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Paying lip service? An investigation into the spatial mismatch between younger and older adults' streetscape perceptual preference and visitation behavior

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ABSTRACT

Do intergenerationally claimed spatial preferences necessarily translate into actual visitation behaviors? This study aims to uncover the phenomenon of "dissonance between perception and behavior" among younger and older adults in Shenzhen's streetscapes—specifically, the spatial mismatch and generational differences between perceived satisfaction and actual visitation patterns. Using computer vision techniques and online surveys grounded in Attention Restoration Theory and the Person-Environment Fit model, we quantitatively assessed pedestrian age groups from street view imagery, as well as generational preferences and real-world visitation patterns. We then explored the driving factors behind this mismatch from both experiential and structural perspectives. The results revealed that older adults exhibit a more pronounced dissonance between streetscape satisfaction and visitation than younger individuals. On streets with lower satisfaction scores, the two generational groups show different streetscape visitation patterns. For younger adults, floor area ratio, Shannon diversity index, and greenery demonstrate synergistic effects in facilitating the transformation of spatial perception into visitation behavior. Critically, no spatial features facilitated this transformation among older adults, revealing systematic perception behavior decoupling that challenges conventional environment behavior theories. Furthermore, green infrastructure and mixed-use spatial morphology enhance satisfaction for both age groups, while street connectivity positively guides intergenerational visitation behavior. These findings offer empirical insights for creating inclusive street environments that promote intergenerational integration.

1. Introduction

Urban streets serve as essential spaces for daily life, fostering social interaction and contributing directly to urban vitality (Mahmoudi Farahani, 2016). Individuals develop emotional attachment and a sense of belonging to the street environment through everyday mobility and social engagement. This phenomenon, known as *place attachment*, functions bidirectionally: on the one hand, it strengthens spatial identity among residents; on the other, it serves as a crucial foundation for creating livable environments (Lewicka, 2008; Manzo & Devine-Wright, 2013). Such positive environment and behavior interactions foster street vitality, enhance spatial attractiveness, and contribute to residents' satisfaction and well-being (Ma et al., 2018; Mouratidis & Yiannakou, 2022).

However, under the forces of globalization, urban streets in Chinese cities are increasingly confronted with intergenerational spatial differentiation, driven by urban regeneration and heightened population mobility (Hu et al., 2024; Zhang & Wang, 2025). This differentiation is reflected both in the physical environment and infrastructure provision, and in the disconnection of environmental perception, which fails to meet the diverse psychological restoration needs of different age groups and does not achieve a functional fit between people and their environments. Attention Restoration Theory (ART) highlights the importance of restorative environmental attributes—such as being away, fascination, extent, and compatibility—in supporting psychological and emotional well-being. Meanwhile, the Person–Environment Fit (P–E Fit) model assesses how environmental demands, individual capabilities, and the degree of fit jointly determine environmental support for human activity. Together, these theories provide complementary perspectives for evaluating perceived street quality, yet research has shown that

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preferences and perceptions of street features often differ in priority and significance across generations (Gaglione et al., 2022; Handy et al., 2006).

While age-friendly urban planning has emerged as a prominent framework grounded in the WHO's participatory approach involving older adults as co-producers of urban knowledge (Plouffe & Kalache, 2010; WHO, 2007), its application to intergenerational street environments requires deeper engagement with co-production methodologies that extend beyond single-generation consultation. This elder-centered planning approach may not fully accommodate the lifestyle needs of younger populations. For instance, reducing spatial intensity, vibrancy, and functional diversity to facilitate older adults' mobility may inadvertently decrease younger adults' willingness to use public space (Brandt, 2021; Holland et al., 2007). Conversely, street environments designed with younger populations in mind, such as those incorporating high-intensity recreational or social amenities, may inadvertently raise participation thresholds or produce excessive noise, thereby discouraging older adults from frequent use (Wendel et al., 2022). These divergent intergenerational needs pose challenges for planners aiming to design street spaces that equitably serve all age groups (Nelischer & Loukaitou-Sideris, 2023). Recent scholarship has emphasized that addressing age-friendly environments requires a spatial justice lens that considers equity and structural inequalities across generations (Buffel et al., 2024; Greenfield, 2018).

Environmental behavior theories suggest that individuals tend to choose environments that evoke feelings of pleasure and comfort (Mehrabian & Russell, 1974). In public space research, the relationship between spatial preferences and behavioral choices has been widely acknowledged, yet emerging evidence reveals a cognitive-behavioral dissonance where stated preferences often diverge from actual visitation patterns. Jan Gehl demonstrated that high-quality public spaces encourage spontaneous activities and foster social interaction, forming a positive feedback loop between spatial attractiveness and usage (Gehl, 1987). However, this classical framework faces challenges when applied to the complex behavioral patterns of contemporary urban residents. This say-do gap, which we term the “lip service” phenomenon, reflects a cognitive and behavioral dissonance where stated preferences fail to predict actual spatial use. This dissonance may arise from cognitive biases in preference articulation (Sheeran, 2002), structural constraints that limit behavioral realization despite stated intentions (Ajzen, 1991), or methodological artifacts inherent in self-reported data (Kollmuss & Agyeman, 2002). Such dissonance exposes the limitations of classical environmental behavior frameworks, which erroneously assume a linear relationship between spatial perception and actual behavior. A critical question thus emerges: do individuals' stated spatial preferences necessarily translate into actual visitation behaviors, or does this perception-behavior linkage vary systematically across age cohorts? Existing research has not sufficiently confronted how intergenerational groups' declared preferences may decouple from their actual spatial behaviors, leaving this theoretical oversimplification largely unchallenged and undermining the empirical foundation for evidence-based urban design. This gap weakens the explanatory power of traditional attraction and visitation models and limits the empirical foundation for microscale urban renewal strategies. Furthermore, conventional methods such as questionnaires and field observations are capable of distinguishing age-based patterns in mobility and space use, but their limited sample sizes, geographic coverage, and high implementation costs constrain large-scale, high-resolution spatial analysis (Mukherjee & Kadali, 2022). In recent years, the integration of street view imagery (SVI) and computer vision has opened new possibilities for urban environmental assessment (Gong et al., 2024; Rui & Xu, 2024). Yet, most existing studies remain focused on static identification of spatial differences, lacking exploration into the behavioral discrepancies between spatial preferences and actual visitation behavior among different age groups.

To address these limitations, this study raises two central questions: Do younger and older adults exhibit a mismatch between their stated spatial preferences and actual street visitation—that is, a form of “cognitive–behavioral dissonance”? Do younger and older adults exhibit a mismatch between their stated spatial preferences and actual street visitation, a ‘lip service’ pattern where environmental satisfaction does not translate into corresponding use? And what environmental factors might drive this divergence? Methodologically, we apply a detection framework based on the DINO model (self-supervised Vision Transformer) integrated with SVI, employing a non-facial human body recognition algorithm to identify younger and older pedestrians in urban streetscapes. Simultaneously, spatial preferences are measured via online surveys grounded in ART and the P–E Fit model. We then analyze the mismatch between preference and visitation using both structural and experiential spatial indicators, combined with interpretable machine learning techniques to uncover potential nonlinear effects. This approach provides an interdisciplinary method to quantify how spatial features shape intergenerational preferences and behaviors, supporting age-friendly urban design.

2. Literature review

2.1. The gap between intergenerational spatial preferences and actual visitation

Differences in spatial preferences across age groups have been widely documented. Younger adults tend to prioritize spatial diversity and social potential due to their exploratory nature, whereas older adults focus more on legible environments and a sense of safety because of physical limitations (Andersson et al., 2018; Kirasic, 2000; Puhakka et al., 2015). These differences contribute to a certain degree of intergenerational spatial segregation (Puhakka et al., 2015). In terms of walking environment preferences, adults over the age of 60 place particular emphasis on barrier-free facilities such as ramps and the quality of pavement surfaces (Guzman et al., 2022), whereas younger pedestrians aged 18 to 24 prefer routes that pass through modern residential and commercial areas (Bafatakis et al., 2015).

Research on visitation behavior has focused on older adults, with limited attention to younger groups and intergenerational comparisons. This research gap is partly due to the anonymization of mobile phone location data, which removes personal demographic information and thus prevents age-based identification. Meanwhile, traditional on-site surveys are limited by human and spatial resource constraints. For instance, a study in Tianjin using GPS data from 20 older adults found that their travel was mainly concentrated around homes of relatives and friends, markets, schools, and hospitals (Sen et al., 2022).

