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Walkable Access to Cultural Tourism Opportunities in Historic Urban Cores: Spatial Mismatch and Interpretable Evidence from Suzhou, China

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Abstract

Under the dual pressures of heritage conservation and tourism growth, improving inclusive access to cultural tourism opportunities in historic urban areas has become an urgent planning issue under Sustainable Development Goal 11 and the Historic Urban Landscape approach. Taking the central urban area of Suzhou, China, as a case study, this study evaluates time-budgeted walkable accessibility, spatial equity, local mismatch, and accessibility-generating conditions from a 15 min city perspective. An integrated analytical framework was developed by combining kernel density analysis, GIS-based network accessibility modelling, Lorenz–Gini equity assessment, bivariate Local Indicators of Spatial Association (LISA), and XGBoost–SHAP interpretation. The results show that cultural tourism opportunities exhibit a clear core polarisation–peripheral attenuation pattern. Within the 15 min threshold, Gusu District records SACR and AAR values of 80.18% and 95.23%, respectively, indicating a pronounced historic-core accessibility advantage. Accommodation-tier differences do not form a simple monotonic relationship with accessibility, but are shaped by the spatial embedding of different accommodation-market segments within the cultural tourism opportunity field. HL units, namely high-tier accommodation near low accessibility, emerge as priority diagnostic areas of local mismatch, while delayed accessibility beyond 30 min becomes particularly evident among elderly visitors. The SHAP interpretation further indicates that leisure-strolling attractions show a more balanced supply–accommodation structure, whereas commercial–cultural mixed and heritage-core attractions are more strongly supply-led. By linking accessibility measurement, equity assessment, local mismatch diagnosis, and mechanism-based explanation, this study provides an operational basis for zonal and typology-oriented optimisation of cultural tourism accessibility in historic urban areas.

Keywords: 15 min city; historic urban core; cultural tourism attractions; walkable accessibility; spatial equity; spatial mismatch; interpretable machine learning

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Academic Editor: Harry Coccossis

Received: 20 April 2026
Revised: 19 May 2026
Accepted: 26 May 2026
Published: 29 May 2026

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1. Introduction

Historic urban areas are increasingly challenged by the dual pressures of cultural heritage conservation and tourism growth. As tourist activities concentrate in historic cores, over-tourism, limited carrying capacity, inadequate pedestrian environments, and competition for public space have become more pronounced, making sustainable governance a pressing concern in both heritage conservation and urban development [1–3]. In

such walking-dominated settings, the key issue is not simply whether cultural tourism attractions exist, but whether different visitors can reach them within limited walking-time budgets. Walkable accessibility and spatial equity are therefore central to sustainable heritage tourism because they affect whether tourism pressure can be redistributed, peripheral opportunities can be activated, and different visitor groups can benefit from cultural tourism resources within realistic walking-time budgets.

The 15 min city has become an important framework for discussing proximity-based access to opportunities, but existing research has mainly focused on residents' daily services, while applications to cultural tourism opportunities and heritage-related visitor contexts remain limited [4–7]. Cultural tourism attractions are also components of urban cultural resources and public service systems, so improving their walkable accessibility can support both tourism organisation and local communities' shared access to cultural resources. This study therefore does not directly apply the 15 min city as a resident-oriented daily service model. Instead, it extracts its core logic of proximity-based access within limited travel time and transforms it into a time-budgeted accessibility perspective for assessing tourists' walking-based access to cultural tourism opportunities. This adaptation is appropriate because historic urban tourism is often organised around short-distance, chained, and time-constrained walking processes shaped by walking ability, street-network continuity, and spatial structure [7–10].

On this basis, walkable accessibility, spatial equity, and spatial mismatch are logically connected but analytically distinct. Walkable accessibility establishes the opportunity-access baseline by measuring which cultural tourism opportunities can be reached within specified walking-time thresholds. Spatial equity evaluates how these accessibility benefits are distributed across accommodation locations, accommodation-market segments, and visitor groups. Spatial mismatch further diagnoses where accommodation-market positioning and nearby accessibility conditions are locally aligned or misaligned. The analytical sequence is therefore accessibility measurement, equity assessment, and mismatch diagnosis.

Although previous studies have examined tourism pressure, spatial vitality, accessibility equity, and spatial diagnosis [3,11–13], systematic evaluation of time-budgeted walkable accessibility to cultural tourism opportunities in historic urban areas remains limited. Three gaps remain. First, although the 15 min city framework has been widely used for resident-oriented services and has recently been extended to cultural-site accessibility, its adaptation to tourism contexts involving temporary visitors remains limited [4–7]. Second, accessibility equity [14–16], age-related mobility differences [17–19], and accommodation-market segmentation [20–23] have usually been examined separately rather than integrated into cultural tourism accessibility evaluation. Third, limited research has explained the mechanisms through which accessibility differences and local mismatches are produced, or how these mechanisms vary across different types of cultural tourism attractions [11–13]. These gaps constrain mechanism-based explanation and the identification of differentiated intervention priorities.

Suzhou provides a representative and critical case for addressing these issues. Its historic urban core contains China's first and currently only National Historical and Cultural City Conservation Zone and is associated with two World Heritage assets: the Classical Gardens of Suzhou and the Grand Canal, including its Suzhou section [24–26]. This distinctive conservation status and internationally recognised cultural-heritage value are combined with concentrated heritage resources, intensive tourism activity, a differentiated accommodation service base, and a water–street spatial structure. The strong contrast between the historic core and surrounding districts further provides a clear core–periphery setting for examining how uneven walkable accessibility and spatial mismatch emerge across districts, accommodation tiers, and visitor groups.

The objective of this study is to evaluate how cultural tourism opportunities in Suzhou's historic urban area are distributed and accessed unevenly under limited walking-time budgets, and to explain how these patterns are associated with accommodation-market structure, visitor heterogeneity, and attraction-type differences. To achieve this objective, this study develops an integrated framework combining network service area analysis, accessibility and equity indicators, bivariate local spatial autocorrelation, and interpretable machine learning. The framework proceeds from pattern identification and equity assessment to mismatch diagnosis and mechanism-based explanation, thereby supporting differentiated optimisation in a heritage-rich historic urban context. Accordingly, this study addresses the following research questions:

- RQ1: What spatial patterns characterise the distribution of cultural tourism attractions and their walkable accessibility in Suzhou's historic urban area?
- RQ2: How do walkable accessibility and spatial equity vary across accommodation-market stratification and age groups, and to what extent are these differences sensitive to time thresholds?
- RQ3: What forms of local alignment or mismatch exist between cultural tourism accessibility and accommodation-market structure, and where are the dominant local mismatch types located?
- RQ4: How do nonlinear drivers differ across attraction types, and how can these differences inform differentiated optimisation?

The main contribution of this study lies in developing an integrated cultural tourism accessibility framework that adapts the 15 min city logic to historic urban tourism and connects opportunity access, spatial equity, local mismatch, and mechanism-based explanation within a single analytical workflow. Theoretically, it extends the 15 min city framework from resident-oriented daily service access to time-budgeted walkable access to cultural tourism opportunities in historic urban areas. Analytically, it moves beyond aggregate accessibility evaluation by linking distributional equity with local mismatch between accommodation-market structure and walkable accessibility. Methodologically, it integrates GIS-based network accessibility modelling, spatial statistical diagnosis, and XGBoost–SHAP interpretation to identify not only where accessibility inequalities occur, but also which type-specific conditions are associated with their formation.

2. Literature Review

2.1. Tourism Pressure and Accessibility in Historic Urban Areas

Historic urban areas are not simply city centres or collections of tourist attractions; rather, they are complex socio-spatial systems in which heritage resources, tourist activities, public space, and conservation constraints are closely intertwined. Existing studies show that tourism development in heritage cities is often accompanied by the simultaneous concentration of attractions, visitor flows, and spatial pressure, making over-tourism, visitor-flow management, carrying-capacity conflicts, and core-area governance central concerns in the study of historic urban areas [1–3]. These pressures are not only spatial, but also closely related to the implementation and governance of cultural heritage projects, where funding constraints, administrative capacity, professional expertise, and coordination among local actors may affect conservation and management outcomes [27]. At the same time, research on urban renewal, historic district vitality, street-network properties, and walkability in cultural heritage sites has shown that street structure, spatial configuration, and place organisation continue to shape activity distribution and patterns of space use in these areas [28–32].

From the perspective of tourist movement, activity in historic urban areas is typically characterised by short-distance, chained, and continuous walking processes [8,9]. This sug-

gests that access to cultural tourism opportunities depends not only on whether attractions are present, but also on whether they can be reached through the actual walkable street network within limited time budgets. In recent years, the 15 min city has become an influential framework for discussing proximity-based access to opportunities, yet the literature has focused primarily on resident-oriented daily services and has paid comparatively limited attention to cultural tourism opportunities in historic urban areas [4–6]. Methodologically, an increasing number of studies have moved beyond Euclidean distance and simple buffer measures by adopting network-based approaches that better capture route continuity, detours, water barriers, and street permeability in the access process [33–38]. This perspective has gradually entered research on cultural resources and historic tourism areas. For example, GIS-based assessments of urban cultural resources and spatial analyses of tourism attractiveness and vitality in Suzhou's old city both suggest that cultural tourism opportunities in historic urban areas are marked by clear spatial differentiation [11,12]. Overall, however, existing scholarship has tended to emphasise either tourism pressure, spatial vitality, and general walkable accessibility in historic urban areas, or the spatial accessibility of basic urban services such as green space, healthcare, and education. As a result, systematic research on cultural tourism opportunities in historic urban areas remains limited.

2.2. From Distributional Equity to Local Mismatch

Accessibility research increasingly emphasises that the key issue lies not only in overall accessibility levels, but also in how accessibility benefits are distributed across spatial units and social groups [39–43]. Discussions ranging from transportation equity to mobility justice have shown that average values and aggregate indicators often conceal structural inequalities in the distribution of opportunities [14,15,39,42]. Accordingly, distributional measures such as the Lorenz curve and Gini coefficient have been widely used to assess equity in access to public transport, green space, and other public services [16,44–46]. For cultural tourism opportunities in historic urban areas, however, large-scale assessments of distributional equity alone are not sufficient. Access to such opportunities is more sensitive to time thresholds and more strongly shaped by visitor heterogeneity than is typically the case for conventional urban services.

For walking-dominated tourism activities, age-related differences in walking ability directly influence whether nearby opportunities are actually reachable, making short time thresholds especially important for understanding uneven access [17–19]. At the same time, individual-level income, expenditure, and visitor-profile data are often unavailable at fine spatial scales in tourism studies. Existing studies have shown that tourism markets can be segmented according to travel expenditure patterns and itemised expenditure behaviour [20,21], while accommodation-market studies have used accommodation attributes, types, and perceived benefits to identify differentiated visitor segments [22,23,47–49]. These studies suggest that accommodation-related variables can reflect market positioning and potential spending differences, but they should not be interpreted as direct measures of tourists' actual income or total expenditure. However, relatively limited attention has been paid to how accommodation-market stratification relates to walkable accessibility and spatial equity in historic urban tourism contexts.

More importantly, overall equity indicators can reveal whether inequality exists, but they say much less about where it occurs, what spatial form it takes, and which areas should be prioritised for intervention. Spatial statistical research has shown that global Moran's I is useful for identifying broad patterns of spatial association, whereas local methods such as Local Indicators of Spatial Association (LISA) can reveal significant clusters, outliers, and localised configurations in more spatially interpretable ways [13,50,51]. In recent years, such approaches have been increasingly applied to transportation equity, environmental justice,

and service-facility imbalance, reflecting a broader shift from aggregate inequality to local spatial diagnosis [43,52,53]. By contrast, in research on cultural tourism opportunities in historic urban areas, local alignment and mismatch remain underexamined. In other words, although previous studies have separately discussed distributional equity, differences in walking ability, and spatial diagnosis, they have rarely integrated these dimensions into a single analytical framework for historic urban area tourism.

2.3. A Comprehensive Research Gap in Cultural Tourism Accessibility

Existing studies have revealed important differences in cultural tourism opportunities within historic urban areas from the perspectives of spatial distribution, attraction attractiveness, and local spatial association [11–13,50–53]. However, research on the accessibility of cultural tourism opportunities remains focused primarily on large-scale pattern description and regional difference identification. Much less attention has been paid to explaining why these differences and local mismatches emerge, and why they take different spatial forms under different attraction types and visitor conditions.

In recent years, interpretable machine learning has increasingly been applied to the study of complex spatial processes, showing particular value in identifying variable contributions, nonlinear relationships, and threshold effects [54]. This development suggests that research on cultural tourism accessibility in historic urban areas should move beyond the identification of local mismatch toward mechanism-based explanation. To do so, type-specific comparison needs to be combined with interpretable machine learning so that differences in spatial patterns can be linked to differences in the underlying driving structure.

Taken together, the existing literature still lacks an integrated analytical framework that combines time-budgeted walkable accessibility, visitor heterogeneity, local mismatch identification, and nonlinear mechanism-based explanation. This study addresses that gap in three steps. First, it identifies the overall spatial pattern of cultural tourism opportunities in the historic urban core and clarifies its core accessibility issues. Second, it diagnoses local mismatch between accommodation-market structure and attraction accessibility from the perspective of accommodation tiers and group-specific differences in walkable accessibility. Third, by combining type-specific comparison with interpretable machine learning, it reveals the nonlinear drivers of accessibility across attraction types and provides a basis for differentiated optimisation pathways.

3. Materials and Methods

3.1. Study Area

This study focuses on the central urban area of Suzhou, China (Figure 1). Covering approximately 1182.2 km^2, the study area comprises four administrative units: Gusu District, Huqiu District, Xiangcheng District, and Suzhou Industrial Park. Together, these units encompass Suzhou's historic urban core and its surrounding major inner-urban areas. Among them, Gusu District forms the historic urban core. Founded in 514 BC, it largely retains the spatial extent of the city established during the Spring and Autumn Period and contains the most concentrated heritage resources, cultural tourism activities, and tourist service functions [12,24]. The surrounding districts, by contrast, constitute the principal expansion spaces connected to the historic core and differ substantially in urban functions, tourist-service intensity, accommodation-market structure, and spatial organisation.

