdistricts/towns in the core city and peripheral cities.

First, both service scale and service level are substantially associated with intercity travel flows within MCRs, but their patterns differ by service type. Consumer services are characterized more by the joint strengthening of scale and level at both the origin and destination. Stronger intercity travel flows are more likely when consumer services at both

the origin and the destination are large in scale and high in level and when differences between the two places are relatively small. The observed associations between consumer services and intercity travel flows may reflect both the attractiveness of subdistricts/towns in the core city and the service demand, daily-life support needs, and consumption capacity of subdistricts/towns in peripheral cities. By contrast, producer services show a stronger combination of an origin-scale foundation and destination-level attraction. A larger producer-service scale at the origin may represent a demand base for intercity business linkages and industrial connections. A higher producer-service level at the destination may reflect the selective attraction of advanced producer-service functions concentrated in subdistricts/towns of the core city.

Second, services at the origin and destination interact in distinct ways. These interaction effects do not take the form of symmetric addition; instead, they are reflected more clearly in the combination of an origin-scale foundation and destination-level attraction. The interaction analysis shows that origin service scale is usually associated with a stable demand and activity base for intercity travel flows. Destination service level more often functions as a conditioning factor in these interactions. In most interaction enhancement combinations, destination service level shows threshold-like characteristics. When destination reaches a sufficiently high service level, the potential demand and functional linkages represented by origin service scale show a clearer positive association with high-intensity intercity travel flows. Intercity travel flows within MCRs are therefore not the simple addition of service functions at the origin and destination. They are relational outcomes formed when a specific scale foundation matches high-level functional attraction.

The contributions of this study are twofold:

First, from the perspective of functional linkages within MCRs, this study extends explanations of intercity travel flows from single-end attributes to the joint and interaction effects of service functions at both ends of origin–destination pairs, revealing that high-intensity intercity travel flows from subdistricts/towns in peripheral cities to those in the core city are associated with specific origin–destination functional combinations.

Second, beyond functional scale, this study further introduces functional level and reveals its important association with the intercity attraction of destination subdistricts/towns in the core city, thereby deepening explanations of intercity functional attraction from the perspective of the non-ubiquity of service functions.

5.2. Discussion

Based on the similarities between service-variable interaction combinations and travel logics identified in Section 4.2, this section further discusses the possible relationships between services and intercity travel flows toward the core city within MCRs. These subdistrict/town-level origin–destination relationships are embedded in the broader functional linkages between the core city and peripheral cities. The following discussion is an interpretive extension based on the interaction results and existing studies rather than a direct identification of travel purposes or causal mechanisms.

The discussion of intercity commuting travel is based mainly on the destination threshold pattern associated with the interaction between the origin consumer-service scale and the destination producer-service level. This result suggests a commuting logic involving residential support and employment attraction. Intercity commuting depends not only on destination employment opportunities but also on origin residential conditions, especially where residence–employment divisions and strong linkages have formed between core and peripheral cities [63]. A higher destination producer-service level may indicate more specialized employment opportunities and career prospects at destination subdistricts/towns in the core city. The threshold pattern further suggests that high-level producer services at

the destination operate less as a generic pull factor than as an important conditioning factor associated with stronger intercity commuting flows. Meanwhile, a larger origin consumer-service scale may reflect daily-life support, basic services, and residential capacity at origin subdistricts/towns in peripheral cities. For commuting linkages, peripheral cities may further improve consumer-service provision to strengthen residential and daily-life support, while the core city may reinforce the agglomeration of specialized and non-ubiquitous producer services to strengthen higher-level employment functions.

The discussion of intercity business travel is based mainly on the destination threshold pattern associated with the interaction between origin producer-service scale and destination producer-service level. This result suggests a business-travel logic involving business linkages associated with subdistricts/towns in peripheral cities and the attraction of higher-level producer services in subdistricts/towns of the core city. Existing studies show that intercity business travel is usually related to industrial linkages such as supply chains and headquarters–branch relationships between cities [11,14]. From this perspective, a larger origin producer-service scale may indicate stronger industrial linkages between subdistricts/towns in peripheral cities and those in the core city and may be associated with stronger demand for intercity business interactions. A higher destination producer-service level may reflect the non-ubiquitous producer services concentrated in subdistricts/towns of the core city. Its threshold-like pattern further indicates that higher-level producer services in subdistricts/towns of the core city are an important conditioning factor associated with intercity business linkages. When subdistricts/towns in the core city have sufficiently strong higher-level producer services, industrial linkages with subdistricts/towns in peripheral cities show a stronger association with stable intercity business travel. For business linkages, peripheral cities may prioritize expanding producer services that match their advantageous industries, while the core city may strengthen the agglomeration of specialized and non-ubiquitous producer services, thereby reinforcing regional business linkages through functional complementarity.