There is often a complex relationship between individuals' spatial preferences and their actual visitation behaviors. A study in the San Francisco Bay Area highlighted that residents' preferred neighborhood types frequently differ from their actual places of residence, with this mismatch shaped by factors such as income and workplace location (Schwanen & Mokhtarian, 2005). Similarly, De Vos et al. found that more than half of university staff and students surveyed did not live in the areas they preferred, with such mismatches being more prevalent among low-income households (De Vos et al., 2012). For older adults specifically, the perception-behavior gap may be amplified by several age-related factors: habitual mobility patterns that emphasize familiar routes and established activity spaces over preferred but unfamiliar environments (Meijering et al., 2024), physical constraints and walking limitations that restrict access to desired destinations despite positive environmental perceptions (Tuomola et al., 2024), and dependencies on social networks for transportation or accompaniment that redirect travel from preferred to socially necessary locations (Abdul Latiff & Mohd, 2023). In terms of walking path choices, discrepancies between stated preferences and actual behavior are also evident: a comparative study in New York City and Hong Kong found that although pedestrians claimed to prioritize route distance and safety, in practice, the availability of amenities had a stronger-than-expected influence on their decisions

(Guo & Loo, 2013). These structural and behavioral constraints suggest that older adults may exhibit greater divergence between their environmental assessments and actual visitation patterns compared to younger cohorts, even when perceptual evaluations of environmental quality are similar across age groups.

Existing data collection paradigms face a dual limitation: mobile location data, due to privacy protections, strip away demographic attributes, rendering intergenerational identification infeasible; meanwhile, traditional field surveys are constrained by sample size and spatial coverage, making it difficult to capture dynamic behavioral differentiation across groups. While previous studies have documented preference-behavior relationships, comparative research examining whether this coupling operates differently across age groups remains absent due to methodological constraints in capturing age-differentiated preferences and behaviors under equivalent spatial conditions.

2.2. The role of street view imagery in capturing spatial preferences and actual visitation

Combining SVI with deep learning techniques has proven to be a reliable and effective method for analyzing residents' spatial preferences and actual visitation behaviors (Liu et al., 2023; Wang et al., 2019). Compared to traditional questionnaire-based approaches, this method offers a more fine-grained quantification of human perceptions and overcomes limitations related to sample size and geographic scope. Building on this, several studies have investigated spatial preferences among specific age groups. For example, a study conducted along the Huangpu River waterfront in Shanghai used wearable GoPro devices to collect street-level imagery and evaluate the walkability of greenways. The results showed that older adults paid particular attention to safety infrastructure, greening indices, and seating availability (Hu et al., 2025). Another study focusing on older populations developed an online street view selection platform using the TrueSkill algorithm to examine perceptual differences among seniors with varying physical abilities (Chen et al., 2024). In a study of children's spatial preferences, researchers combined a narrative empathy-based questionnaire with child-centered street view images to gather feedback across five dimensions of child-friendly urban environments (Yang et al., 2024). These age-specific studies offer valuable insights into spatial needs across different life stages. However, comparative studies on spatial preferences between younger and older adults remain scarce.

In terms of actual visitation, recent research has begun to explore the use of SVI to directly quantify pedestrian flows in urban spaces. Garrido-Valenzuela et al. (2023) extracted pedestrian presence from nationwide Dutch SVI as a proxy for spatial density and examined its relationship with urban features through regression analysis. Yin et al. (2015) analyzed over 200 Google Street View segments across Buffalo, Washington, D.C., and Boston (MA) to estimate pedestrian volumes, demonstrating the reliability of image-based pedestrian counts. Similarly, Chen et al. (2020) applied machine learning techniques to assess pedestrian flow automatically from SVI on over 700 streets in Tianjin. The results, when compared with field observations, achieved acceptable (Cronbach's alpha $\geq$0.70) or good ($\geq$ 0.80) levels of reliability.

Currently, most human attribute recognition techniques focus on facial analysis, which is useful for inferring emotional or demographic characteristics (Wei et al., 2021). However, such methods often raise privacy concerns and are unsuitable for large-scale application. In contrast, non-facial human attribute recognition, which is a computer vision approach that identifies human characteristics based on body posture, size, clothing, and movement rather than facial features, offers a promising alternative. Since SVI data typically blur faces during collection, non-facial recognition provides a feasible solution for age classification in this study. Despite its potential, no existing study has integrated SVI-based age recognition with matched perceptual assessments to test whether stated preferences predict visitation equivalently across generational cohorts. One exception is the study by Liu et al. (2023), which analyzed more than 70,000 SVIs in Hong Kong to identify the number of older adults on the streets. The researchers then evaluated street friendliness for older adults by comparing detected older adults with residential population ratios. Nevertheless, most existing studies lack fine-grained age classification due to limitations in training datasets and the specificity of research objectives, thus falling short of addressing intergenerational spatial issues in depth. Emerging transgenerational design approaches and recent intergenerational validation studies using the Age-Friendly Cities and Communities Questionnaire in Russia and Japan have demonstrated that multiple generations can appraise urban age-friendliness in similar ways, suggesting that younger and older cohorts share substantial perceptual consensus when evaluating environmental quality (Marston et al., 2022; Yamada et al., 2023; Ziganshina et al., 2025).

3. Data and methodology

3.1. Study area

Shenzhen is located in southern Guangdong Province and serves as both a major economic hub in China and a nationally recognized model for innovation. According to the *Guangdong Statistical Yearbook (2022)* (http://stats.gd.gov.cn/gdtjnj/), by the end of 2022, the city comprised 10 administrative districts, covering a total area of 1997.47 km^2, with a resident population of approximately 17.66 million. Shenzhen's 14th Five-Year Housing Development Plan emphasizes the importance of enhancing residential quality during the stage of refined urban renewal, with the goal of creating livable communities characterized by convenient transportation, comprehensive facilities, and a pleasant environment. The plan also promotes the organic renewal of urban villages, the development of green buildings, and the overall improvement of living environments. As a result, evaluating the outcomes of refined residential upgrades, examining the age-friendliness of neighborhood spaces, and identifying spatial disparities within residential streetscapes have become pressing challenges.

In this study, we collected Baidu Street View images of Shenzhen from the years 2018 and 2023, totaling 55,197 and 49,390 images respectively. During the data cleaning process, invalid images (e.g., those captured inside tunnels) were removed—339 from the 2018 dataset and 412 from the 2023 dataset. The study area was defined based on locations where Baidu Street View imagery was available for both time points. After screening, the final selected areas included Futian District, Nanshan District, Longhua District, Bao'an District, Guangming New District, Yantian District, and parts of Luohu and Longgang Districts (Fig. 1).

3.2. Identifying street preferences and actual visitation

3.2.1. SVI acquisition and semantic segmentation

We employed the DeepLab v3+ model, which has been widely used in SVI segmentation research. The SVI images were captured using standardized street-level cameras mounted at approximately 2.5 m height (Ringland et al., 2019), ensuring consistent horizontal perspectives across sampling points. DeepLab v3+ was proposed by Chen et al. (2018) and introduces a new decoder module to refine segmentation results, particularly around object boundaries. It also incorporates multiple parallel atrous convolutions with different dilation rates, enabling the model to capture multi-scale contextual information and thereby improve recognition performance. The ADE20K dataset, developed by the Computer Science and Artificial Intelligence Laboratory at the Massachusetts Institute of Technology, is a large-scale benchmark widely used in computer vision tasks. It contains approximately 22,210 training images and 2000 validation images with varying resolutions, offering rich visual content and detail. Accordingly, we applied DeepLab v3+ in combination with the ADE20K dataset to perform semantic segmentation on the SVI. The segmented SVI results

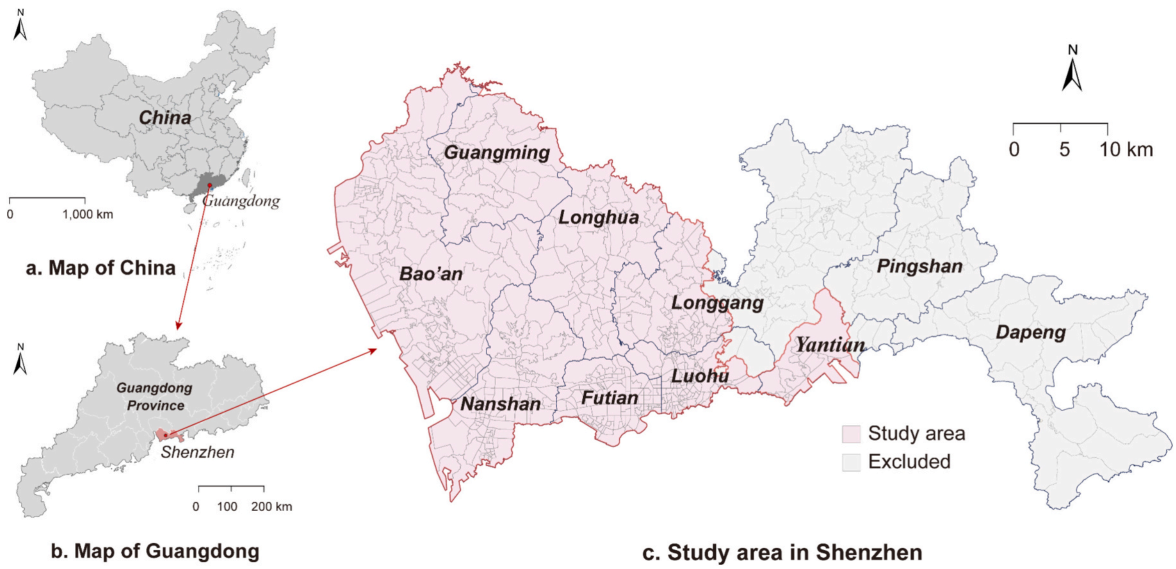


Fig. 1. Study area.

and the legend of street scene elements are presented in Fig. 2.