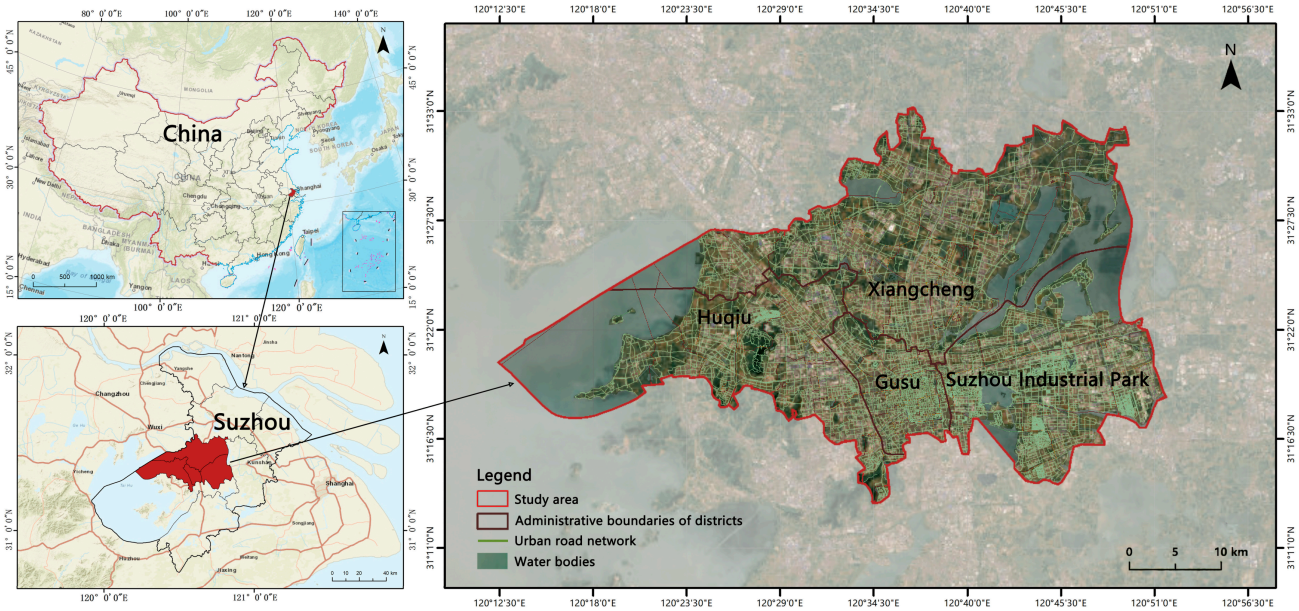


Figure 1. Map of the study area. http://bzdt.ch.mnr.gov.cn/index.html, accessed on 17 July 2025.

Gusu District contains China's first and currently only National Historical and Cultural City Conservation Zone, giving Suzhou particular relevance to historic-city conservation and renewal in China [24]. Its heritage resources are not organised only as isolated scenic sites, but are embedded in an integrated urban heritage landscape. The classical gardens are recognised as representative masterpieces of Chinese classical garden art, while the Grand Canal heritage is closely connected with the inner-city water system and historic urban fabric [25,26]. This integrated heritage structure is further shaped by the characteristic spatial form of a historic Jiangnan city, in which water and land run in parallel and rivers and streets are closely intertwined [24]. Such a water–street morphology makes walkable accessibility strongly dependent on actual street-network continuity, bridge crossings, and water-related barriers.

The central urban area of Suzhou presents a marked tension between heritage concentration and sustainable tourism governance. In 2024, it received more than 120 million tourist visits, accounting for over 60% of the citywide total, and contained eight World Cultural Heritage components and 1294 cultural tourism attractions. Heritage resources, high-value attractions, and intensive tourism activity are strongly concentrated in the historic urban core, whereas peripheral areas remain comparatively weaker in attraction distribution, walkable accessibility, and access to cultural tourism opportunities. This spatial imbalance increases pressure on the historic core in terms of over-tourism, spatial carrying capacity, and heritage conservation. In this context, analysing cultural tourism opportunities in Suzhou's central urban area helps reveal uneven accessibility patterns, inform differentiated optimisation, alleviate pressure on the historic core, and support the sustainable governance of historic urban areas.

3.2. Data Sources and Processing

This study draws on four types of spatial data: cultural tourism attraction data, tourism accommodation data, walkable street network data, and water-body data. To reduce temporal mismatch across datasets, all data were collected within a concentrated period from February to May 2024 and were subsequently cleaned, verified, and processed prior to analysis.

Cultural tourism attraction POI data were collected from the Gaode Open Platform on 10 March 2024 and then supplemented, cross-checked, and de-duplicated using

Baidu Maps, Tianditu, and the List of Suzhou Gardens published by the Suzhou Municipal People's Government. This process yielded 1294 valid cultural tourism attractions. For subsequent type-specific comparison, these attractions were further classified into three categories: 645 leisure-strolling attractions, 180 commercial–cultural mixed attractions, and 469 heritage-core attractions (Figure 2a).

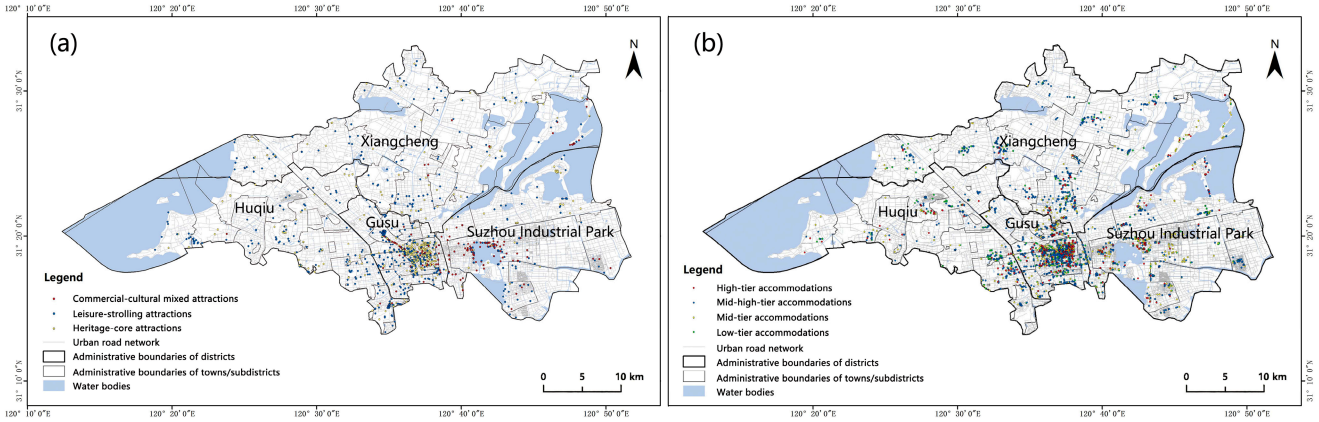


Figure 2. Spatial distribution of cultural tourism opportunities (**a**) and tourism accommodations (**b**) in the central urban area of Suzhou.

Tourism accommodation data were collected from Ctrip on 24 May 2024 through Python-based web scraping. The dataset included accommodation type, price, service attributes, and user ratings. To improve locational accuracy and ensure spatial consistency, these records were manually matched and integrated with accommodation POI data from the Gaode Open Platform. The final dataset contained 3453 accommodation samples, which were further classified into four accommodation tiers to represent accommodation-market stratification (Table 1; Figure 2b). Following studies on tourism expenditure patterns and accommodation-market segmentation [20–23], this tier classification was used to describe the supply-side structure of the accommodation market and to operationalize accommodation-market stratification, market positioning, and potential spending capacity in subsequent analyses.

Table 1. Classification of tourism accommodation tiers.

Tier	Category	Key Characteristics	Price Range	Indicative Market Positioning	Representative Examples	Number of Samples
Low-tier	Hostels/Guesthouses	Basic facilities, limited additional services, low-cost options for short stays	≤150 CNY	Budget travellers, including students and backpackers	Xingda Inn, Yuji Youth Apartment	541
Mid-tier	Economy Hotels/B&Bs	Standardised services; proximity to transit hubs; cost-effective pricing; wide spatial distribution	150–350 CNY	Families, SME business travellers, and independent tourists	Youju Youzhu, Suzhou Muhe Apartment	1228
Mid–high-tier	Standard Hotels	Distinctive design; comprehensive facilities; quality service; culturally oriented experiences	350–800 CNY	Affluent families, business travellers, and cultural tourists	Courtyard by Marriott; Jielu Yinshi Boutique Homestay	1427
High-tier	Luxury Hotels/Boutique Resorts	Premium facilities; greater privacy; culturally integrated settings; personalised services	≥800 CNY	High-net-worth individuals and international tourists	Park Hyatt Suzhou, Tongli Bloom Boutique	257

The accommodation dataset contains only publicly available listing attributes and does not include personal or sensitive information.

Walkable street network data were obtained from OpenStreetMap on 16 February 2024. Road centre lines were extracted and used to construct the walkable street network for subsequent network-based accessibility modelling. Water-body data were collected in April 2024 from OpenStreetMap polygon features. Major rivers, lakes, and canal boundaries were then manually checked and corrected, where necessary, using high-resolution basemaps. Together, these datasets provide the empirical basis for analysing the spatial distribution, walkable accessibility, spatial equity, and local mismatch of cultural tourism opportunities in Suzhou's historic urban core.

3.3. Methodology

The methodology of this study follows an integrated analytical framework that links spatial pattern identification, walkable accessibility and equity assessment, local mismatch diagnosis, and mechanism-based explanation, thereby corresponding to the study's progression from overall pattern recognition to differentiated optimisation (Figure 3). Based on attraction POIs, accommodation data, walkable street-network data, and water-body data, the analysis proceeds in four steps. First, kernel density analysis is used to identify the overall and type-specific spatial patterns of cultural tourism opportunities. Second, network-based service area modelling, together with SACR, AAR, and Lorenz–Gini analysis, is employed to evaluate walkable accessibility and distributional equity across attraction types, accommodation tiers, and age groups. Third, global bivariate Moran's I and local bivariate LISA are applied to diagnose localised patterns of alignment and mismatch between accommodation-market structure and attraction accessibility. Finally, XGBoost–SHAP analysis is used to interpret type-specific nonlinear accessibility-generating conditions, thereby supporting the interpretation of variation in local mismatch patterns across attraction types and providing a methodological basis for differentiated optimisation pathways in historic urban areas.

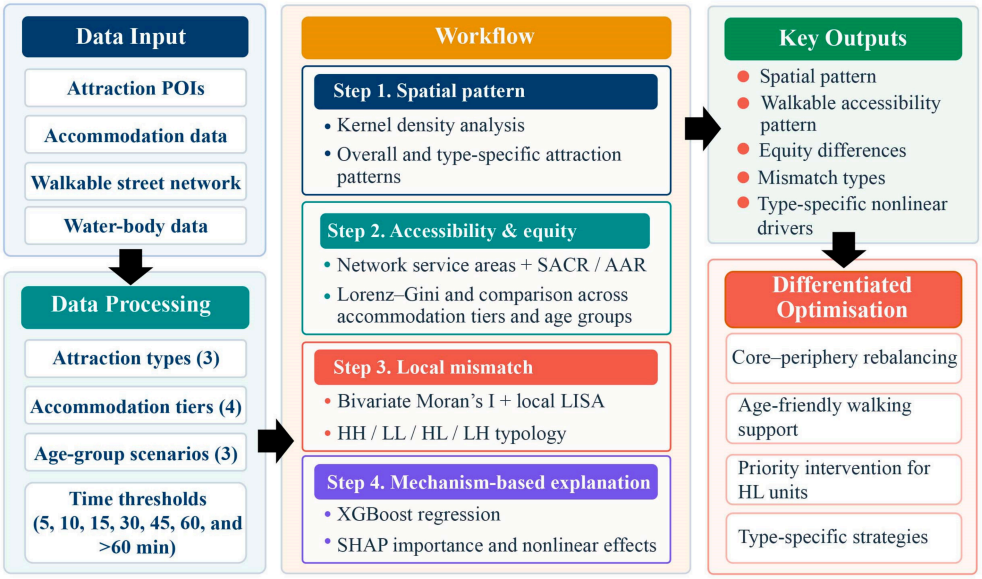


Figure 3. Technical framework of the study.

3.3.1. Kernel Density Analysis

Kernel density analysis was used to identify the supply-side concentration and type-specific spatial patterns of cultural tourism attractions. This method has been applied in studies on urban cultural resources and historic-district tourism facilities to reveal the clustering intensity, hotspot distribution, and spatial differentiation of point-based resources [11,12]. In this study, it was applied to all cultural tourism attractions and to the

three attraction types separately, namely leisure-strolling attractions, commercial–cultural mixed attractions, and heritage-core attractions. This provides the spatial basis for subsequent walkable accessibility and spatial mismatch analyses. The kernel density function is expressed as follows:

$$f(x) = \frac{1}{nh}\sum_{i-1}^{n} k\left(\frac{x - x_i}{h}\right) \quad (1)$$

where $f(x)$ denotes the estimated kernel density at location x, n is the total number of cultural tourism attractions, h is the search radius (bandwidth), and x_i represents the location of each attraction point. Higher kernel density values indicate stronger spatial concentration of cultural tourism attractions.

The bandwidth h was set to 1500 m based on the intra-urban scale of the study area, the density of attraction points, and the need to balance local hotspot identification with overall pattern continuity. To reduce parameter arbitrariness, bandwidths of 500 m, 1000 m, 1500 m, 2000 m, and 3000 m were compared. The core concentration–peripheral attenuation pattern remained stable across these settings, while 1500 m provided an appropriate balance between local detail and spatial continuity. Therefore, 1500 m was adopted as the final bandwidth for kernel density estimation.

3.3.2. Network-Based Accessibility Modelling

Network-based accessibility modelling was conducted in ArcGIS 10.8.1 using the Network Analyst extension. Road centre lines in Suzhou's central urban area were converted into a walkable street network, in which road segments were treated as edges and intersections as nodes. Because pedestrian accessibility depends on the continuity and quality of the walkable network rather than Euclidean proximity alone [35,38], the road network was refined before modelling. Non-walkable road types were excluded where applicable, and basic topology checks were conducted to reduce disconnected segments, duplicated lines, and invalid intersections. Given Suzhou's dense canal system, bridges and pedestrian passages represented in the source network were retained as valid walking links, whereas water bodies were not treated as walkable surfaces. Cultural tourism attractions were defined as service facilities (destinations), while accommodation points were used as origin proxies for tourists. Walking was treated as the only travel mode because it reflects the dominant short-distance and chained movement patterns of cultural tourism activities in historic urban areas [8,9]. On this basis, walkable accessibility from accommodation points to cultural tourism attractions was evaluated for the historic urban core and its surrounding inner-urban areas.