The discussion of intercity service-seeking travel is based mainly on three interaction patterns between origin and destination consumer services: the interaction enhancement pattern, the destination threshold pattern, and the origin threshold pattern. Overall, these results suggest that intercity service-seeking travel may be related to both service demand in peripheral cities and high-level service supply in the core city. The interaction between origin consumer-service scale and destination consumer-service level shows an interaction enhancement pattern. This suggests that a larger consumer-service scale in subdistricts/towns of peripheral cities may indicate a larger population and greater economic capacity for intercity travel, leading to more active demand for consumer services [12]. Strong consumer-service demand in subdistricts/towns of peripheral cities and high-level consumer-service supply in subdistricts/towns of the core city form a relatively stable joint enhancement relationship. The interaction between origin consumer-service scale and destination consumer-service scale shows a destination threshold pattern. This means that a relatively large consumer-service supply in subdistricts/towns of the core city is associated with stronger and more sustained attraction. Intercity service-seeking travel is therefore associated not only with service level but also with the scale and concentration of service supply in subdistricts/towns of the core city. In addition, the interaction between origin consumer-service level and destination consumer-service level shows an origin threshold pattern. This indicates that intercity service-seeking travel is more likely to occur when subdistricts/towns in peripheral cities already have a relatively high consumer-service level, and residents have stronger demand for higher-level services. As demand for higher-level services becomes stronger among residents in peripheral cities, higher-level consumer services in subdistricts/towns of the core city are more likely to be associated with significant

intercity attraction. For service-seeking linkages, peripheral cities may enrich service types and increase the provision of non-ubiquitous consumer services while improving overall consumer-service provision, whereas the core city may further strengthen the diversity and concentration of non-ubiquitous consumer services to enhance regional service attraction.

5.3. Limitations and Future Directions

First, the conclusions of this study are grounded in the specific regional context of China's Yangtze River Delta MCR. The region has relatively well-developed intercity transport infrastructure, a high level of service sector development, and a relatively clear functional division of labor between the core city and peripheral cities. In this context, relatively low intercity travel impedance makes the relationship between functional linkages and actual travel flows more readily observable, allowing the associations of service scale, service level, and their origin–destination combinations with intercity travel flows to be identified more clearly. For other MCRs with less developed transport infrastructure, weaker service functions, or less established intercity functional division of labor, the conclusions of this study require further verification.

Second, this study empirically focuses on intercity travel flows from peripheral cities to the core city within an MCR. Shanghai's central urban area has a substantially greater service scale and service level than the peripheral cities and therefore exerts stronger functional attraction. This setting is therefore suitable for identifying the associations between the intercity attraction of destinations with stronger service functions and origins with relatively weaker service functions. Reverse flows from the core city to peripheral cities, as well as intercity flows among peripheral cities within the MCR, may correspond to different destination functions and patterns of association. Future research should therefore examine these different types of travel flows separately and compare their potentially different mechanisms.

Third, this study uses integrated origin–destination travel time to control for intercity travel impedance but does not further distinguish among specific transport modes, such as high-speed railway, intercity railway, urban rail, bus, and private car. Because these modes differ in speed, cost, service frequency, and transfer convenience, the findings should not be directly translated into policy implications for any single transport mode. Future research could use mode-specific travel-flow data, ticketing data, or more detailed route-planning data to compare the relationships between origin–destination service-based functional linkages and intercity travel flows under different transport conditions.

Fourth, future research could further distinguish the specific purposes of intercity travel flows, such as commuting, business, and service-seeking travel. Distinguishing between weekdays and weekends may help identify these travel purposes more accurately. The results of this study suggest that different combinations of service functions may correspond to different types of functional linkages, but this interpretation remains an interpretive extension based on the interaction results. More refined data that directly identify travel purposes would help reveal the formation logic of different types of intercity travel flows more accurately and deepen understanding of the relationship between MCR functional linkages and intercity mobility.

In addition, this study still has several limitations related to the data, measurement, and modeling. First, although the data cover a relatively regular travel period in June, a single month cannot fully represent intercity travel patterns across different months or seasons. Second, this study uses cross-sectional observational data and interpretable machine learning methods; the identified relationships should therefore be interpreted as associations rather than causal effects. Finally, this study primarily examines the associations between

service functions and intercity travel flows and cannot completely exclude potential reverse relationships or the influence of individual attributes and other unobserved factors.

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