3.2.2. Identifying street satisfaction preferences among younger and older adults

To explore the potential mismatch between stated spatial preferences and actual behavioral patterns across generational groups, this study designed a questionnaire based on two complementary theoretical frameworks: ART and the P–E Fit model. By integrating these perspectives, we constructed a comprehensive evaluative framework that spans both psychological restoration and functional adaptation. ART focuses on environmental comfort and emotional recovery (Ma et al., 2024), while P–E Fit assesses the extent to which the built environment supports the activities of younger and older adults. Together, these perspectives enable a holistic analysis of intergenerational differences in both perception and behavior within public street spaces.

ART was developed by environmental psychologists Rachel Kaplan and Stephen Kaplan. It suggests that directed attention gradually becomes fatigued and can be restored by exposure to certain types of environments (Kaplan et al., 1972). The theory identifies four key attributes for evaluating the restorative quality of urban and natural environments: (i) being away, (ii) fascination, (iii) extent, and (iv) compatibility. Studies have confirmed the benefits of interaction with natural environments, such as reduced anxiety and stress (Berman et al., 2008; Capaldi et al., 2014). ART has been widely applied to assess restorative qualities in tourism environments, including blue and green spaces and walkable areas (Fan et al., 2024), particularly for older adults

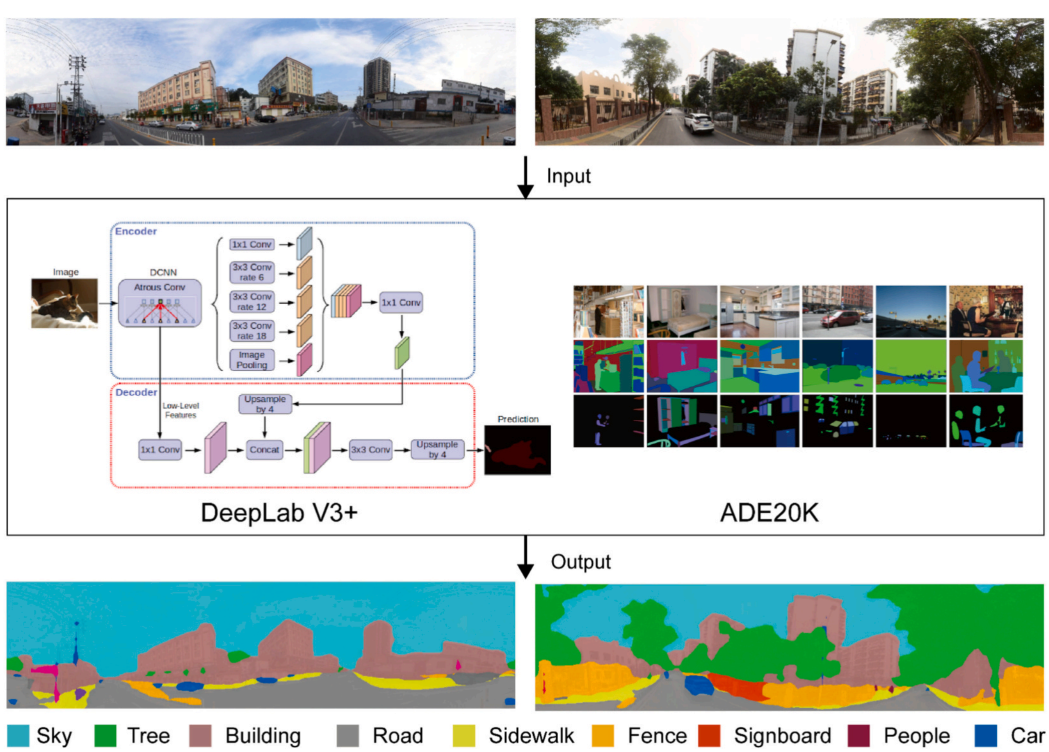


Fig. 2. Street view image sampling and semantic segmentation with DeepLab V3+ model.

and other sensitive populations. In this study, the "extent" dimension was excluded. This is because extent, which emphasizes the cognitive continuity and exploratory potential of an environment, is more relevant to natural landscapes and less applicable to the compact, fragmented street environments typical of high-density urban areas. Its influence on residents' day-to-day satisfaction in such settings is considered indirect.

The P-E Fit model emphasizes the alignment between an individual's abilities and environmental demands. It posits that better alignment between a person and their environment leads to more favorable outcomes (Edwards et al., 1998), whereas mismatches or conflicts may result in stress, fatigue, or maladaptation. The model focuses on three components: Environmental Press, Competence, and Fit. P-E Fit has been widely applied to understand individual adaptability in workplace settings and the relationship between environmental design and human behavior. Its relevance is particularly notable among younger and older adults, for whom the adaptability of the environment to support functional living is crucial.

The sampling strategy adopted an age-based grouping: 200 participants were targeted for each group—young adults (aged 18–35) and older adults (aged 60 and above). The sampling strategy adopted an age-based grouping with convenience sampling: 200 participants were targeted for each group, younger adults (aged 18–35) and older adults (aged 60 and above), recruited through community centers and online platforms to ensure demographic diversity. The survey was distributed and collected between October 1 and December 1, 2024. This study received ethics approval exemption from the institutional Research Ethics Committee as it involved minimal-risk research with anonymous survey data from adult participants (aged 18 years and above) and secondary analysis of publicly available street view imagery. A total of 387 valid responses were obtained (195 from the younger group and 192 from the older group), yielding an overall effective response rate of 96.75 %. The data cleaning process followed a three-stage quality control protocol. First, extreme outliers (12 questionnaires exceeding 3 times the interquartile range) were removed using the boxplot method. Second, 8 questionnaires with low variance (variance $\leq$1) were identified and excluded through Levene's test. Third, 5 logically inconsistent responses were eliminated via a logic check. This process resulted in 362 valid samples (183 from the younger group and 179 from the older group).

The study constructed a comprehensive environmental perception index by aggregating seven core indicators using equal weighting (ω = 1/7). These indicators include being away, fascination, extent, compatibility, as well as the classical environmental psychology constructs of environmental press, competence, and Fit. All variables were standardized using Z-score transformation and combined into an overall street satisfaction index. The composite score demonstrated a high correlation with participants' self-rated overall satisfaction (Pearson's r = 0.824, $p < 0.001$), confirming the validity of the indicator system. Internal consistency analysis revealed acceptable reliability among the seven indicators (Cronbach's Alpha = 0.78), supporting the appropriateness of equal weighting in the composite index construction. This strong alignment can be attributed to the guided and conceptually grounded design of the questionnaire. Specifically, a contextualized prompting strategy was employed during scale administration, with each indicator accompanied by everyday scenario examples. Additionally, the measurement of overall street satisfaction included a tiered explanation: following the core scale, participants were asked to provide a global satisfaction rating (on a 1–5 scale) based on their holistic experience. Accordingly, this study adopts participants' self-reported overall satisfaction as the measure of street space preference (Table 1).

3.2.3. *Identification of younger and older adults on streets*

Our approach captures observed spatial presence rather than comprehensive visitation behavior. The cross-sectional SVI analysis represents momentary presence and does not account for visit frequency, duration, or purpose. We therefore use 'observed spatial

Table 1
Definitions and results of street satisfaction survey indicators based on ART and P-E Fit theory.

Indicator	Definition	Example Question	Mean	S.D.
ART				
Being away	Refers to the psychological sense of distance from daily routines experienced in an environment, which helps relieve stress and restore attention.	When walking through this street/ neighborhood, do you feel you can temporarily escape from everyday chores or worries?	3.753	0.672
Fascination	Refers to the features of an environment that naturally attract an individual's interest and attention without requiring much mental effort.	The scenery or elements here (e.g., greenery, public art, small installations) naturally catch your eye and make you want to look more.	2.895	0.255
Compatibility	Refers to the degree to which the environment matches an individual's needs, supporting their psychological and emotional restoration.	The design and facilities of this street meet your needs for walking, leisure, or social interaction.	3.085	0.369
P-E fit				
Environmental Press	Refers to the demands or pressures exerted by the environment on individuals, including how external factors influence behavior and adaptation.	The sidewalks on this street are smooth and wide enough; you don't feel crowded or worried about tripping while walking.	2.497	0.366
Competence	Refers to an individual's abilities or resources (psychological, cognitive, emotional, etc.) that enable them to cope with environmental demands and adapt effectively.	Your current physical or mobility condition is suitable for walking on this street; you don't feel too tired.	2.864	0.402
Person–Environment Fit	Refers to the degree of match between individual needs and environmental demands. High compatibility supports psychological well-being.	Overall, do you feel that this street presents a "moderate level of challenge" for you—neither too difficult nor overly simple or boring?	3.012	0.288
Overall Street Satisfaction	Refers to individuals' overall evaluation of the environment or activity,	After walking or staying here for a while, do you feel more pleasant and relaxed	3.128	0.294

(*continued on next page*)

Table 1 (*continued*)

Indicator	Definition	Example Question	Mean	S.D.
	combining subjective satisfaction and actual restoration effects.	physically and mentally?		