To capture differences in walking ability across age groups, three age-specific baseline scenarios were established: elderly, middle-aged, and young visitors. Drawing on accessibility and pedestrian studies concerning age-related walking-speed differences [19,55–59], walking speeds were set at 55 m/min, 75 m/min, and 65 m/min, respectively. These speeds were used as baseline scenario parameters for comparative accessibility modelling rather than as real-time observed tourist walking speeds. Walking time was used as the impedance measure and was calculated from network distance and age-specific walking speed. Time thresholds of 5, 10, 15, 30, 45, 60, and more than 60 min were used to generate service areas for cultural tourism attractions. Among these thresholds, 15 min represents the core time-budget benchmark, while the other thresholds capture stricter short-distance access, extended walking budgets, and delayed accessibility among different age groups [33,37,60,61]. These service areas were overlaid with accommodation origins to count reachable attractions, providing the basis for subsequent accessibility assessment, equity analysis, and local mismatch identification.

3.3.3. Indicator-Based Accessibility Assessment

Based on the network service area results, indicator-based accessibility assessment was conducted using GIS overlay analysis of service areas, administrative boundaries, cultural tourism attractions, and accommodation points. Similar proportion-based indicators derived from service area outputs have been widely used to evaluate spatial coverage and opportunity access under specific time thresholds [62,63].

For each age-specific scenario and walking-time threshold, attraction-based service areas were overlaid with the study area and district boundaries to calculate spatial coverage. Overlapping service areas were dissolved to avoid double-counting. The same service areas were then overlaid with accommodation origins to identify reachable attractions and to calculate the number of reachable attractions for each accommodation point. Because service areas were generated from attraction POIs, an attraction was considered reachable when its service area contained at least one accommodation origin under the corresponding scenario.

For different walking-time thresholds and age-specific scenarios, two indicators were constructed. The first, Service Area Coverage Ratio (SACR), measures the proportion of a spatial unit covered by the dissolved attraction service areas:

$$\mathrm{SACR}_{s,t} = \frac{A_{s,t}^{cov}}{A_s} \times 100\% \quad (2)$$

where A_s denotes the walkable land area of spatial unit s, excluding major water barriers, and $A_{s,t}^{cov}$ denotes the area of that land unit covered by the dissolved service areas under scenario t.

The second, Accessible Attraction Ratio (AAR), measures the proportion of cultural tourism attractions that are reachable from accommodation origins within a given time budget:

$$\mathrm{AAR}_{s,t} = \frac{N_{s,t}^{reach}}{N_s^{total}} \times 100\% \quad (3)$$

where $N_{s,t}^{reach}$ denotes the number of attractions in spatial unit s whose service areas contain at least one accommodation origin under scenario t, and N_s^{total} denotes the total number of cultural tourism attractions in that spatial unit.

SACR reflects the spatial extent of walkable service-area coverage, whereas AAR reflects the degree to which the attraction system is reachable from accommodation origins. At the accommodation level, the number of attraction service areas containing each accommodation point was recorded as its reachable-attraction count, which was then used in the subsequent Lorenz–Gini equity assessment and local mismatch analysis.

3.3.4. Distributional Equity Assessment: Lorenz Curve and Gini Coefficient

This study employs the Lorenz curve and Gini coefficient to assess the distributional equity of cultural tourism accessibility in Suzhou's historic urban area. Although these two indicators were originally developed to measure income inequality, they have been widely applied in accessibility research to evaluate the distribution of opportunities across different origins and population groups [15,64]. In this study, the accessibility value of each accommodation point is defined as the number of cultural tourism attraction POIs reachable within a given time budget. Accommodation points are then ranked in ascending order of accessibility, and the cumulative proportion of accommodation points and their corresponding cumulative accessibility values are calculated to construct the Lorenz curve and quantify inequality in accessibility benefits [44–46]. Accordingly, this study adopts an equal-weighted opportunity-count approach, which is consistent with its POI-level destination framework. This approach measures the availability of reachable

cultural tourism opportunities rather than visitor-flow-weighted attractiveness, because consistent data on visitor flows, scenic-area size, and official grades cannot be matched to all 1294 attraction POIs.

Let R_k denote the cumulative proportion of accommodations up to rank k (with $k = 0, 1, \ldots, n$), and let C_k denote the cumulative proportion of total accessibility contributed by those accommodations. The Gini coefficient (Gi) is calculated as:

$$G_i = 1 - \sum_{k=1}^{n} (C_k + C_{k-1})(R_k - R_{k-1}) \tag{4}$$

where G_i ranges from 0 to 1. Values closer to 0 indicate a more equitable distribution of attraction accessibility, whereas values closer to 1 indicate greater concentration of accessibility benefits among a limited number of accommodations. The Lorenz curve plots C_k against R_k, and its deviation from the 45° line of equality visually reflects the degree of inequality. To further examine stratified differences, Lorenz curve and Gini coefficient results were compared across accommodation tiers, which were used here as an operational proxy for accommodation-market stratification and market positioning.

3.3.5. Bivariate Spatial Autocorrelation and Local Mismatch Typology

To identify the spatial alignment and mismatch between accommodation-market structure and walkable accessibility to cultural tourism attractions in the historic urban core and its surrounding districts, this study employed bivariate spatial autocorrelation analysis. Accommodation tier, used as a proxy for market positioning [20–23], was paired with attraction accessibility under the age-specific walking scenarios described above. Both variables were aggregated to a 500 m × 500 m grid covering the study area. This grid size was selected to balance local sensitivity, data comparability, and statistical stability in a heterogeneous historic urban setting. Previous studies on spatial accessibility and fine-grained urban spatial analysis have suggested that a 500 m grid at the intra-urban scale can help mitigate MAUP-related scale bias, retain local spatial variation, and support multi-source data integration [65,66]. A spatial weights matrix, $W = \{w_{ij}\}$, was then constructed to represent neighbourhood relationships among grid cells. Following the Local Indicators of Spatial Association (LISA) framework, overall spatial association was further decomposed into statistically interpretable local configurations [13,51].

Using GeoDa 1.18.0, both global and local bivariate Moran's I statistics were calculated. The global statistic measures the overall spatial association between accommodation tier (X) at location i and neighbouring accessibility values (Y) at location j:

$$I = \frac{n}{S_0} \cdot \frac{\sum_i \sum_j w_{ij}(x_i - \overline{x})(y_j - \overline{y})}{\left(\sum_i (X_i - \overline{X})^2 \sum_{i=1}^{n} (Y_j - \overline{Y})^2\right)^{1\backslash 2}} \tag{5}$$

where n is the number of grid cells, w_{ij} denotes the spatial weight between units i and j, and $\overline{X}$ and $\overline{Y}$ are the global means of X and Y, respectively, and $S_0 = \sum_i \sum_j w_{ij}$. Positive values indicate that high (or low) accommodation tiers tend to be located near-high (or low) accessibility, whereas negative values indicate spatial mismatch.

To identify where such alignment or mismatch occurs, local bivariate Moran's I (bivariate LISA) is further calculated as:

$$I_i = z_{x,i} \sum_j w_{ij} z_{y,j} \tag{6}$$

where $z_{x,i}$ denotes the standardised value of accommodation tier at location i, and $z_{y,j}$ denotes the standardised value of neighbouring accessibility. Statistical significance was

assessed using permutation tests. Significant grid cells were classified into four local LISA types based on the standardised scatterplot quadrants: HH (high-tier near-high accessibility), LL (low-tier near low accessibility), HL (high-tier near low accessibility), and LH (low-tier near-high accessibility).

The purpose of this local analysis is not merely to identify significant clusters or outliers, but to translate localised patterns of alignment and mismatch between accommodation-market structure and attraction accessibility into planning-relevant spatial types. In this study, spatial mismatch refers to localised inconsistencies between accommodation-market positioning and the walkable accessibility of cultural tourism opportunities. Such inconsistencies may reflect situations in which accommodation tiers, attraction supply, walkable street-network conversion, and spatial barriers do not provide corresponding levels of time-budgeted access. In this way, the analysis provides a spatial basis for identifying advantage-coupling areas, peripheral deprivation areas, and locally mismatched areas requiring differentiated intervention [12].

3.3.6. Extreme Gradient Boosting (XGBoost) Regression Model

Extreme Gradient Boosting (XGBoost) is a high-performance machine-learning algorithm built on the Gradient Boosting Decision Tree (GBDT) framework. Because it can capture complex nonlinear relationships and interaction effects without requiring a pre-specified functional form, it is well suited to identifying the multi-factor driving mechanisms underlying walkable accessibility to cultural tourism attractions [67–69].

In this study, XGBoost regression models were developed for four scenarios: all attractions, leisure-strolling attractions, commercial–cultural mixed attractions, and heritage-core attractions. For each scenario, attraction accessibility at the analytical-unit level was used as the dependent variable. The explanatory variables included accommodation kernel density, the kernel density of the corresponding attraction type, accommodation spending, transport-node kernel density, road-network density, and water-body proportion. These variables were used to model the nonlinear relationships between walkable accessibility and the surrounding spatial environment. The objective function of the XGBoost model can be expressed as follows:

$$L(t) = \sum_{i=1}^{n} l\left(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)\right) + \Omega(f_t) \tag{7}$$

where $L(t)$ denotes the objective function at the t-th iteration, l is the differentiable loss function, $\hat{y}_i^{(t-1)}$ is the predicted value from the previous iteration, $f_t(x_i)$ is the output of the newly added tree at iteration t, and $\Omega(f_t)$ is the regularisation term used to control model complexity.

Model training was conducted in Python 3.14.0. For each attraction-type scenario, the dataset was randomly divided into a training set (80%) and an independent test set (20%), with random_state = 42 used to ensure reproducibility. Hyperparameter tuning was conducted on the training set using Optuna 4.7.0 with the tree-structured Parzen estimator (TPE) algorithm [70,71]. The search space covered parameters controlling the learning rate, tree complexity, sample and feature sampling, ensemble size, and regularisation, including eta, max_depth, min_child_weight, subsample, colsample_bytree, n_estimators, reg_alpha, and reg_lambda. A total of 50 optimisation trials were conducted, with the objective of maximising the five-fold cross-validated R^2. The final tuned models were evaluated on the independent test set using R^2, mean absolute error (MAE), and root mean square error (RMSE), thereby allowing comparison of model performance and explanatory patterns across attraction types.

3.3.7. Shapley Additive Explanations (SHAP)

Although XGBoost provides strong predictive performance for complex nonlinear relationships, its limited interpretability constrains direct understanding of how individual explanatory variables contribute to model outputs. To improve model interpretability, this study employed Shapley Additive Explanations (SHAP) to quantify the contribution of each variable to the prediction of walkable accessibility [72,73]. Rooted in cooperative game theory, SHAP assigns an importance value to each feature for each sample, thereby estimating the marginal contribution of that feature to the model prediction. The SHAP value is calculated as follows:

$$\varphi_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!(|F| - |S| - 1)!}{|F|!} [f(S \cup \{i\}) - f(S)] \quad (8)$$

where φ_i denotes the SHAP value of feature i, S denotes a feature subset that excludes feature i, $f(S)$ is the model prediction based on subset S, and $|F|$ is the total number of features. Larger positive SHAP values indicate a stronger positive contribution of a feature to the model prediction, whereas smaller or negative values indicate weaker or negative effects.

To interpret model outputs, three SHAP-based visualisations were used: the mean(|SHAP value|) bar chart, the SHAP beeswarm plot, and the SHAP dependence plot. The mean(|SHAP value|) bar chart was used to compare the relative importance of explanatory variables across the full sample. The SHAP beeswarm plot was used to show both the direction and distribution of variable effects. The SHAP dependence plot was used to identify nonlinear relationships and potential threshold effects between key variables and model predictions. By applying the SHAP framework across the four attraction-type scenarios, this study further compares common driving factors and differentiated nonlinear drivers of walkable accessibility across attraction types.

4. Results

4.1. Spatial Patterns of Cultural Tourism Opportunities

4.1.1. Supply-Side Spatial Patterns

Kernel density results reveal a clear pattern of core concentration and peripheral attenuation in the distribution of cultural tourism attractions across Suzhou's historic urban area (Figure 4). High-density clusters are concentrated primarily in Gusu District and its adjacent eastern areas, forming a compact core of cultural tourism opportunities. Beyond this core, attraction density declines progressively toward surrounding areas, where the spatial pattern is dominated by scattered low-density points and fragmented patches rather than continuous clusters. Overall, the attraction system is therefore not evenly distributed across the study area, but strongly concentrated around the historic urban core.

Type-specific kernel density patterns further refine this overall structure. Leisure-strolling attractions show the greatest outward diffusion, with low- and medium-density clusters extending more clearly into peripheral areas beyond the historic core (Figure 4b). Commercial–cultural mixed attractions also display a compact spatial pattern, with their principal high-density clusters concentrated in Gusu District and its adjacent eastern areas, whereas peripheral distributions remain sparse and discontinuous, indicating strong dependence on the historic core (Figure 4c). Heritage-core attractions are the most spatially concentrated, with high-density clusters tightly anchored in Gusu District and its immediately adjacent areas, showing the closest spatial association with the historic urban core (Figure 4d). Although the three attraction types differ in their degree of outward extension, their shared pattern of core concentration and peripheral attenuation further

confirms that Suzhou's historic urban area should be interpreted as a zonally differentiated cultural tourism space rather than a homogeneous attraction field.

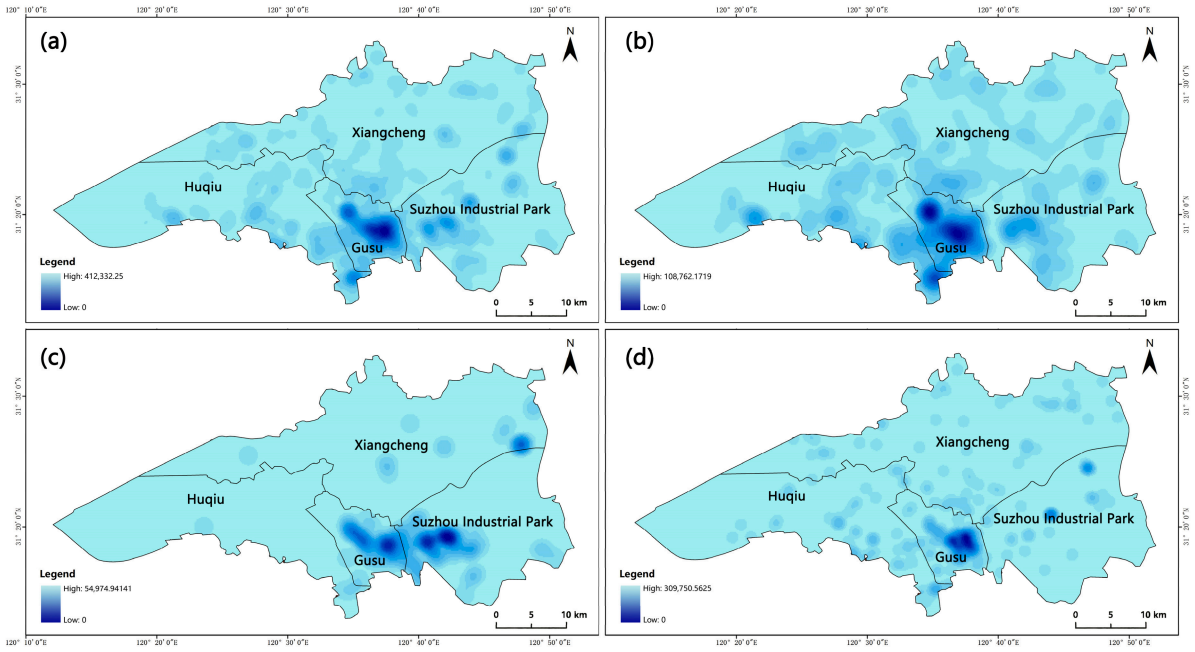


Figure 4. Kernel density of cultural tourism attractions in the central urban area of Suzhou: all attractions (**a**), leisure-strolling attractions (**b**), commercial–cultural mixed attractions (**c**), and heritage-core attractions (**d**).

4.1.2. Overall Accessibility Pattern Under the 15-min City Framework

Using a 15 min walking threshold, this study evaluated the walkable accessibility of cultural tourism attractions from 3453 accommodation origins across Suzhou's historic urban area. The results reveal a clear zonal accessibility structure centred on the historic urban core, with Gusu District forming the main high-accessibility zone and the surrounding districts showing weaker and more fragmented short-budget access (Table 2; Figure 5a). Under the 15 min threshold, Gusu District achieved the highest levels of both Service Area Coverage Ratio (SACR) and Accessible Attraction Ratio (AAR), reaching 80.18% and 95.23%, respectively. By contrast, accessibility in the surrounding and peripheral districts was substantially weaker under this short walking-time budget. Huqiu District recorded the lowest AAR, at 49.58%, whereas Xiangcheng District and Suzhou Industrial Park reached 58.05% and 74.29%, respectively. Several peripheral areas—including the eastern side of Jinji Lake in Suzhou Industrial Park, the area south of Caoshan Wetland Park in Xiangcheng District, and the corridor along Tongshu Road in Huqiu District—remained outside the main 15 min accessible range, with SACR values below 30%.

Table 2. District-level service-area coverage and attraction accessibility under the 15 min walking threshold.

District	Area (km^2)		Number of Attractions	15 min Service Area (km^2)	Covered Attractions	Uncovered Attractions	SACR (%)	AAR (%)
	Land	Water Barrier						
Gusu	76.24	4.51	608	61.12	579	29	80.18	95.23
Huqiu	217.10	117.55	236	70.39	117	119	32.42	49.58
Xiangcheng	377.37	112.96	205	115.95	119	86	30.73	58.05
Suzhou Industrial Park	208.93	67.63	245	94.90	182	63	45.42	74.29
Total	879.64	302.65	1294	342.36	997	297	38.92	77.05

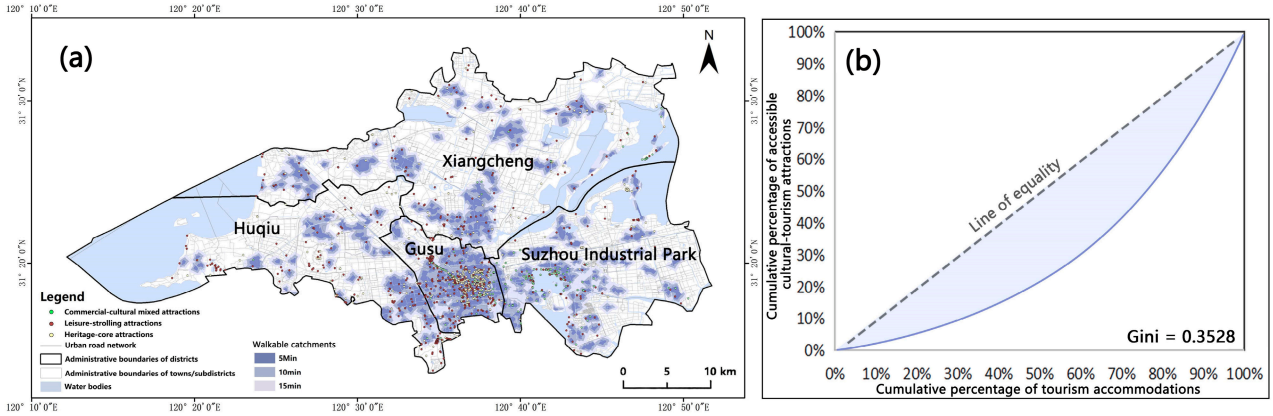


Figure 5. The 15 min walkable accessibility and equity of cultural tourism attractions: walkable catchments (**a**) and Lorenz curve (**b**).

This core–periphery contrast can be further specified as a district-based zonal accessibility pattern in terms of coverage area and attraction reachability. Under the 15 min threshold, Gusu District had a covered area of 61.12 km^2 and included 579 of its 608 attractions within the accessible range. Huqiu District, despite having a larger administrative extent, had a covered area of 70.39 km^2 but included only 117 of 236 attractions. Xiangcheng District and Suzhou Industrial Park showed intermediate patterns, with covered areas of 115.95 km^2 and 94.90 km^2, respectively. Across the entire study area, the 15 min service areas covered 342.36 km^2, corresponding to an SACR of 38.92%, and included 997 of 1294 attractions, yielding an overall AAR of 77.05%.

The Lorenz curve and Gini coefficient further indicate that accessibility benefits were unevenly distributed across accommodation origins (Figure 5b). The Lorenz curve deviates noticeably from the line of equality, and the corresponding Gini coefficient of 0.3528 indicates a moderate degree of distributional inequality in access to cultural tourism attractions. Taken together, these findings show that cultural tourism opportunities display a clear zonal structure under the policy-relevant 15 min threshold: the historic core combines high attraction concentration with high short-budget reachability, whereas surrounding and peripheral districts show more fragmented and discontinuous walkable access.

4.2. Group-Specific Differences in Accessibility and Equity

4.2.1. Differences in Accessibility and Equity Across Accommodation Tiers

To examine how access to cultural tourism opportunities varies across accommodation-market stratification, the 3453 accommodation samples were classified into four tiers: low-tier, mid-tier, mid-high-tier, and high-tier. For each tier, walkable accessibility was evaluated using the mean number of cultural tourism attractions reachable within a 15 min walking budget and the Gini coefficient of the accessibility distribution.

Within the 15 min threshold, high-tier accommodation showed the highest mean accessibility (2.60 accessible attractions) and the lowest Gini coefficient (0.1863), indicating the strongest and most even accessibility performance under a short walking-time budget (Figure 6). Low-tier accommodation ranked second, with a mean accessibility of 1.36 and a Gini coefficient of 0.2587. By contrast, mid-tier and mid-high-tier accommodation recorded the same mean accessibility (0.67), although mid-tier accommodation showed a higher level of distributional inequality (Gini = 0.3274) than mid-high-tier accommodation (Gini = 0.2821). In terms of sample composition, mid-tier and mid-high-tier accommodation together accounted for 76.89% of all accommodation samples, whereas high-tier accommodation accounted for only 7.44% (Table 3). Overall, these results indicate

that differences in walkable accessibility exist across accommodation tiers, but they do not follow a simple monotonic gradient.

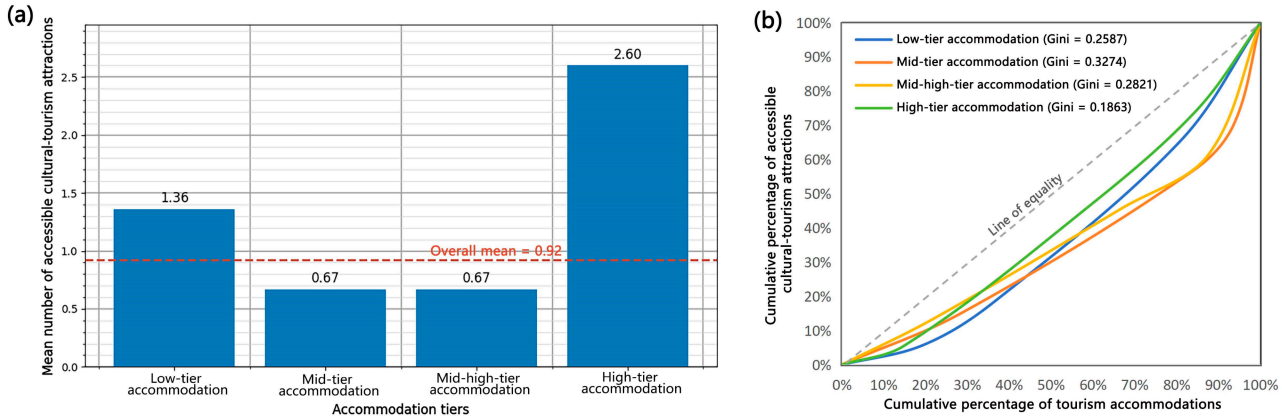


Figure 6. Accessibility and equity across accommodation tiers under the 15 min threshold: mean accessibility (**a**) and Lorenz curves (**b**).

Table 3. Sample composition, core–periphery distribution, and 15 min accessibility and equity metrics across accommodation tiers.

Tier	Core Zone (n)	Periphery (n)	Core Zone (%)	Periphery (%)	Total Sample (%)	15 min Accessible Attractions (n)	Gini
Low-tier	239	302	44.18	55.82	15.67	737	0.2587
Mid-tier	678	550	55.21	44.79	35.56	824	0.3274
Mid-high-tier	640	787	44.85	55.15	41.33	962	0.2821
High-tier	109	148	42.41	57.59	7.44	667	0.1863

Spatially, these tier-based differences are embedded within the accessibility structure centred on the historic urban core, but their spatial distributions are not identical (Figure 7). The share of accommodation located within the core accessible area is relatively similar across tiers, ranging from 42.41% to 55.21% (Table 3), suggesting that tier differences cannot be explained solely by whether accommodation is located inside or outside the core area. At the same time, low-tier and high-tier accommodation are more concentrated in the historic core and its immediate surroundings, particularly in Gusu District, whereas mid-tier and mid-high-tier accommodation are more widely distributed across peripheral urban areas. These spatial embedding differences indicate that, under a 15 min walking budget, variation in accessibility across accommodation tiers is not organised as a simple hierarchical gradient.

Type-specific comparison further shows that these tier differences vary across attraction types (Figure 8). Across all three attraction categories, high-tier accommodation consistently recorded the highest mean accessibility, whereas commercial–cultural mixed attractions showed the weakest overall accessibility. Low-tier accommodation did not consistently perform worst across attraction types, and the performances of mid-tier and mid-high-tier accommodation remained relatively close. Taken together, these results suggest that accessibility differences across accommodation tiers are more closely associated with different spatial embedding patterns in the opportunity field of the historic urban core than with a simple consumption-based hierarchy.

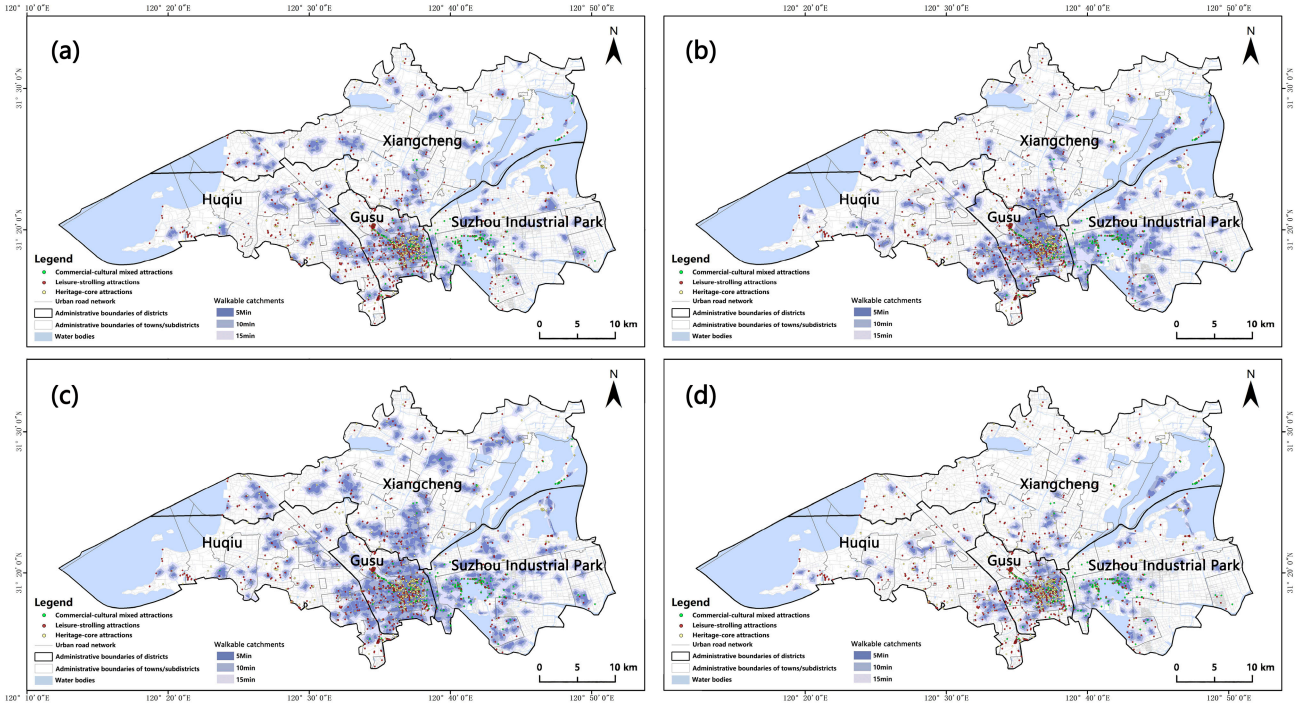


Figure 7. Walkable accessibility to cultural tourism attractions across accommodation tiers under the 15 min threshold: low-tier (**a**), mid-tier (**b**), mid-high-tier (**c**), and high-tier (**d**).

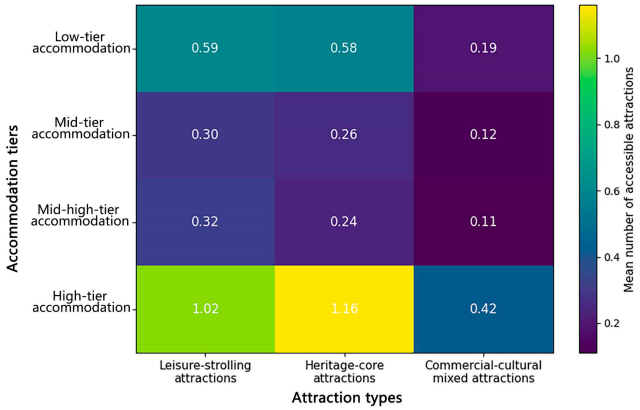


Figure 8. Type-specific mean accessibility across accommodation tiers within the 15 min threshold.