Note: All items were measured using a 5-point Likert scale, where respondents rated their level of agreement from 1 (strongly disagree) to 5 (strongly agree) based on their perception. The Mean and S.D. values represent aggregated statistics for the entire sample (N = total respondents) rather than averaged values across age groups.

presence' as a proxy indicator for visitation patterns.

We first integrated data from three sources: JAAD, MIAP, and our custom-developed SVI dataset. Approximately 20 % of the images from the SVI dataset were manually annotated for age classification using the LabelMe tool, which involved categorizing pedestrians into distinct age groups. In total, 9975 individuals were labeled, including 2784 older adults and 3164 younger adults, with the remaining assigned to other age categories. After data cleaning, all annotated images were randomly split into training (70 %), validation (15 %), and test sets (15 %), ensuring a roughly consistent distribution of age groups across all subsets.

In terms of model architecture, we adopted the state-of-the-art DINO detector (Caron et al., 2021) as the core detection framework and embedded the Tokens-to-Token Vision Transformer (T2T-ViT) as its backbone (Yuan et al., 2021). DINO utilizes a self-attention mechanism to integrate pedestrian detection and localization into an end-to-end pipeline, thereby eliminating the need for hand-crafted components such as anchor boxes and non-maximum suppression. It also demonstrates strong robustness in crowded scenes. The T2T-ViT backbone progressively aggregates image patches, effectively fusing local details with global contextual features. This design is advantageous for detecting small-scale and distant pedestrians in street scenes, such as identifying head contours. Additionally, we introduced a parallel branch in the output layer of the DINO transformer decoder to directly classify pedestrian age groups, enabling simultaneous processing of bounding box detection and age classification.

The training strategy was structured in two phases. In the first phase, we pretrained the model on the JAAD and MIAP datasets to allow it to learn general pedestrian appearance, attributes, and postures. In the second phase, we fine-tuned the model on the customized SVI dataset to better address the specific challenges of street scenes, including large variations in distance, lighting conditions, and camera angles. To enhance model robustness, we employed advanced data augmentation techniques such as multi-scale training to accommodate different pedestrian sizes, random cropping and rotation to simulate diverse imaging conditions, AutoAugment for automated augmentation strategy optimization, and attention regularization to guide the transformer's focus on meaningful features. For optimization, we used the AdamW optimizer and adjusted the learning rate with cosine annealing over approximately 120 training epochs, gradually decreasing the learning rate after epoch 90 to improve the model's ability to identify edge cases and small targets.

During the testing phase, we evaluated the model on the official test sets of JAAD and MIAP, as well as our own SVI test set. The DINO detector with the T2T-ViT backbone achieved a mean average precision (mAP) of 90.2 % on JAAD and 91.8 % on MIAP. On the more challenging SVI dataset, which features complex backgrounds and variable imaging conditions, the model maintained an mAP of 88.5 %, indicating strong accuracy and generalization capabilities. For age group classification, the model achieved an average accuracy of 89.4 % across three categories, with the younger group reaching 91.2 % accuracy and the older adults' group achieving 87.1 %. The slightly lower performance in the older adults' category is likely due to a smaller sample size and higher intra-group visual variability. This variability stems from greater diversity in posture (stooped versus upright walking), frequent use of assistive devices such as canes and walkers that obscure body features, and wider variations in clothing styles ranging from traditional to contemporary fashion among older adults. Attention heatmap visualizations revealed that the T2T-ViT backbone assigns greater weights to the head and hair regions, which are critical features for age estimation. Overall, this study demonstrates the feasibility and effectiveness of Vision Transformers for pedestrian detection and attribute recognition in street-level imagery, laying a solid technical foundation for their future large-scale deployment. While this detection framework effectively identifies age-differentiated spatial presence, the cross-sectional nature of the data means we assess momentary occupancy rather than longitudinal visitation behavior (Fig. 3).

3.3. *Measurement of spatial experiential and structural indicators (independent variable)*

3.3.1. *Spatial experiential indicators from bottom-up perspectives*

We selected spatial experiential indicators and spatial structural indicators as independent variables. Spatial experiential indicators include greenness, openness, building continuity, walkability, and imageability. These indicators are based on a resident-centered perspective and reflect individuals' subjective experiences within their living environments.

Greenness reflects the presence of green landscape elements such as grass, trees, vegetation, and green belts, aiming to capture the extent and distribution of vegetation along streets and enhance active environmental awareness (Samus et al., 2022). Openness refers to the spatial characteristics of unobstructed and expansive areas within the urban landscape, which contribute to the perceived spaciousness and sense of freedom in the built environment. For building continuity, we refined the traditional global-scale computation approach by incorporating geographic variation (Koohsari et al., 2013). Specifically, a 10-m buffer was created for each street segment, within which all sampling points were identified. The building ratio at each sampling point was compared with the average building ratio of the corresponding street. The absolute difference between the two was subtracted from 1 to quantify continuity (Table 2). This improved method accounts for differences in street width, type, and geographic location, thereby avoiding the biases introduced by applying a uniform formula across diverse street types such as rural paths, residential roads, urban expressways, and main arterial roads. Walkability assesses the extent to which the outdoor environment supports pedestrian activity, operationalized here as the ratio of sidewalk width to driveway width (Ewing & Handy, 2009). Imageability captures the visual richness and memorability of the built environment, characterized by the presence of objective street elements such as signage, sculptures, people, and benches (Samus et al., 2022).

3.3.2. *Spatial structural indicators from top-down perspectives*

The selected spatial structural indicators are derived from macro-level data sources such as remote sensing imagery and urban maps. These indicators reflect the objective physical characteristics of the built environment and are commonly used by planning authorities for top-down monitoring and management. The indicators include the Normalized Difference Vegetation Index (NDVI), road width, Floor Area Ratio (FAR), betweenness centrality (BtA), and the Shannon Diversity Index (SHDI) (Fig. A2).

NDVI is an index that measures vegetation density and health, calculated by comparing the reflectance of red and near-infrared bands. Consistent with other studies (Chen et al., 2023), NDVI was used to detect vegetation growth and coverage within a regional scope.

Road width refers to the actual physical width of a road. We obtained different street grades from OSM, and according to the Technical standard of highway engineering published by the Ministry of Transport of

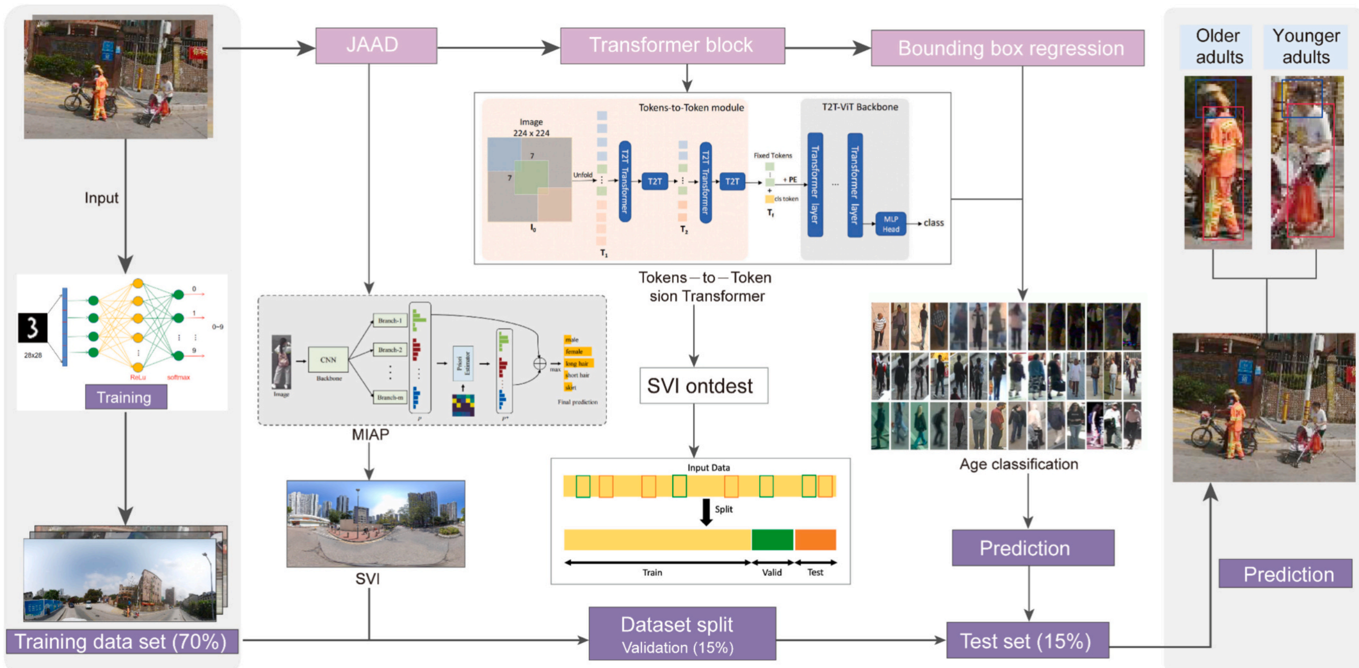


Fig. 3. Workflow diagram of a multi-source pedestrian age classification framework using token-to-token vision transformer and joint detection-attribute modeling in urban street scenes.