4.2.2. Age-Stratified Threshold Effects Across Attraction Types

To examine age-related differences in walkable accessibility, three age-specific scenarios were established—elderly, middle-aged, and young visitors—and attraction accessibility was assessed under multiple time thresholds. As shown in Figures 9 and 10, cumulative accessibility exceeded 98% for all age groups within a 60 min walking budget. Under shorter walking-time thresholds, however, differences between age groups became much more pronounced, particularly for the elderly group.

For all attractions, accessibility across time thresholds generally followed a stable ranking of middle-aged, young, and elderly visitors (Figure 10a). This difference was most pronounced under short walking-time budgets and gradually narrowed as the threshold increased. The 15–30 min interval marks the key range in which age-related differences remained visible but began to contract; beyond 30 min, the gap among age groups converged further and became much less pronounced than under short thresholds. This pattern suggests that age-related differences are reflected more in delayed accessibility than in absolute spatial inaccessibility. A similar pattern can be observed in the accessibility surfaces shown

in Figure 9a–c, where the elderly scenario displays a broader extent of low-accessibility areas outside the historic urban core.

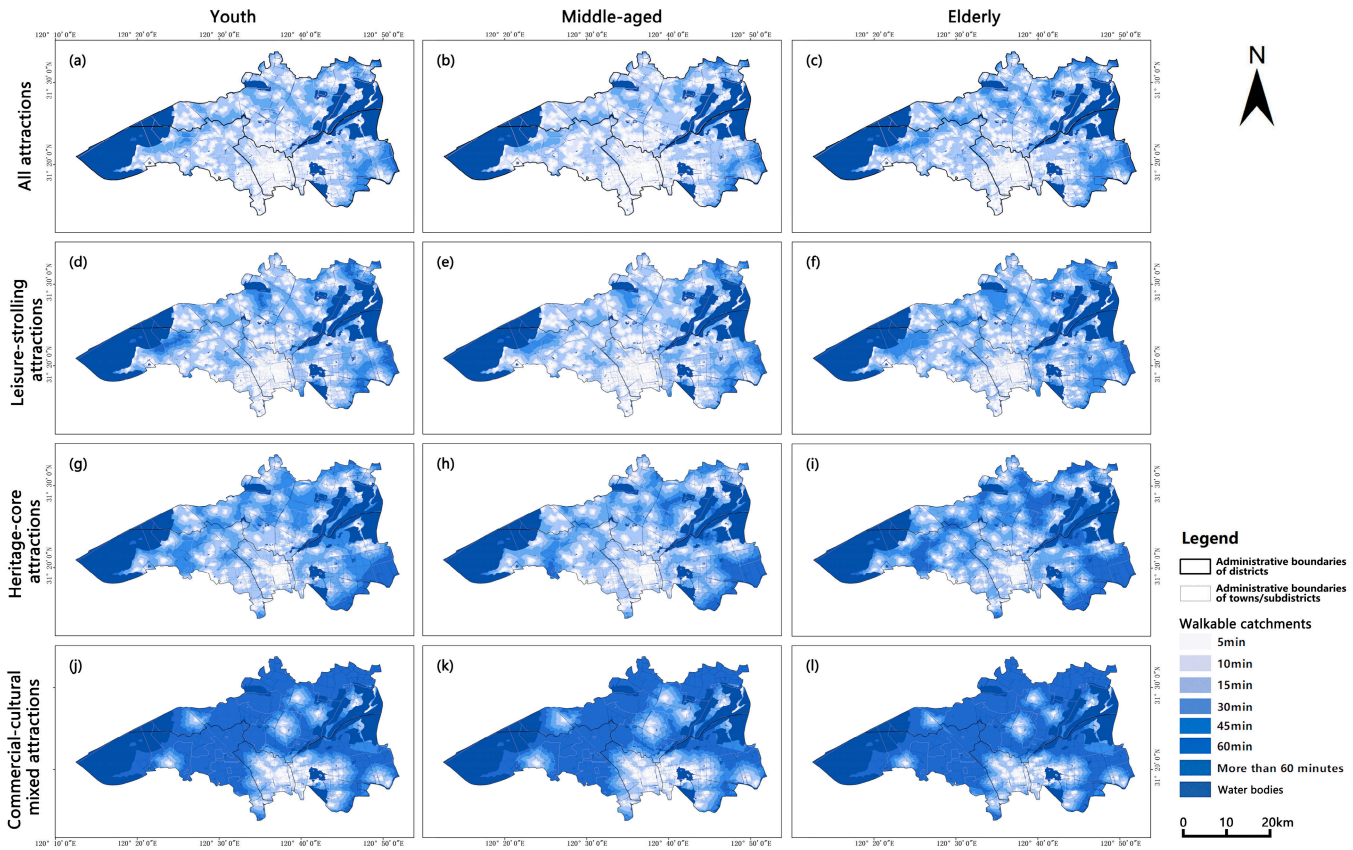


Figure 9. Age-specific walkable accessibility across attraction types: all attractions (**a**–**c**), leisure-strolling attractions (**d**–**f**), heritage-core attractions (**g**–**i**), and commercial–cultural mixed attractions (**j**–**l**).

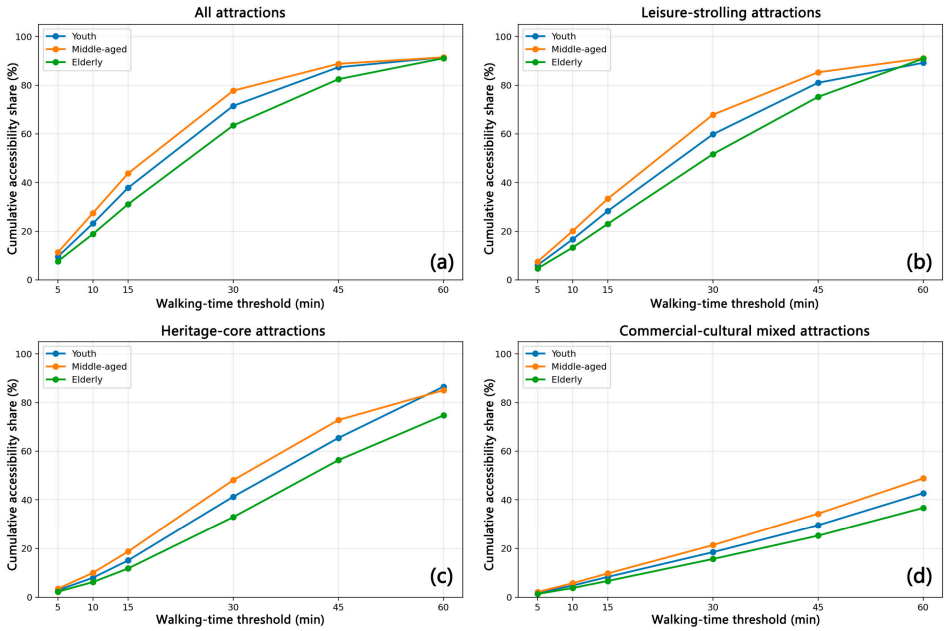


Figure 10. Cumulative accessibility shares across age groups for different attraction types: all attractions (**a**), leisure-strolling attractions (**b**), heritage-core attractions (**c**), and commercial–cultural mixed attractions (**d**).

Type-specific results further indicate that age-stratified differences unfold differently across attraction systems (Figure 10b–d). Leisure-strolling attractions show a relatively broad spatial extension, and the gap between age groups narrows more clearly as walking-time thresholds increase, indicating a stronger delayed-compensation effect. Spatially, accessible areas for this attraction type extend more continuously from the historic core toward surrounding areas, allowing elderly visitors to recover part of their accessibility disadvantage under longer walking budgets (Figures 9d–f and 10b). By contrast, heritage-core attractions show a more persistent age gradient. Their accessible areas remain more tightly concentrated in the historic urban core, and elderly visitors continue to lag behind middle-aged and young visitors even as time thresholds increase, indicating that longer walking budgets can only partially reduce age-related accessibility barriers in this attraction system (Figures 9g–i and 10c). Commercial–cultural mixed attractions present a third pattern, with the lowest overall accessibility and clear age-group differences maintained across all thresholds, reflecting the combined effects of limited opportunity distribution and variation in walking ability (Figures 9j–l and 10d). Taken together, these findings indicate that age-related inequalities in walkable accessibility are shaped not only by differences in walking ability, but also by the spatial organisation of different attraction types within the historic urban core.

These age-stratified differences are particularly visible in peripheral areas, especially north of Xuguan Wharf, south of Cao Lake Wetland Park, and in parts of Suzhou Industrial Park, where the coverage of elderly visitors is noticeably more limited than that of young and middle-aged visitors. Overall, Figures 9 and 10 show that access to cultural tourism opportunities in Suzhou's historic urban area is strongly sensitive to both the age and time threshold, and that the magnitude, persistence, and spatial expression of these differences vary substantially across attraction types.

4.2.3. A Comparative Synthesis of Group-Specific Accessibility Inequality

Taken together, Sections 4.2.1 and 4.2.2 show that inequality in walkable accessibility does not arise from a single mechanism. Differences across accommodation tiers are more closely associated with structural spatial embedding differences within the opportunity field of the historic urban core, whereas age-stratified differences are more strongly shaped by threshold sensitivity under varying levels of walking ability. The former reflects the positional differences in accommodation-market segments within the core–periphery structure, while the latter highlights the inclusiveness thresholds faced by different age groups when accessing cultural tourism opportunities under limited walking-time budgets.

These two dimensions jointly indicate that inequality in walkable accessibility to cultural tourism opportunities in Suzhou's historic urban area is shaped by both structural spatial lock-in and time-threshold sensitivity. This comparative synthesis also provides the analytical basis for the next step of the study: identifying how group-specific differences are translated into localised patterns of spatial alignment and mismatch, and how these patterns can be further interpreted through local mismatch typologies.

4.3. Spatial Mismatch Between Attraction Accessibility and Accommodation Tier Across Age Groups and Attraction Types

To identify the spatial alignment and mismatch between accommodation-market structure and walkable accessibility to cultural tourism attractions, bivariate spatial autocorrelation analysis was conducted using accommodation tier as a proxy for market positioning and grid-based attraction accessibility as the outcome variable. The analysis was carried out across different age groups and attraction types in order to compare how accommodation-market structure relates to walkable accessibility under different scenario conditions.

At the global level, the bivariate Moran's *I* values for all attractions were −0.115 for young visitors, −0.102 for middle-aged visitors, and −0.115 for elderly visitors, indicating a generally weak negative spatial association between accommodation tier and attraction accessibility in Suzhou's historic urban area. In other words, accommodation-market positioning and walkable accessibility do not exhibit a strong overall coupling pattern, and some degree of spatial mismatch is present in the distribution of cultural tourism opportunities. Comparison across attraction types in Figure 11 further shows that the strength of this negative relationship varies by both age group and attraction type, suggesting that attraction-type conditions influence the spatial mismatch pattern between accommodation tier and accessibility.

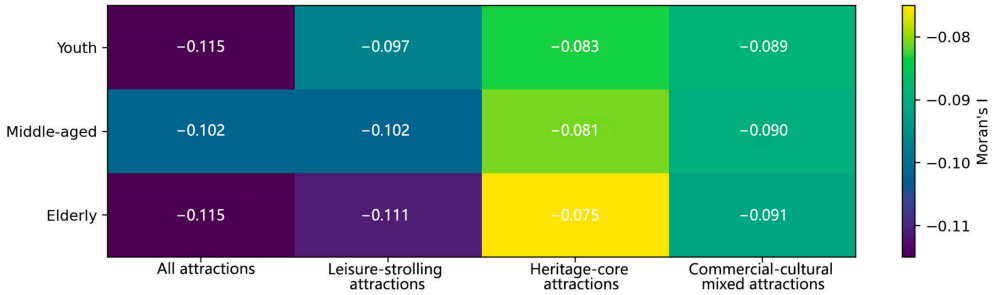


Figure 11. Global bivariate Moran's *I* between accommodation tier and cultural tourism attraction accessibility across age groups and attraction types.

Local bivariate LISA results further reveal clear differences in mismatch configurations across attraction types and age scenarios. Taking all attractions as the baseline, LH (low-tier near-high accessibility) is the most common individual local type, while LL, HL, and HH also account for a relatively large share, indicating a mismatch-dominated but multi-type local structure in which localised inequality is widespread (Figure 12a–c). Leisure-strolling attractions and heritage-core attractions show relatively similar local patterns, both with a relatively high proportion of LH units alongside widespread LL and HL units, suggesting more mixed local relationships between accommodation-market structure and accessibility (Figure 12d–i). By contrast, commercial–cultural mixed attractions display a more strongly differentiated local structure: the number of non-significant grid cells decreases markedly, LL and HL units increase substantially, and HH units become relatively rare. This indicates that, under the commercial–cultural mixed attraction scenario, local patterns are more strongly organised around low-accessibility contexts in which mismatch and weak alignment coexist (Figure 12j–l). Overall, compared with age-specific differences, the spatial structure of attraction types exerts a stronger influence on local mismatch patterns.

From a spatial perspective, these local types also show clear locational differentiation across the study area. Except for the commercial–cultural mixed attraction scenario, HL and LL units are concentrated mainly in the historic urban core and in some areas adjacent to eastern Suzhou Industrial Park, indicating that some areas with high-tier accommodation do not correspond to equivalent walkable accessibility advantages. HH units are distributed mainly in banded or patch-like forms in northern Xiangcheng District, where local alignment between accommodation-market structure and accessibility is relatively stronger. By contrast, LH units occur more frequently in transitional belts around the core and in some peripheral areas, suggesting that some low-tier accommodation is embedded in relatively high-accessibility cultural tourism environments (Figure 12a–i). Commercial–cultural mixed attractions show the most distinctive spatial pattern, with a stronger concentric and clustered structure and multiple localised cores (Figure 12j–l). It should also be noted that the large contiguous low-accessibility grids on the western side of Figure 12 correspond mainly to large open water bodies and their surrounding

edges. These areas reflect accessibility constraints imposed by water barriers rather than generalised accommodation-market mismatch within the continuous built-up area.

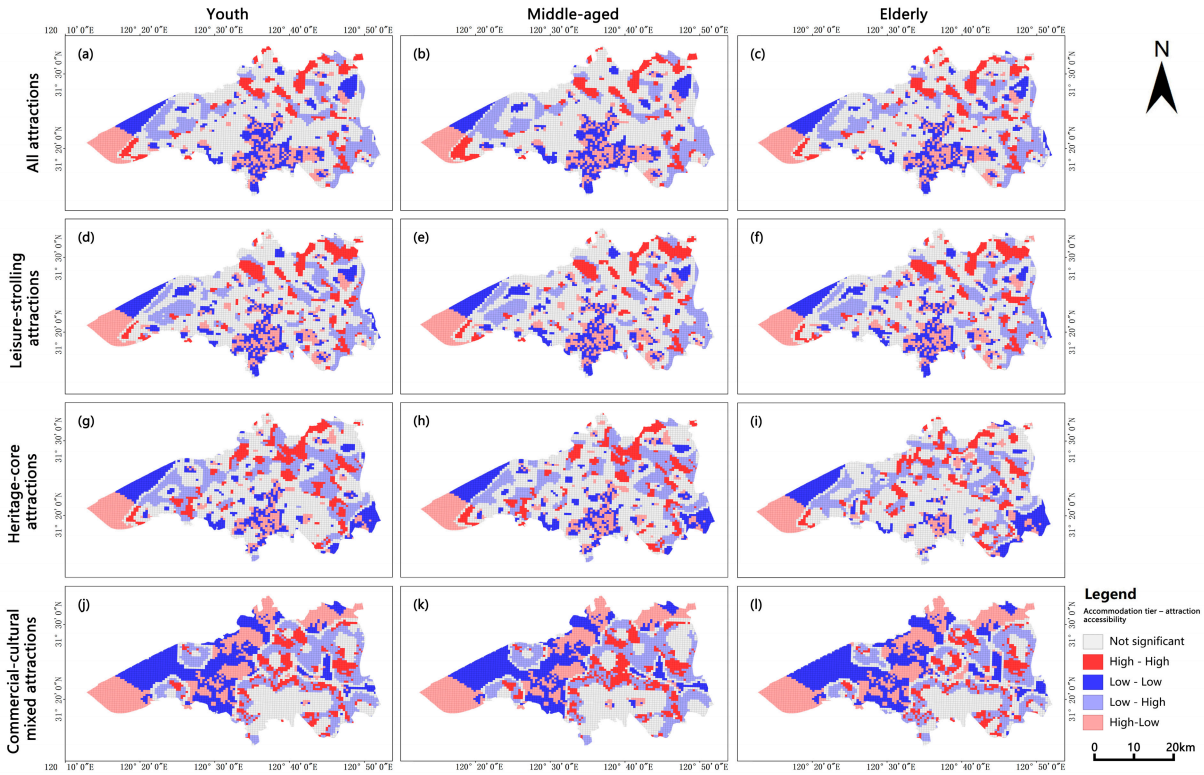


Figure 12. Significant bivariate LISA cluster maps between accommodation tier and cultural tourism attraction accessibility across age groups and attraction types: all attractions (**a**–**c**), leisure-strolling attractions (**d**–**f**), heritage-core attractions (**g**–**i**), and commercial–cultural mixed attractions (**j**–**l**).

Overall, inequality in walkable accessibility to cultural tourism opportunities in Suzhou's historic urban area is expressed less as a simple linear relationship between accommodation tier and attraction accessibility than as a highly localised and typified pattern of spatial mismatch. Attraction types show distinct local mismatch structures, and the accommodation-tier and age-stratified differences identified in the previous section are further translated here into spatially identifiable mismatch units, providing the empirical basis for the subsequent type-specific explanation and differentiated intervention strategies.

4.4. Interpretable Machine Learning Analysis of Accessibility Drivers

Given that age-related differences in walkable accessibility have already been examined in the previous section, this section does not repeat machine learning interpretation across all age groups. Instead, the young group was selected as the reference scenario because its walking ability and accessibility outcomes occupy an intermediate position among the three age groups. Under this reference scenario, XGBoost models were developed for four attraction-type settings: all attractions, commercial–cultural mixed attractions, leisure-strolling attractions, and heritage-core attractions. Building on the local mismatch types identified above, these models were used to examine type-specific accessibility-generating conditions associated with variations in local mismatch patterns across attraction systems. SHAP was then applied to interpret feature contributions to model predictions and nonlinear statistical associations related to walkable accessibility. The explanatory variables included accommodation kernel density, the kernel density of the corresponding attraction type, accommodation spending, transport-node kernel density, road-network density, and water-body proportion. This modelling strategy keeps the number of models analytically

manageable while providing a unified basis for type-specific comparison. The model evaluation results indicate that all four models achieved good predictive performance and generalisation ability. For the all-attraction, commercial–cultural mixed, leisure-strolling, and heritage-core models, the test-set R^2 values were 0.8150, 0.8585, 0.8442, and 0.7921, the RMSE values were 5.8599, 6.6699, 6.0288, and 7.2209, and the MAE values were 4.4735, 5.1263, 4.6075, and 5.6634, respectively. In terms of test-set R^2, the commercial–cultural mixed attraction model showed the strongest predictive performance, whereas the heritage-core attraction model showed comparatively lower predictive strength.

4.4.1. SHAP-Based Model Interpretation Results

Overall, the SHAP results reveal a common supply–accommodation structure across the four models, but the relative weight of these components varies markedly by attraction type. In the model for all attractions, accommodation kernel density is the most important variable, with a mean (|SHAP value|) of 6.13, followed by overall attraction kernel density at 4.18. This indicates a relatively balanced dual-core explanatory structure in which both accommodation support and opportunity supply make substantial contributions to walkable accessibility. In the leisure-strolling attraction model, the kernel density of leisure-strolling attractions ranks first at 8.51, followed by accommodation kernel density at 4.01, suggesting a similar dual-core structure but with a stronger supply-side emphasis. By contrast, the commercial–cultural mixed and heritage-core models show much more concentrated supply-led structures. In the former, the kernel density of commercial–cultural mixed attractions reaches 13.57, far exceeding accommodation kernel density (1.71), while in the latter, the kernel density of heritage-core attractions reaches 10.73, also substantially higher than accommodation kernel density (2.35). Taken together, these results indicate that walkable accessibility across attraction types is consistently shaped by supply–accommodation coupling, but the relative weighting of these two components differs clearly by attraction type. All attractions and leisure-strolling attractions are closer to a dual-core driving structure, whereas commercial–cultural mixed and heritage-core attractions are more strongly supply-led (Figure 13).

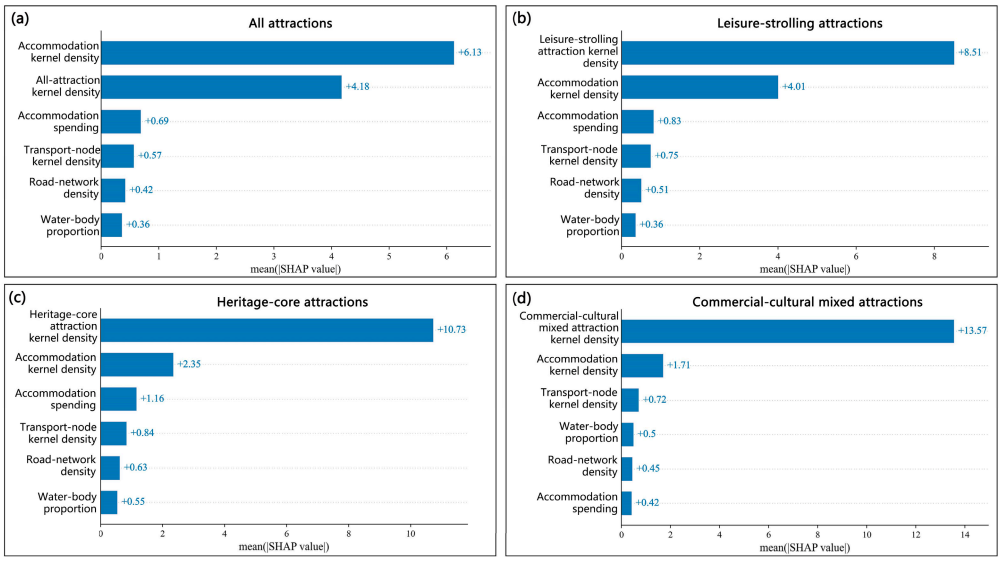


Figure 13. Bar charts of mean (|SHAP value|) across attraction types.

The SHAP beeswarm plots further clarify the direction and distribution of these model-based associations (Figure 14). Across all models, higher attraction kernel density and higher accommodation kernel density are generally associated with positive SHAP values, indicating that denser opportunity supply and denser accommodation support are the basic

conditions for improving walkable accessibility. However, the role of secondary variables differs across attraction types. In the all-attraction and leisure-strolling models, accommodation spending, transport-node kernel density, road-network density, and water-body proportion are distributed mainly around zero, suggesting relatively weak overall effects. In the heritage-core model, accommodation spending shows greater relative importance than in the other models, indicating that accessibility to heritage-core opportunities is more sensitive to accommodation-market stratification. In the commercial–cultural mixed model, by contrast, accommodation spending has the weakest role, while transport-node kernel density and water-body proportion are comparatively more prominent, suggesting a stronger dependence on local nodal conditions and spatial environmental characteristics (Figures 13 and 14).

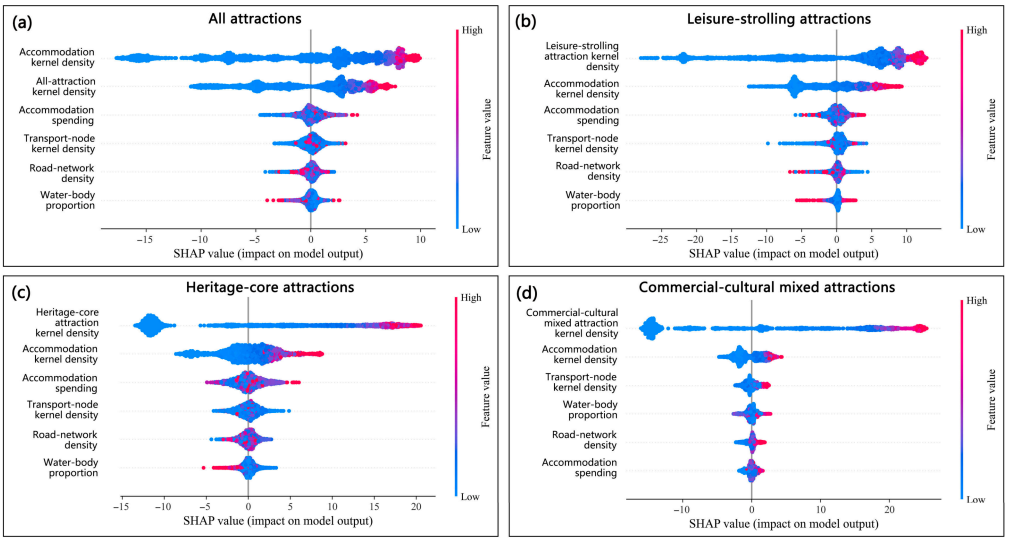


Figure 14. SHAP beeswarm plots across attraction types.

Taken together, Figures 13 and 14 show that the model results do not point to a single transport or market factor as the dominant explanation for walkable accessibility; rather, they indicate that accessibility is primarily shaped by the spatial coupling between cultural tourism opportunity supply and the accommodation support system. The main difference across attraction types lies not in whether core drivers exist, but in how concentrated the driving structure is and how strongly secondary variables regulate it. These results suggest that the core polarisation–peripheral attenuation pattern, accommodation-tier differences, and local mismatch structures identified in the previous sections do not correspond to a single explanatory pattern, but instead exhibit clear type-conditioned differences.

4.4.2. Nonlinear Relationships Between Key Influencing Factors and Model Predictions

Figure 15 further shows that the relationships between key explanatory variables and model predictions are distinctly nonlinear and, in many cases, threshold-dependent. In the all-attraction model, both accommodation kernel density and overall attraction kernel density display clear positive threshold relationships, rising rapidly at lower values before gradually levelling off. This suggests that higher predicted walkable accessibility is associated with a certain level of agglomeration in both opportunity supply and accommodation support. By contrast, transport-node kernel density shows only a weak positive effect, accommodation spending remains relatively limited in influence, and road-network density exhibits an inverted-U-type relationship rather than a continuously increasing effect. In other words, moderate road-network density is more conducive to improving walkable accessibility, whereas very high road-network density does not generate the same degree of

additional gain. Water-body proportion has a comparatively weak overall effect, remaining slightly negative or close to neutral (Figure 15).

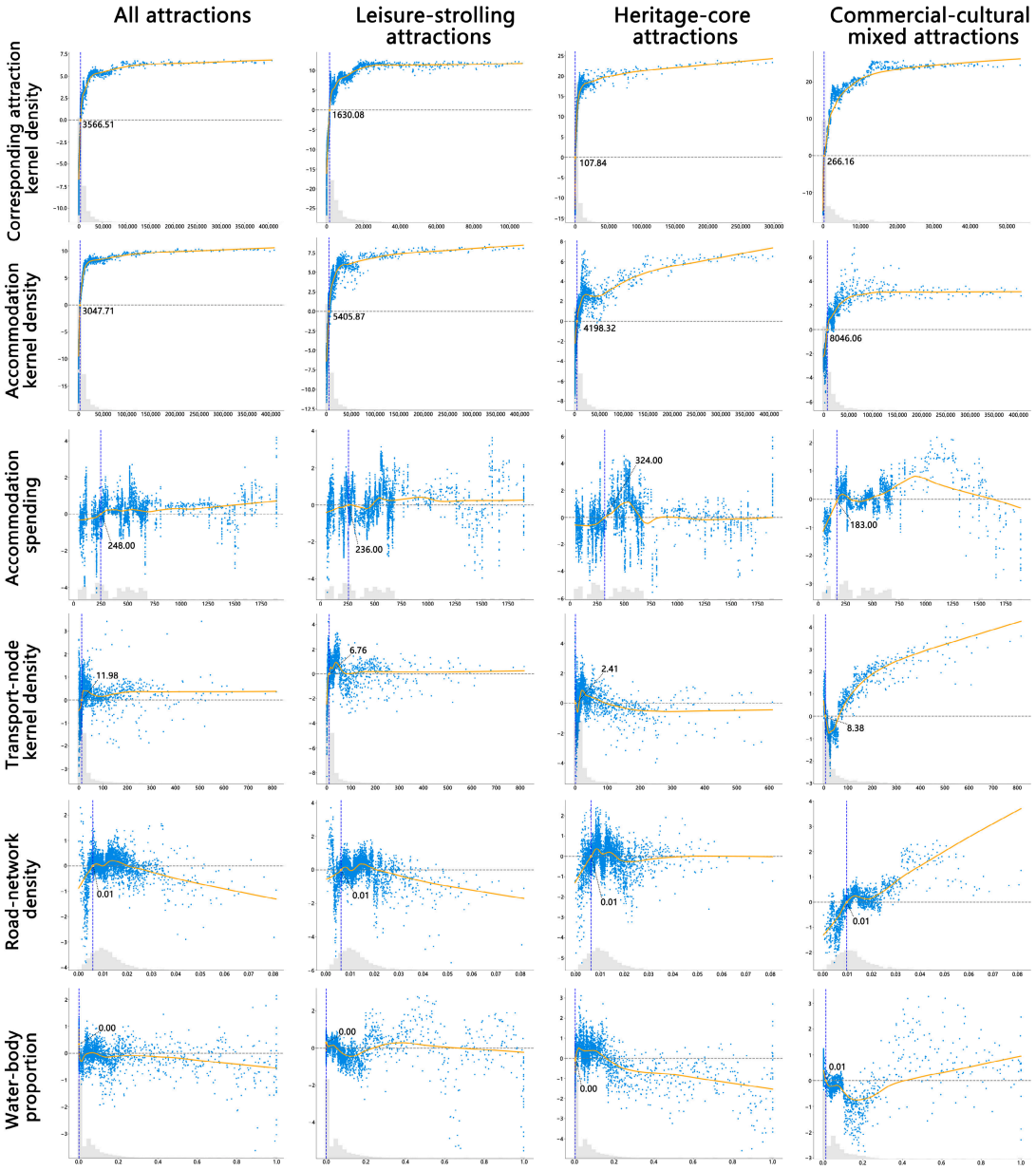


Figure 15. SHAP dependence plots of key explanatory variables across attraction types.