Table 2
Formulas and explanations of spatial experiential indicators.

Indicators	Formulas	Explanations
Greenness	$G_i = \frac{\sum_{i=1}^{2} GP_i}{\sum_{i=1}^{2} P_i}$	GP_idenotes the proportion of green pixels, including plant, tree and grass; P_i is the total number of pixels in image i.
Openness	$O_i = \frac{SP_i}{P_i}$	SP_idenotes the proportion of sky pixels.
Building continuity	$BC_i = 1 - \lvert B_i - \overline{B_i} \rvert$	B_i denotes the proportion of building pixels, $\overline{B_i}$ represents the average value of building pixels on the road at that sampling point.
Walkability	$W_i = \frac{\sum_{i=1}^{2} P1_i}{\sum_{i=1}^{2} (R_i + P1_i)}$	R_i denotes the proportion of road pixels, and $P1_i$ denotes the proportion of sidewalk pixels.
Imageability	$I_i = \frac{1}{2}\sum_{i=1}^{2} (S_i + S1_i + B_i + P2_i + B1_i)$	S_i denotes the proportion of signboard pixels, $S1_i$ denotes the proportion of sculpture pixels, $P2_i$ denotes the proportion of person pixels, $B1_i$ denotes the proportion of bench pixels.

China (https://xxgk.mot.gov.cn/2020/jigou/glj/202006/P020200623696253534010.pdf), assigned different widths to different roads: 47.5 m for expressways, 40 m for primary roads, 30.5 m for secondary roads, 20.5 m for tertiary roads, and 3 m for other roads.

FAR refers to the ratio of the total floor area of a building to the area of its plot, used to assess the development density of a plot. We obtained the latest building data from the Shenzhen Municipal Government Open Data Platform (including building footprint and floors) and calculated the FAR value for each study unit.

Within the Spatial Design Network Analysis (sDNA) framework, betweenness is a key metric for measuring the strategic importance of nodes or paths in a network. This study selected a 500-m radius as the analysis scale for pedestrian street connectivity (Betweenness Angular 500, i.e., BtA500), which is the comfortable walking distance for pedestrians used in existing research (Sarkar et al., 2015). Within this range, by calculating the betweenness of street nodes or paths, we can identify key connection points and paths in the pedestrian network.

Finally, SHDI was applied to calculate the spatial diversity index. We collected a large number of Points of Interest (POI) data using the Baidu API and categorized these data into six different types (Table 3). Based on these classifications, SHDI was calculated to quantify the diversity and even distribution of POI types within a region.

3.4. Model architecture

We selected the Light Gradient Boosted Machine (LightGBM) (Ke et al., 2017) as our primary model for predicting key audio-visual perception variables. Additionally, we employed LightGBM to analyze the intricate relationships between key spatial structural variables, spatial experiential variables, and the complex perceptions of the older and younger adults. The decision to use LightGBM was based on several critical factors: Firstly, LightGBM exhibits superior training speed and efficiency compared to many other algorithms, an advantage that stems from its unique histogram-based splitting algorithm. This algorithm accelerates the training process by discretizing continuous feature values into several distinct bins. Secondly, it reduces memory consumption by converting continuous values into discrete bins. Most importantly, thanks to its leaf-wise splitting strategy, as opposed to the conventional level-wise approach, LightGBM is capable of constructing more complex tree structures, thereby surpassing other boosting algorithms in terms of accuracy.

We conducted our model analysis using the Python Scikit-Learn library. During the parameter tuning process, a random search method was employed, initially defining an extensive grid encompassing a variety of potential parameters, including the maximum depth of the tree, number of trees, learning rate, minimum loss reduction required for further splitting, L1 and L2 regularization parameters, minimum weight needed for a child node, the proportion of columns sampled per tree, and the proportion of the subsample. We implemented the random search through the RandomizedSearchCV tool, comprehensively evaluating

Table 3
Formulas and explanations of spatial structural indicators.

Indicators	Formulas and explanations	Data sources
NDVI	$NDVI = \frac{(NIR - RED)}{(NIR + RED)}$ NIR represents the reflectance in the near-infrared band, and RED represents the reflectance in the red-light band.	United States Geological Survey (https://www.usgs.gov/landsat-missions/landsat-normalized-difference-vegetation-index)
Road width	Widths of different road classes.	OpenStreetMap (OSM) (https://www.openstreetmap.org/#map=8/23.611/120.768)
FAR	$FAR = \frac{\text{Total Floor Area of the Building}}{\text{Area of the Plot}}$	Shenzhen Municipal Government Open Data Platform (https://opendata.sz.gov.cn/data/dataSet/toDataDetails/29200_00300237)
BtA500	$\text{Betweenness}(x) = \sum_{y \in N} \sum_{z \in R_y} W(y)W(z)P(z)OD(y,z,x)$ Here, x is a given node in the network, N is the set of all nodes in the network, R_y is the set of all nodes that are reachable from node y, $W(y)$ and $W(z)$ are weight functions, representing the weight of nodes y and z, respectively, $P(z)$ represents the number of shortest paths passing through node z, $OD(y,z,x)$ is a function that indicates the proportion of all shortest paths from y to z that pass through node x.	OpenStreetMap (OSM) (https://www.openstreetmap.org/#map=8/23.611/120.768) sDNA (https://sdna.cardiff.ac.uk/sdna/)
SHDI	$SHDI = -\sum_{i=1}^{n} (p_i \times \log(p_i))$ Here, p_i represents the proportion of POIs of type i relative to the total number of POIs, and n is the total number of POI categories	BaiduMap (https://lbsyun.baidu.com/)

different parameter combinations through 5-fold cross-validation. This process not only assisted in identifying the optimal parameter combination but also provided the corresponding best scores. The detailed information on hyperparameters can be found in Appendix B. Model performance and hyperparameters for LightGBM models.

Subsequently, we employed GeoShapley to describe the dependency of street satisfaction preferences among older and younger adults on experiential and structural spatial indicators. GeoShapley is an interpretability method that accounts for spatial dependence (Li, 2024). Traditional SHAP assigns contribution values to individual features based on their influence on model predictions (Lundberg & Lee, 2017). In contrast, GeoShapley incorporates spatial relationships, making it particularly suitable for handling geographically distributed data. Given that the LightGBM model does not capture spatial variation in feature influence, this study utilized GeoShapley to provide spatially explicit interpretations.

4. Results

4.1. Intergenerational differences in street visitation and satisfaction

This study employs spatial behavioral analysis to reveal intergenerational differences between younger adults and older adults in Shenzhen in terms of street visitation patterns and street satisfaction assessments (Fig. 4). The findings indicate disparities between the two groups in both the spatial distribution of street activities and dimensions of streetscape satisfaction. Notably, older adults demonstrate a more balanced spatial distribution of activities and relatively higher levels of streetscape satisfaction—especially pronounced in emerging urban areas such as Longhua District.

Regarding street visitation behavior, younger adults exhibit a clear spatial clustering pattern: their core activity zone is concentrated around the Shenzhen North Railway Station transport hub in Longhua District (a high-density core), with secondary clusters in the eastern urban villages of Luohu District, Loucun Community in Guangming District, and the eastern industrial zones of Bao'an District. In contrast, the northern industrial zone of Bao'an and Dameisha Village in Yantian District show distinctly low activity levels. Older adults, by comparison, demonstrate a multi-centered and dispersed visitation pattern, with relatively high densities observed across all administrative districts; however, there is a noticeable dip in activity within the traditional urban centers of Futian and Luohu. This counterintuitive pattern, wherein older adults exhibit lower engagement in well-established central districts, may be attributable to multiple factors, including traffic congestion, higher living costs, limited accessible seating and rest facilities, and a preference among older adults for quieter, community-based environments closer to their residences. Comparative analysis reveals pronounced differences in visitation intensity between the two age groups in transport hubs, urban villages, and industrial zones, reflecting a typical spatial clustering effect. This may be closely related to younger adults' commuting demands, housing affordability, and employment opportunities.