The leisure-strolling attraction model also shows strong positive relationships dominated by attraction density and accommodation density, but the response curves of the secondary variables are more complex. Both leisure-strolling attraction kernel density and accommodation kernel density exhibit rapid positive increases followed by gradual flattening, indicating that accessibility to leisure-strolling opportunities also depends on the dual agglomeration of supply and accommodation. However, transport-node kernel density, road-network density, water-body proportion, and accommodation spending do not follow stable monotonic trends; instead, they show more evident fluctuations and marginal reversals. In particular, road-network density gradually turns negative at relatively high values, while accommodation spending follows a more oscillating pattern of initial increase, subsequent decline, and later fluctuation. These results suggest that walkable accessibility

to leisure-strolling attractions depends more strongly on multi-factor interaction than on supply agglomeration alone (Figure 15).

Commercial–cultural mixed attractions show a different pattern. Their accessibility remains strongly dependent on attraction supply, while the responses to transport-node density and water-body proportion are comparatively more pronounced than in the other attraction types. This suggests that accessibility to commercial–cultural mixed opportunities is more sensitive to local nodal conditions and spatial environmental context, rather than being shaped primarily by accommodation-market factors.

The heritage-core attraction model shows the clearest supply-led pattern. Heritage-core attraction kernel density exhibits one of the strongest positive threshold relationships, indicating that the agglomeration of heritage opportunities is the primary condition underlying accessibility in this system. Accommodation kernel density also maintains a stable positive effect. However, compared with the commercial–cultural mixed model, transport-node kernel density, road-network density, accommodation spending, and water-body proportion show more obvious nonlinear fluctuations and marginal reversals. Specifically, transport-node kernel density shows a brief positive window at lower values, weakens gradually, and becomes negative at higher intervals. Road-network density is associated with higher predicted accessibility mainly at low-to-medium levels, but tends toward neutrality or negativity at higher levels. Accommodation spending shows a more complex fluctuating pattern, while water-body proportion becomes negative overall after an initial increase. These results indicate that accessibility to heritage-core attractions is shaped not only by supply agglomeration, but also by the combined effects of historic spatial structure, walkable street-network constraints, and market differentiation (Figure 15).

Taken together, the nonlinear relationships shown in Figure 15 further demonstrate that no single factor explains walkable accessibility across all attraction types. All attractions and leisure-strolling attractions more clearly reflect a dual-core driving structure shaped by both attraction supply and accommodation support. Commercial–cultural mixed attractions show the strongest sensitivity to supply concentration, nodal conditions, and water-related environmental context. Heritage-core attractions, while also strongly supply-led, display more evident network constraints and spatial sensitivity. In this sense, the core–periphery pattern, accommodation-tier differences, and local mismatch structures identified in the previous sections are not explained by a single transport or market condition alone, but are more consistently associated with different modes of supply–accommodation coupling and the nonlinear regulatory effects of network and market variables under different attraction-type scenarios.

5. Discussion

5.1. A Historic-Core-Dominated Accessibility Gradient

The historic-core-dominated accessibility gradient identified in this study suggests that spatial inequality in cultural tourism opportunities is not produced by attraction distribution alone, but by the way concentrated opportunities are converted into short-budget walkable access through the historic street network. Cultural tourism attractions are densely clustered in Gusu District and its adjacent areas, but beyond this core they rapidly shift toward a fragmented and discontinuous low-density pattern. This general pattern is consistent with previous observations on the concentration of cultural resources and tourism activity in Suzhou's old city [11,12], and also echoes broader studies showing that street structure, spatial configuration, and place organisation shape activity distribution and patterns of space use in historic urban areas [28–32]. However, the present study further demonstrates that this supply-side concentration is not merely a static distributional pattern; under the 15 min walking threshold, it becomes an accessibility gradient because the dense

opportunity field of the historic core is more readily transformed into short-budget walkable access through relatively compact street-network connections and clustered destination settings. The markedly higher SACR and AAR values in Gusu District therefore indicate not only a supply advantage, but also a stronger capacity of the historic core to transform nearby cultural tourism resources into modelled short-budget walkable access.

In this sense, the core polarisation–peripheral attenuation pattern reflects a combined mechanism of opportunity concentration, network-based conversion, and historic-core functional dominance. This interpretation is consistent with network-based accessibility studies that emphasise the role of route continuity, detours, barriers, and street permeability in shaping actual access processes [33–38]. In Suzhou, the historic core functions not only as the primary supply centre of cultural tourism opportunities, but also as the key area where dense resources are most effectively converted into short-budget walkable access. If such an advantage continues to intensify, it may further increase pressure on the historic urban core in terms of heritage conservation and sustainable tourism governance [1–3]. Under peak tourism conditions, however, this modelled accessibility advantage may be partially offset by congestion, reduced walking speed, queuing, and competition for limited pedestrian space, meaning that real-time accessibility in the historic core may be lower than the baseline network-based estimates and that accessibility efficiency may decline as tourism pressure intensifies. From this perspective, the accommodation-tier differences, age-stratified threshold effects, and local mismatch patterns discussed below are not isolated empirical phenomena; they are secondary expressions of a broader opportunity structure in which the historic core concentrates resources, converts them more efficiently into short-budget access, and simultaneously accumulates tourism pressure. Differentiated optimisation therefore needs to begin from this structural imbalance between the historic core and the surrounding districts.

5.2. Spatial Embedding Logic of Accommodation-Tier Differences

The accommodation-tier differences identified in this study suggest that market segmentation in historic urban tourism is spatially mediated rather than directly translated into walkable access to cultural tourism opportunities. Although accommodation attributes, types, and perceived benefits have been widely used to identify differentiated market segments [22,47–49], accommodation-market stratification cannot be treated as a direct proxy for walkable access to cultural tourism opportunities. The relative advantage of high-tier accommodation arises mainly from its repeated spatial embedding within the high-density opportunity field of the historic urban core, where attraction concentration, tourist-service functions, and walkable network connectivity are more likely to overlap. At the same time, low-tier accommodation does not remain consistently disadvantaged. When low-cost accommodation is located along the edge of the historic core or near concentrated opportunity clusters, its accessibility advantage is generated less by market hierarchy than by proximity to the same opportunity field that supports higher-tier accommodation. By contrast, although mid-tier and mid-high-tier accommodation account for a much larger share of the total sample, their broader and more dispersed spatial distribution means that they are less consistently embedded within the historic-core opportunity field, producing more homogeneous but less advantaged accessibility outcomes. In this sense, accommodation-tier differences are not organised as a simple monotonic relationship between accommodation tier and accessibility, but as the spatial outcome of how different market segments are embedded within the historic core, its edge areas, and the surrounding opportunity fields.

From the perspective of accessibility equity, this finding reinforces the argument that aggregate accessibility indicators may conceal uneven opportunity distributions across

spatial units and social groups [39–43]. In historic cities such as Suzhou, where heritage resources and cultural tourism opportunities are highly concentrated within a clearly defined core, such unevenness is further shaped by how different accommodation-market segments are spatially positioned within the core opportunity field. The relative accessibility advantage of low-tier accommodation points to the possibility of low-cost access to high-opportunity environments, but it may also indicate potential inconsistencies between accessibility advantage and the quality of on-site tourism experience. Conversely, the persistent accessibility advantage of high-tier accommodation suggests that higher-positioned accommodation locations are more frequently situated where short-budget access to cultural tourism opportunities can be captured within the historic core. The issue, therefore, is not simply one of market hierarchy, but of how different accommodation tiers are spatially positioned within a highly concentrated opportunity structure. This further underscores the need for differentiated optimisation aimed at reducing core–periphery structural imbalance while supporting more inclusive access to cultural tourism opportunities in historic urban areas.

5.3. Age-Stratified Threshold Effects and Inclusive Optimisation Pathways

The age-stratified threshold effects identified in this study suggest that accessibility inequality in historic urban tourism is produced not only by differences in walking speed, but also by how limited walking-time budgets mediate the conversion of nearby opportunities into actual reachable opportunities. The 15–30 min interval therefore functions as a key transition window: within shorter time budgets, age-related differences appear as immediate exclusion from nearby opportunities, whereas beyond 30 min they are expressed more as temporal delay and additional walking burden among elderly visitors than as absolute spatial inaccessibility. This interpretation is consistent with accessibility equity and age-related mobility studies that emphasise how mobility constraints can reshape the distribution of opportunity access across social groups [18,39–43]. In historic urban areas, age-related inequality should therefore be understood not only as a difference in whether destinations can eventually be reached, but also as a difference in sensitivity to time thresholds and accumulated walking burden under constrained walking ability.

These threshold effects are further mediated by the spatial organisation of different attraction systems. For leisure-strolling attractions, age-related gaps converge more clearly as walking-time thresholds increase because their more continuous distribution along streets and open spaces creates a higher degree of temporal compensability. Additional walking time can therefore partially offset slower walking speeds by allowing elderly visitors to gradually connect to a wider leisure-strolling opportunity field. By contrast, heritage-core attractions are more likely to produce persistent age thresholds, with clear inter-group differences remaining even under extended walking-time budgets. This suggests that heritage-core attraction nodes require more explicit inclusive optimisation. Commercial–cultural mixed attractions show the lowest overall accessibility together with persistent age-related differences, reflecting both the smaller opportunity scale of this attraction type and its more concentrated spatial distribution, which in turn amplifies the constraints imposed by differences in walking ability.

Building on this threshold-based interpretation and proximity-oriented planning studies [18,74], areas under the heritage-core attraction scenario where elderly visitors require more than 30 min of walking time can be interpreted as priority zones for age-friendly support interventions. As shown in Figure 16, heritage-core attractions remain strongly concentrated in Gusu District, whereas the priority intervention zones for elderly visitors are located mainly in the surrounding districts and in areas adjacent to the historic core. The aim is not to alter the overall destination structure, but to decompose walking processes

that exceed 30 min into more manageable 15–30 min segments through buffer facilities that integrate rest, seating, shading, barrier-free guidance, assistance, and information services within the existing opportunity structure. In this way, the time-threshold exclusion effect in access to cultural tourism opportunities can be reduced while preserving the basic spatial organisation of the historic urban area.

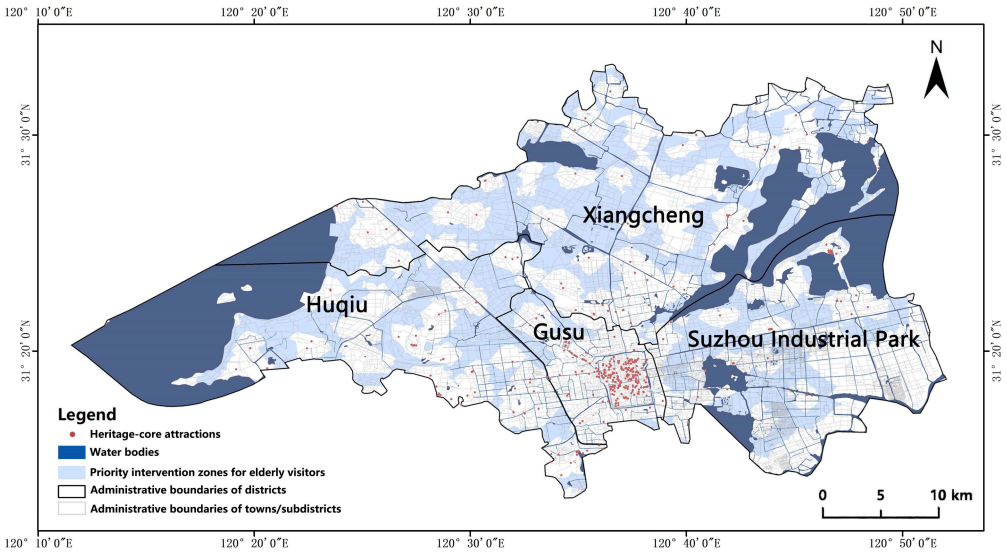


Figure 16. Priority intervention zones for elderly visitors under the heritage-core attraction scenario (>30 min walking time).

5.4. Differentiated Optimisation Pathways Based on Spatial Mismatch Types and Driving Mechanisms

Within a highly heterogeneous historic urban tourism system, the most planning-relevant issue is not low accessibility in general [51–53], but localised mismatch between accommodation-market structure and walkable accessibility to cultural tourism opportunities. Among the four local configurations identified by bivariate LISA, the HL type, namely high-tier accommodation near low accessibility, is the most critical diagnostic category. Compared with HH, LL, and LH units, HL units reveal situations in which strong accommodation agglomeration and high market positioning are not translated into equivalent short-budget walkable accessibility. Because accommodation tier is used in this study as an operational proxy for accommodation-market positioning and potential service demand rather than as a direct measure of tourists' actual income or expenditure, HL units should not be interpreted as direct evidence of individual-level consumption inequality. Instead, they indicate a potential service–access mismatch between accommodation-market positioning and nearby cultural tourism opportunity access, and therefore provide priority diagnostic units for differentiated planning intervention.

Spatial mismatch in this study reflects localised inconsistencies among accommodation-market positioning, opportunity supply, walkable street-network conversion, and spatial barriers. Consistent with studies that use LISA to move from global association to localised clusters and outliers [13,50–53], bivariate LISA identifies where such inconsistencies occur, while SHAP-based explanatory patterns help interpret the accessibility-generating conditions associated with different attraction systems [54,69–73]. The SHAP results are interpreted as feature contributions to model predictions and nonlinear statistical associations, rather than as direct causal effects. Figure 17 further shows that HL-type mismatch is not randomly distributed. HL units for all attractions and heritage-core attractions are more closely associated with Gusu District and its adjacent areas, whereas commercial–cultural mixed HL units are more widely distributed across the surrounding districts, especially in Huqiu District, Xiangcheng District, and parts of Suzhou Industrial Park. Leisure-strolling

HL units occupy an intermediate pattern, appearing both within and beyond the historic core. This spatial differentiation indicates that optimisation should distinguish between the historic urban core and surrounding districts, while also considering attraction-type-specific mismatch patterns.

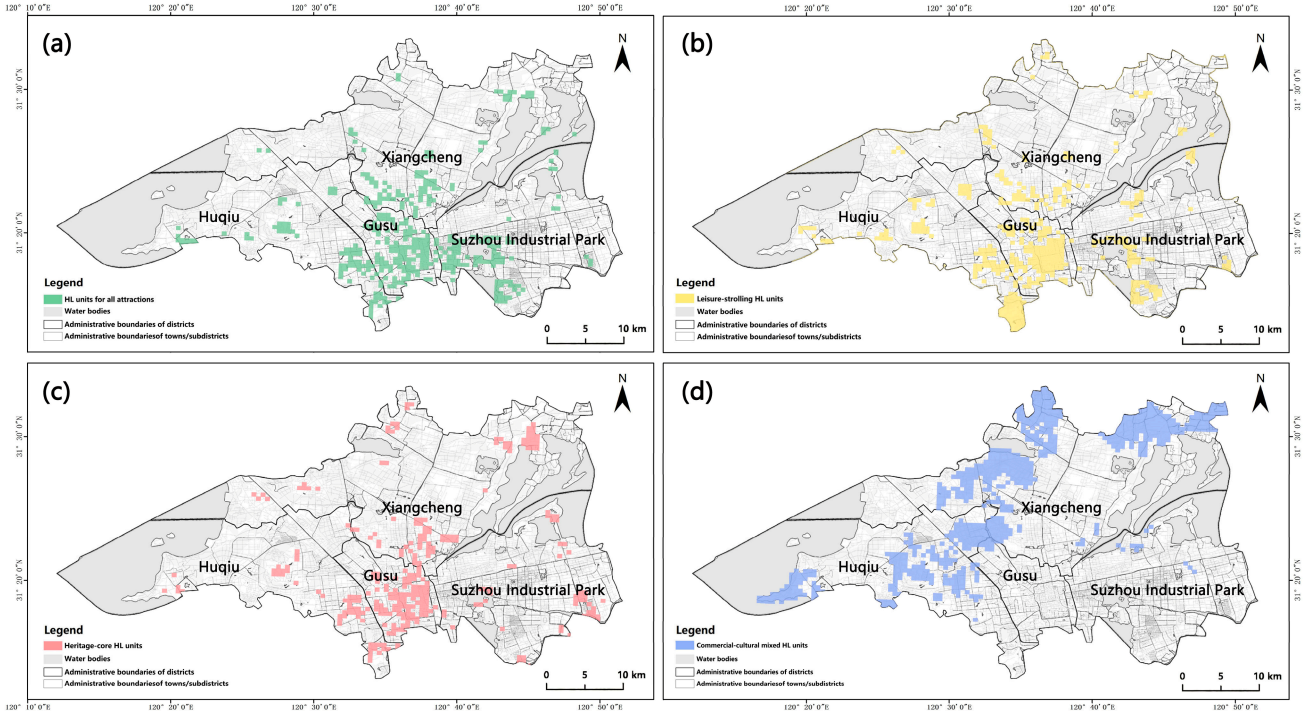


Figure 17. Spatial distribution of HL-type mismatch units across attraction systems: HL units for all attractions (**a**), leisure-strolling HL units (**b**), heritage-core HL units (**c**), and commercial–cultural mixed HL units (**d**).

For Gusu District, which forms the historic urban core, the main issue is not the absence of cultural tourism resources. The area already contains the highest concentration of heritage resources, cultural tourism attractions, tourist accommodation, and short-budget walkable accessibility. However, Figure 17a,c show that all-attraction and heritage-core HL units are still concentrated in and around this core. This suggests that even in areas with abundant resources and strong accommodation markets, short-budget walkable accessibility may be weakened by the complexity of the historic street network, bridge and water-related barriers, high visitor intensity, congestion, queuing, and competition for limited pedestrian space. Therefore, optimisation in Gusu District should not focus on further increasing attraction density, accommodation agglomeration, or road density. Instead, it should prioritise micro-scale improvement of the walkable street network, repair of critical connection breakpoints, better organisation of walking routes between high-value heritage destinations, improved bridge and passage connectivity, and visitor guidance that supports route distribution and congestion-sensitive movement. In this way, the optimisation of walkable accessibility would move beyond improving network connectivity and walking-time efficiency alone, and would also enhance the pedestrian experience—such as comfort, legibility, safety, crowding management, and shared public-space use—for both visitors and local communities. For heritage-core attractions, these interventions should be implemented through low-impact renewal and heritage-sensitive pedestrian organisation, so that walkable accessibility can be improved without increasing excessive development pressure on the historic urban fabric.

For the surrounding districts, namely Huqiu District, Xiangcheng District, and Suzhou Industrial Park, the mismatch mechanism is different. These areas do not have

the same concentration of heritage-core resources as Gusu District, and their cultural tourism opportunities are more fragmented and discontinuous. Figure 17d shows that commercial–cultural mixed HL units form multiple localised clusters in the surrounding districts, while Figure 17b indicates that leisure-strolling HL units also extend beyond the historic core into transitional and water-adjacent areas. In these areas, the problem is not simply a lack of individual attractions, but the insufficient connection between accommodation clusters, local opportunity nodes, open spaces, waterfront areas, and transport or service nodes. This mechanism echoes proximity-based and network-accessibility studies showing that opportunity access depends not only on the presence of facilities, but also on the continuity and organisation of walkable links among them [4–7,33–38]. Optimisation should therefore avoid simply replicating the heritage-core model of Gusu District. Instead, surrounding districts should develop complementary cultural tourism functions, strengthen walkable links between local commercial–cultural clusters, fill broken segments between opportunity nodes, improve slow-mobility corridors, and add leisure-support facilities such as rest, orientation, and information nodes. Such improvements can also strengthen local communities' access to cultural facilities, waterfront spaces, open spaces, and neighbourhood-level public services, thereby linking tourism optimisation with community-oriented urban improvement. For high-tier accommodation clusters with weak nearby access, the priority should be to build continuous short-budget opportunity networks rather than to add isolated attractions.

Overall, HL-type mismatch exposes the structural disconnection between accommodation agglomeration, opportunity supply, and pedestrian organisation in Suzhou's historic urban tourism system. The optimisation of cultural tourism opportunities should therefore move beyond generalised average catch-up strategies and adopt a zonal and typology-oriented approach, consistent with the broader shift in accessibility-equity research from aggregate comparison to spatially differentiated intervention [39–43,53]. In Gusu District, the priority should be to improve the efficiency and quality of walkable accessibility, while strengthening opportunity networks along the edges of the historic core and improving their effective connections with surrounding areas. In the surrounding districts, the priority is to cultivate complementary cultural tourism functions and repair fragmented access networks. Across attraction types, heritage-core attractions require heritage-sensitive route organisation, leisure-strolling attractions require continuous slow-mobility and open-space linkages, and commercial–cultural mixed attractions require stronger connections among localised service nodes. This approach links spatial mismatch diagnosis, attraction-type differentiation, and core–periphery governance, thereby providing a more operational basis for balancing heritage conservation, sustainable tourism development, and spatial equity in historic urban areas.

6. Conclusions

This study developed an integrated analytical framework for examining walkable access to cultural tourism opportunities in historic urban cores. Taking the central urban area of Suzhou as a case, the study combined kernel density analysis, network-based accessibility modelling, accessibility and equity indicators, bivariate local spatial autocorrelation, and XGBoost–SHAP interpretation to examine spatial patterns, group-specific differences, local mismatch, and type-specific accessibility-generating conditions under a time-budgeted 15 min city perspective.

The main findings are as follows. First, cultural tourism opportunities in Suzhou's historic urban area show a pronounced pattern of core polarisation–peripheral attenuation. This supply-side concentration is further translated into a historic-core-dominated gradient of modelled walkable accessibility under the 15 min walking threshold. Within this thresh-

old, Gusu District records SACR and AAR values of 80.18% and 95.23%, respectively, which are substantially higher than the study-area averages of 38.92% and 77.05%. The overall Gini coefficient of 0.3528 further indicates a moderate degree of distributional inequality in walkable accessibility to cultural tourism opportunities.

Second, accommodation-tier differences do not form a simple monotonic relationship between accommodation tier and accessibility. High-tier accommodation shows the highest mean accessibility and the lowest degree of inequality, with 2.60 accessible attractions on average and a Gini coefficient of 0.1863. However, low-tier accommodation is not consistently the most disadvantaged, with a mean accessibility of 1.36, which is higher than that of both mid-tier and mid-high-tier accommodation. This suggests that accommodation-market stratification is better understood as a pattern of spatial embedding differences within the cultural tourism opportunity field, rather than as a linear relationship between accommodation tier and accessibility. Age-related inequality is also strongly threshold-sensitive: the accessibility gap is most evident within 15 min, the 15–30 min interval represents a key transition window, and beyond 30 min the difference is expressed mainly as delayed accessibility among elderly visitors.

Third, the global relationship between accommodation tier and attraction accessibility is weak, but clear spatial relationship types emerge at the local scale. Under the all-attraction scenario, global bivariate Moran's I values across age groups range from -0.102 to -0.115, indicating that accommodation-market positioning and attraction accessibility do not form a stable overall spatial coupling pattern. Among the local LISA configurations, HL units—that is, high-tier accommodation near low accessibility—represent the primary priority mismatch type because they reveal localised disconnection between accommodation-market positioning and the effective transformation of cultural tourism opportunities into short-budget walkable access.

Fourth, XGBoost–SHAP interpretation shows that walkable accessibility does not follow a single explanatory pattern across attraction types. Leisure-strolling attractions are characterised by a relatively balanced dual structure shaped by both attraction supply and accommodation support. Commercial–cultural mixed attractions show the strongest dependence on supply concentration, with the mean ($|$SHAP value$|$) of attraction kernel density reaching 13.57; they are also more sensitive to transport-node conditions, street-network organisation, and water-related spatial context. Heritage-core attractions are also strongly supply-led, but their accessibility is more evidently constrained by historic spatial structure, walkable street-network conditions, and accommodation-market stratification. These SHAP-based results should be interpreted as nonlinear statistical associations and feature contributions to model predictions, rather than as direct causal effects.

From a policy perspective, the findings suggest that the optimisation of cultural tourism accessibility in historic urban areas should move beyond generalised average catch-up strategies and adopt zonal and typology-oriented pathways. In Gusu District, which forms the historic urban core, the priority should not be to further increase attraction density or accommodation agglomeration, but to improve the efficiency and quality of walkable accessibility through micro-scale street-network repair, bridge and passage connectivity, heritage-sensitive route organisation, visitor guidance, and congestion-sensitive pedestrian management. At the same time, opportunity networks along the edges of the historic core should be strengthened to improve their effective connections with surrounding districts and to help redistribute pressure from the core. In Huqiu District, Xiangcheng District, and Suzhou Industrial Park, optimisation should focus on cultivating complementary cultural tourism functions, repairing fragmented access networks, strengthening links among local commercial–cultural clusters, open spaces, waterfront areas, and transport or service nodes, and building continuous short-budget opportunity networks around accommodation

clusters. Across attraction types, heritage-core attractions require heritage-sensitive route organisation, leisure-strolling attractions require continuous slow-mobility and open-space linkages, and commercial–cultural mixed attractions require stronger connections among localised service nodes. These pathways support not only more efficient visitor access to cultural tourism opportunities, but also local communities' shared access to cultural resources, public spaces, and everyday walkable environments.

This study also has several limitations that indicate directions for future research. First, accommodation facilities were used as origin proxies for tourism activity, which provides a stable representation of overnight visitors but does not directly capture day-trippers, multi-stop trip chaining, real-time detours, or individual visitor preferences [47,48]. Second, this study used an equal-weighted POI-based opportunity count to measure reachable cultural tourism opportunities. Although this approach is consistent with the POI-level destination framework adopted in this study, it does not capture differences in attraction size, carrying capacity, symbolic importance, or visitor flows. Third, the age-specific walking speeds and time thresholds should be understood as baseline modelling assumptions; tourist congestion, queuing, crowding-induced speed reductions, and the quality of the pedestrian experience may make real-time accessibility lower than the baseline network-based estimates. Fourth, accommodation tier was used as a supply-side proxy for accommodation-market positioning and potential service demand, rather than as a direct measure of tourists' actual income or expenditure. Future research could incorporate mobile-phone signalling, trajectory data, pedestrian observation, questionnaires, travel diaries, visitor perception data, residential community data, visitor-flow records, attraction grades, site capacity, ticketing data, and platform popularity data to validate tourist origins, chained movement patterns, congestion-sensitive impedance parameters, weighted accessibility measures, and local community benefits. With more continuous or fine-grained mobility data, future studies could further move beyond comparisons at discrete walking-time thresholds and treat accessibility as a time-dependent profile or curve, thereby examining how different visitor groups gain access to cultural tourism opportunities as walking-time budgets increase [75,76]. Future research could also extend the framework to multimodal tourism mobility at larger urban or regional scales and compare different types of historic urban areas to test the transferability of the proposed approach.

Author Contributions: Conceptualization, F.L. and T.S.; methodology, F.L., T.S. and K.Y.; software, F.L. and T.S.; validation, F.L., T.S. and K.Y.; formal analysis, F.L., T.S. and Y.S.; investigation, F.L., T.S., K.Y. and Y.S.; resources, F.L.; data curation, F.L., Y.H. and Y.L.; writing—original draft preparation, F.L. and T.S.; writing—review and editing, F.L., T.S., K.Y. and Y.L.; visualisation, F.L., T.S., K.Y. and Y.S.; supervision, F.L., K.Y. and Y.L.; project administration, F.L., Y.H. and Y.L.; funding acquisition, F.L. and Y.H. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The original source data are publicly available from the platforms cited in the text. The processed dataset supporting the findings of this study is available from the corresponding author on reasonable request, subject to the data-use and redistribution restrictions of the source platforms.

Conflicts of Interest: The authors declare no conflicts of interest.

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