In terms of streetscape satisfaction, both age groups reported higher levels of satisfaction in urban core districts such as Nanshan and Futian, whereas Longhua District consistently received lower ratings. Cross-group comparisons show that older adults have a higher proportion of positive evaluations regarding overall streetscape satisfaction than younger adults. Spatial heterogeneity analysis further reveals that while Longhua and Longgang Districts show stable intergenerational gaps in streetscape satisfaction, other areas exhibit highly fragmented and mixed patterns of intergenerational differences.

4.2. Intergenerational differences in perceived street environment satisfaction

To examine the influence of intergenerational variation on public space perception, we normalized the evaluations of younger and older adults across six dimensions of streetscape satisfaction—being away, fascination, compatibility, environmental press, competence, and person–environment fit—and calculated the intergenerational differences (Fig. 5; see also Fig. A1 for extended spatial visualization).

For the being away dimension, the most prominent perceptual disparities were observed in Futian, Nanshan, and Luohu districts, where younger adults perceived these areas as offering greater psychological detachment and relaxation. This may be attributed to their preference for open landscapes and vibrant urban environments (Fig. 5a). In the fascination dimension, intergenerational differences appeared more evenly distributed across the city, though several high-difference clusters were identified in parts of Bao'an and Longhua. These results suggest that younger adults tend to rate these areas as less engaging, potentially due to their higher expectations for novelty and diversity in urban experiences (Fig. 5b).

With regard to compatibility, significant spatial clusters of intergenerational difference emerged in northern Longhua and western Longgang. Younger adults perceived a lower degree of alignment between environmental attributes and personal needs in these areas, possibly influenced by deficiencies in public services, spatial scale, or functional integration (Fig. 5c). For environmental press, perceptual gaps were mainly concentrated in southern Futian, Nanshan, and Bao'an, where younger adults were more sensitive to the sensory stimuli and informational density of central urban areas, reflecting their stronger motivation for exploration and activity (Fig. 5d).

In the competence dimension, older adults in Nanshan and Futian gave consistently higher evaluations, likely due to their greater reliance on infrastructure, healthcare services, and accessible facilities, which enhance their sense of environmental adaptability (Fig. 5e). In contrast, younger adults showed lower scores in person–environment fit, possibly

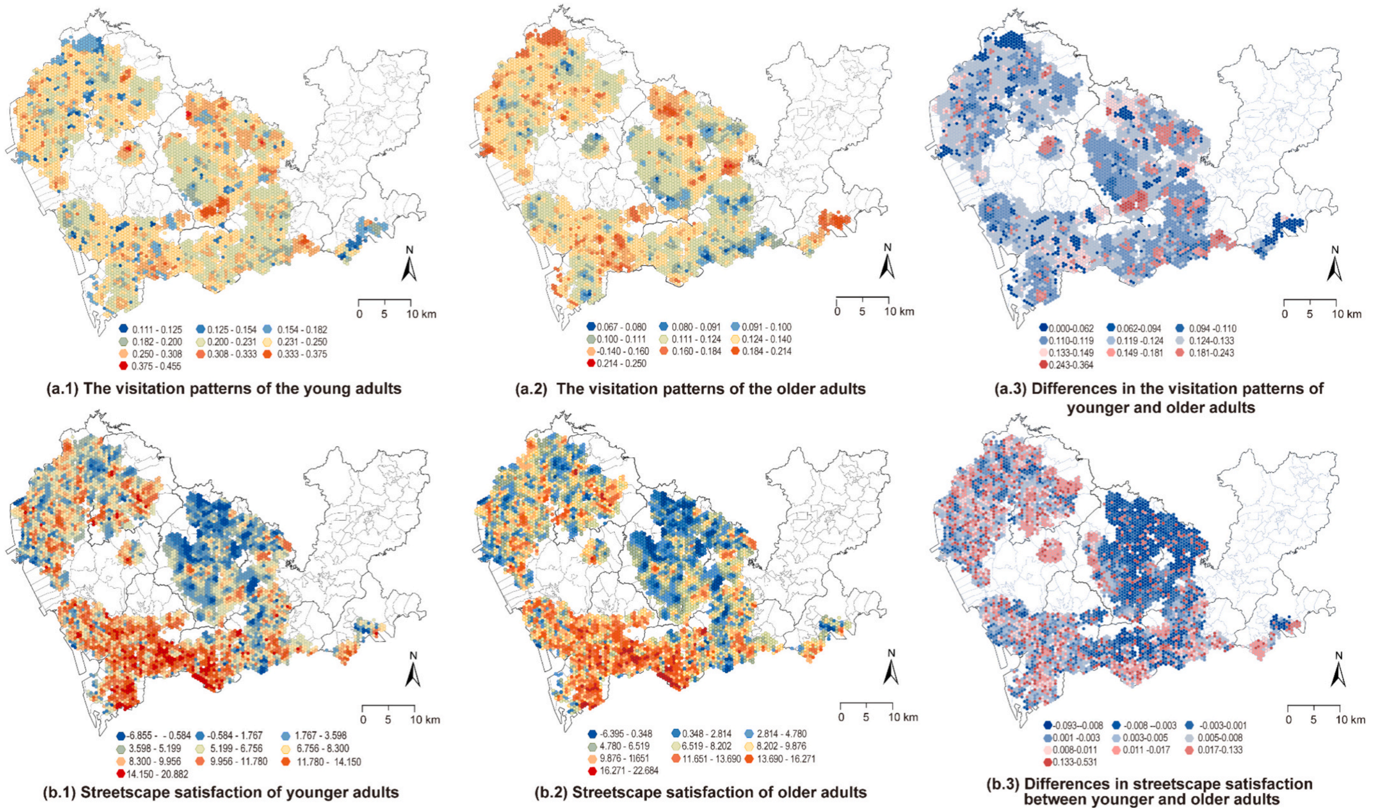


Fig. 4. Spatial distribution and intergenerational differences in street visitation patterns and street satisfaction among younger and older adults in Shenzhen.

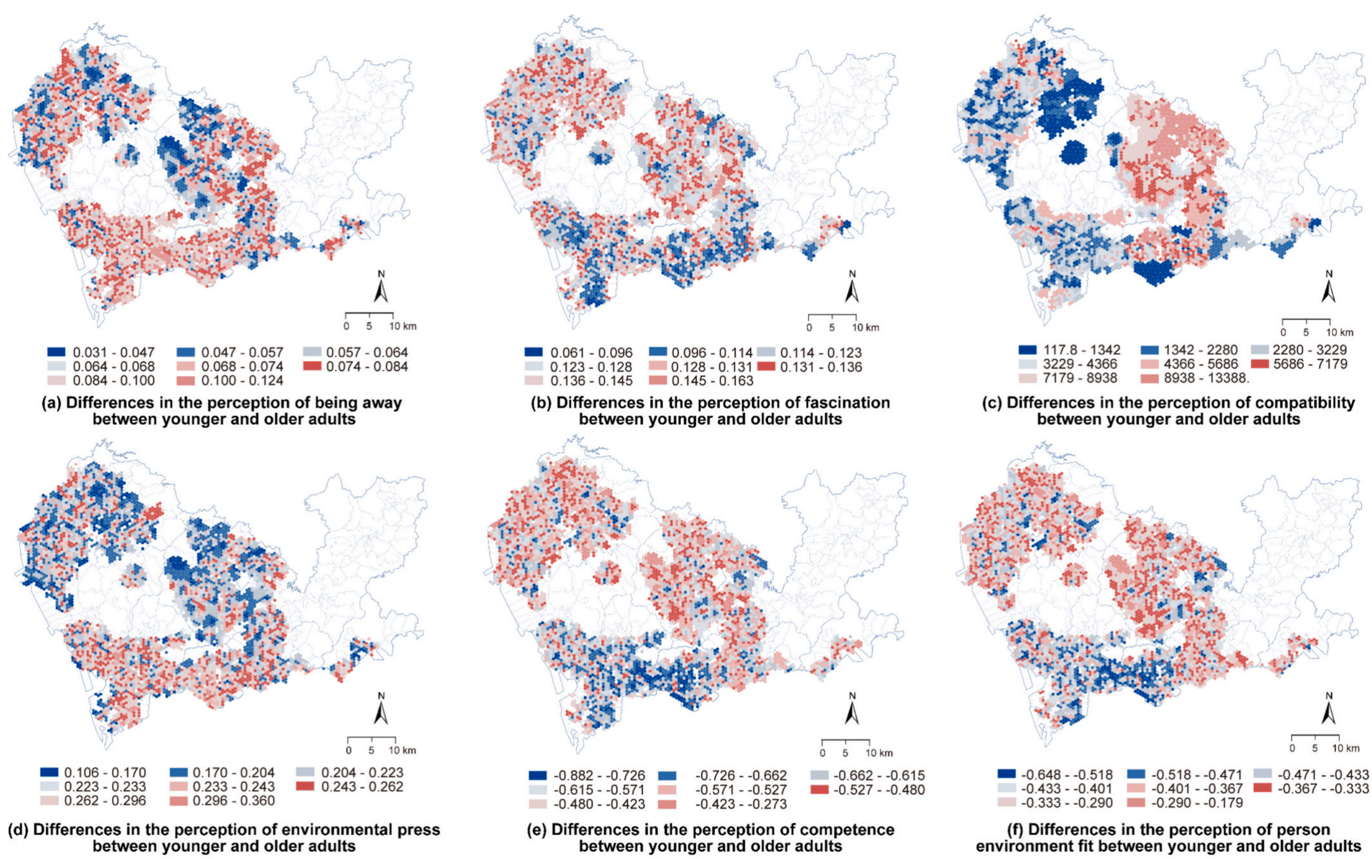


Fig. 5. Spatial differences in perceived street environment dimensions between younger and older adults across six cognitive domains in Shenzhen.

due to cognitive desensitization from frequent exposure to central districts or a persistent mismatch between personal aspirations and the urban environment (Fig. 5f).

See also Fig. A4 (Appendix A) for the spatial distribution of perceived environmental qualities across age groups.

4.3. Intergenerational analysis of spatial visitation and satisfaction alignment

Fig. 6 illustrates the spatial distribution patterns resulting from the cross-classification of actual spatial visits and perceived satisfaction among younger and older adults. By combining high and low levels of spatial visitation (H/L) with high and low satisfaction (H/L), four categories are derived: HH (High Visits + High Satisfaction), HL (High Visits + Low Satisfaction), LH (Low Visits + High Satisfaction), and LL (Low Visits + Low Satisfaction). To operationalize this classification, we employed a quantile-based approach, dividing both street visitation frequencies and satisfaction scores at their respective median values to distinguish between high (H) and low (L) categories for each dimension.

The analysis reveals a general phenomenon of "cognitive-behavioral dissonance" in spatial experience across both age groups. However, in areas with optimal spatial fit, as represented by the HH category, there is a notable geographical convergence between generations, with both groups concentrated in the core areas of Nanshan, Futian, and Bao'an. This spatial consistency is likely attributable to the well-developed public service infrastructure and multifunctional urban environments in these regions, which collectively accommodate the spatial needs and satisfaction of diverse age groups.

In contrast, the eastern industrial park zone of Bao'an displays intergenerational divergence. While younger adults tend to cluster in the HH category, older adults exhibit low visitation rates and inconsistent satisfaction. This disparity may be linked to the mono-functional nature of the industrial area, the lack of age-friendly amenities, and accessibility barriers for older adults.

Furthermore, in peripheral non-central urban areas characterized by low satisfaction for both groups, intergenerational differences become more pronounced. In the northern parts of Bao'an, Yantian, and Longhua, both age groups report low satisfaction, yet older adults show higher actual visitation compared to youth, who tend to avoid these spaces. Conversely, in the northwest of Longgang, an area also marked by low satisfaction across generations, younger adults demonstrate high visitation. This may reflect a passive spatial choice driven by housing affordability, wherein commuting youth are compelled to use these areas due to residential location constraints under conditions of job–housing separation.

4.4. Comparative analysis of multi-model predictions of spatial visitation and satisfaction differences

To uncover the underlying mechanisms driving differences in actual spatial visitation and perceived satisfaction between older and younger adults, we constructed predictive models for four scenarios (Fig. 7).

Overall, LightGBM demonstrated the best performance across all scenarios, with Adjusted R^2 values ranging from 0.542 to 0.612, outperforming the other models. It also achieved the lowest error metrics, with RMSE ranging from 0.014 to 0.203 and MAPE ranging from 0.048 to 0.062, indicating its strong capacity for handling high-dimensional nonlinear features and capturing the complex relationships between spatial behaviors and perceptions of different age groups.

XGBoost, SVR, and Decision Tree models performed moderately well, showing better performance than the OLS model in terms of both Adjusted R^2 and error metrics (MAPE and RMSE), though their stability varied across scenarios. In predicting actual visitation among younger adults, SVR achieved an Adjusted R^2 of 0.502, closely approaching that of LightGBM (0.542), yet its performance in other scenarios was relatively weaker.

In contrast, the OLS model consistently showed the lowest performance, with Adjusted R^2 values ranging from 0.237 to 0.433, suggesting that linear regression is inadequate for capturing the complex mechanisms underlying spatial visitation and perception patterns.

LightGBM offers superior stability and predictive power across multiple scenarios, and was thus selected for subsequent GeoShapley analysis to further explore the contribution of spatial features to behavioral and perceptual differences between older and younger populations. Detailed model parameters and performance metrics are provided in Fig. A3 and Table A1.

4.5. Spatial distribution of model performance and error analysis

We conducted a weighted analysis of the prediction models for actual spatial visitation and perceived satisfaction among younger and older adults, calculating the mean explained variance (MEV) and residuals (Fig. 8). MEV is a high-level indicator of a model's explanatory power—the closer the value is to 1, the better the prediction performance. Residuals reflect the difference between predicted and actual values, with absolute values closer to 0 indicating lower prediction error. To visually represent prediction performance, we applied a septile classification method. Colors closer to the middle of the scale (orange and yellow) indicate better model fit. The results reveal a mixed spatial distribution of predictive performance across both age groups, with older adults' models performing slightly better overall.

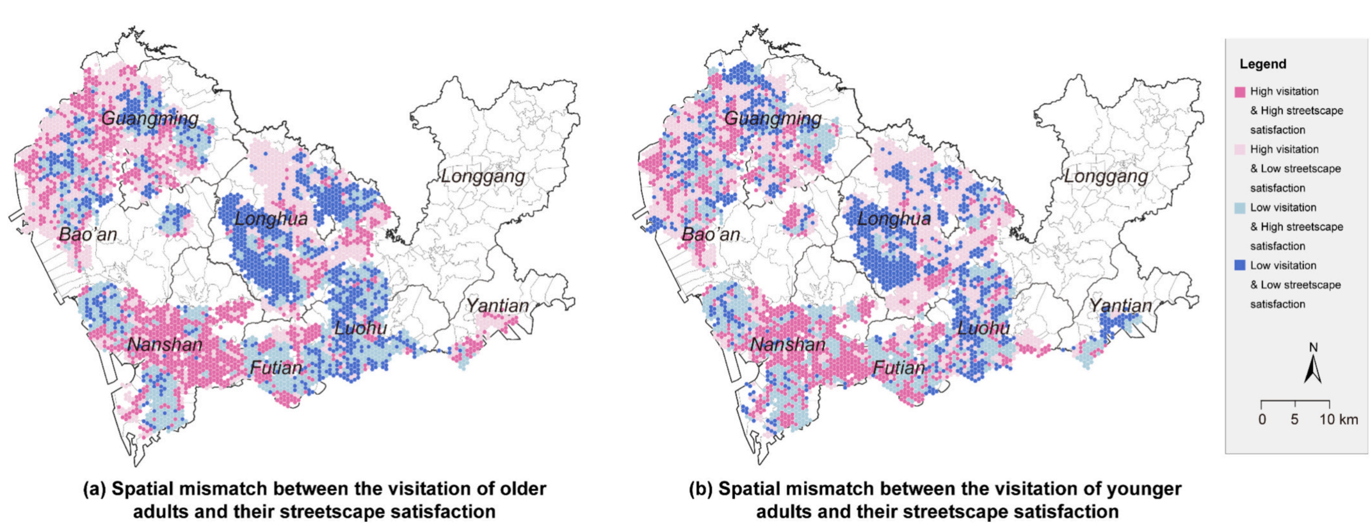
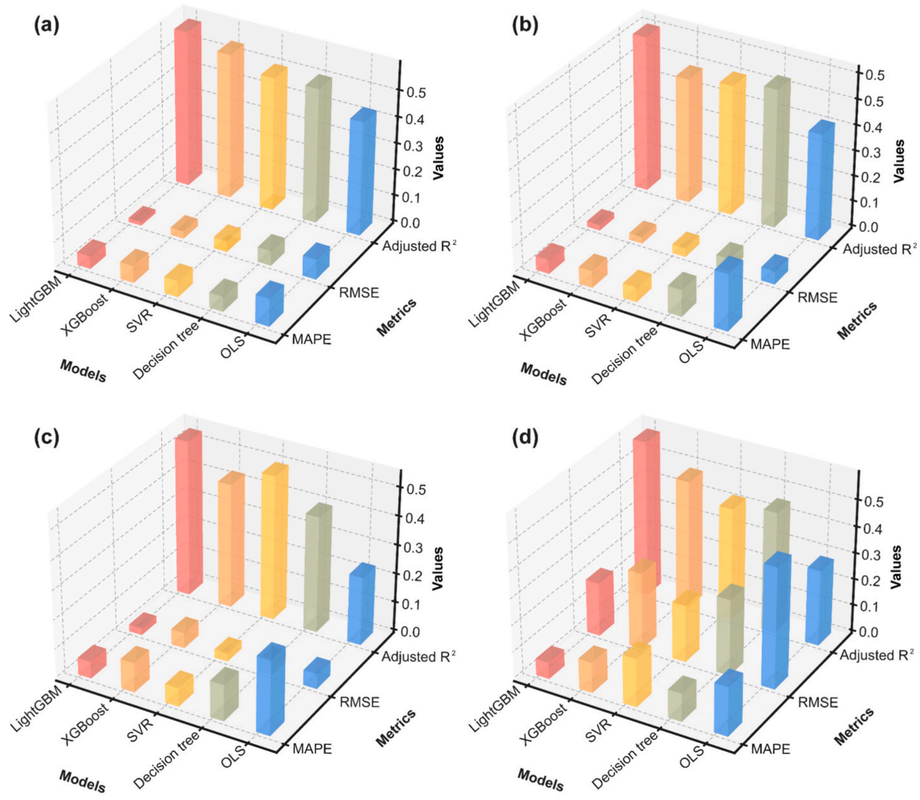


Fig. 6. Spatial alignment and mismatch between street visitation and satisfaction among older and younger adults in Shenzhen.



(a) The visitation of the older adults; (b) The streetscape satisfaction older adults
(c) The visitation of the younger adults; (d) The streetscape satisfaction od younger adults

Fig. 7. 3D bar chart of model performance metrics for predictions using linear and nonlinear regression models.

MEV values for both age groups are mostly concentrated around 1, with similar spatial patterns and no clear clustering effects. Older adults show slightly higher MEV values, ranging from 0.523 to 2.012, while the range for younger adults is narrower, from 0.484 to 1.927. Residual analysis further highlights differences in prediction errors. Residuals for older adults range from 0.014 to 0.173, while those for younger adults range from 0.018 to 0.180, suggesting that the prediction error is slightly lower for older adults. Additionally, both groups show widespread areas with residuals close to 0, indicating low prediction errors in most regions.

The MEV and residual heatmaps reveal that the model predicting actual visitation for older adults shows the most concentrated distributions, with values clustering near the point (1,0). Specifically, MEV values are concentrated between 0.8 and 1.4, while residuals are clustered between 0.02 and 0.04. In contrast, the parameter distributions for other models are more dispersed, indicating that the visitation prediction model for older adults is comparatively more stable.

4.6. *Nonlinear and combinatorial effects underlying intergenerational differences in visitation and streetscape satisfaction*

We further applied GeoShapley analysis to the predictive factors in the LightGBM models to reveal how spatial structural and experiential indicators influence the actual visitation and perceptual satisfaction of younger and older adults (Fig. 9). Detailed quantitative SHAP value distributions and ranges for all spatial indicators are provided in the Supplementary Materials (Table S1). The results indicate a degree of behavioral-perceptual synergy among the younger group, whereas street visitation and satisfaction among older adults appear to be driven by different mechanisms. Regardless of age, environments characterized by high greenness and spatial diversity tend to enhance environmental perception, while overly open spaces reduce perceived comfort.

Younger adults exhibit stronger behavioral-perceptual coherence in relation to certain spatial indicators. FAR, SHDI, and greenness have a positive influence on both actual visitation and perceived satisfaction for the younger group. Among these, FAR and SHDI exert a stronger influence on actual visitation, suggesting that younger adults are more active in areas with high functional density and spatial diversity, and this behavioral preference aligns with their environmental perceptions. Greenness has a similar influence across both dimensions, reflecting the stable appeal of green spaces for younger individuals. Notably, NDVI has a positive influence on perception but a negative effect on actual visitation. This divergence may stem from the fact that NDVI reflects vegetation density and health—high NDVI values often correspond to large greenfield areas that, while visually pleasing, may lack functional amenities and accessibility.

In contrast, none of the indicators show a consistent and directional influence on both behavior and perception for older adults, implying that their spatial actions and environmental perceptions may be governed by distinct decision-making logics. Several indicators, while showing similar magnitudes of influence, reveal completely opposite effects across dimensions. For instance, FAR and sDNA negatively affect older adults' visitation but positively influence their perceptual satisfaction. This contrast may arise because high-density development and strong connectivity, while offering convenience and diverse choices, often involve complex mobility environments, which older individuals may prefer to avoid due to navigational challenges or perceived discomfort.

From a cross-group perspective, NDVI, SHDI, greenness, and FAR all exert a positive influence on perceived satisfaction for both younger and older adults. This suggests that, regardless of age, good vegetation coverage, rich spatial form, and appropriate development intensity

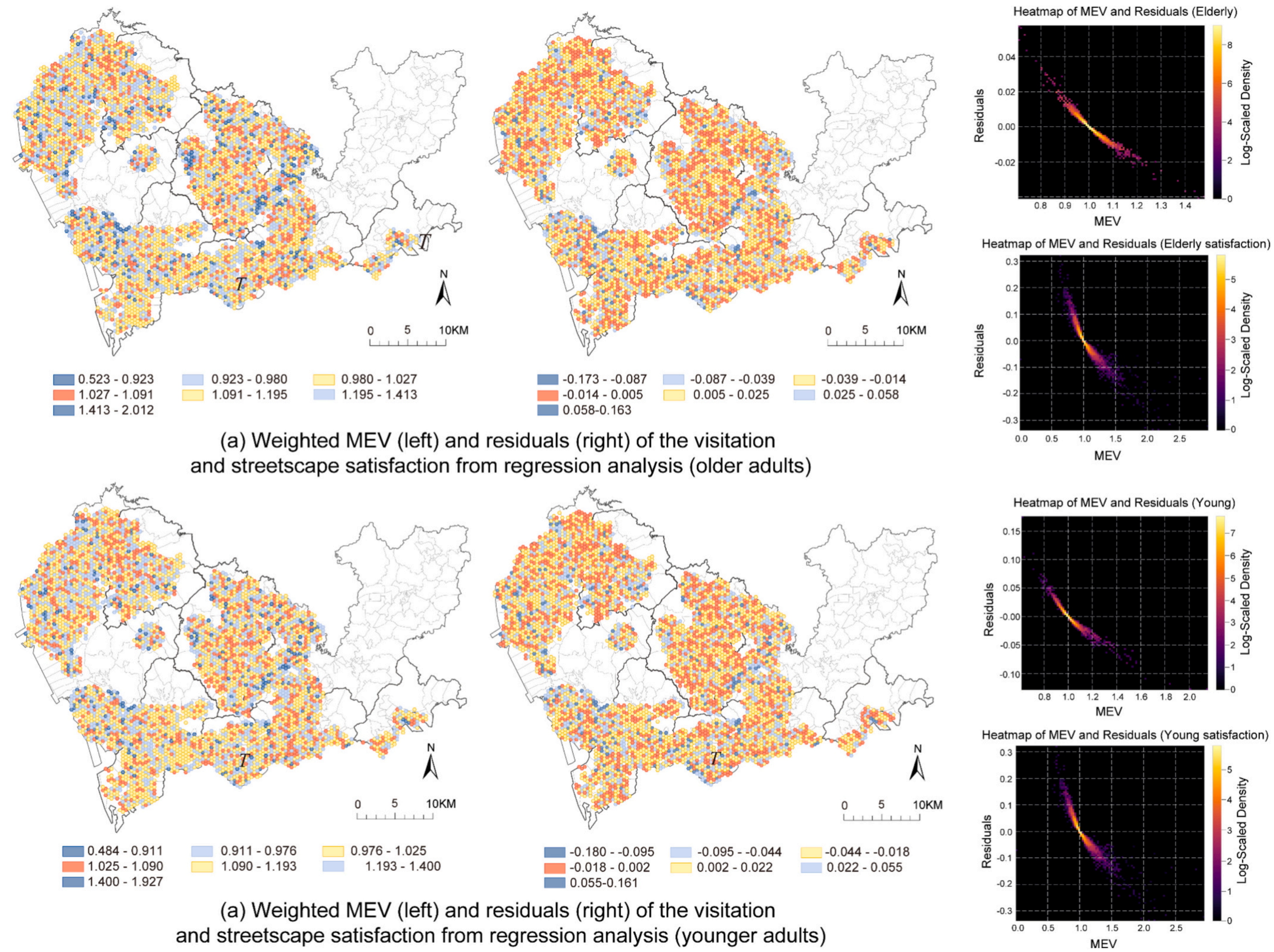


Fig. 8. Spatial distribution and density heatmaps of weighted mean explained variance (MEV) and residuals for visitation and streetscape satisfaction models across age groups.

contribute positively to environmental perception. Conversely, road width and spatial openness have a negative impact on perceptual satisfaction across both groups, indicating that excessively wide roads and open spaces may reduce the subjective environmental quality.

Regarding actual visitation, road width is the only factor that positively influences both age groups. Wide roads improve accessibility and convenience for both younger and older individuals, and they allow for more rational spatial allocation of traffic rights—for example, dedicated lanes for vehicles, bicycles, and pedestrians, along with buffer zones and safety islands. These features effectively separate different modes of travel, thereby enhancing safety. This positive effect is more pronounced among younger adults, likely due to their higher travel frequency, whether for commuting or recreational purposes.

5. Discussion

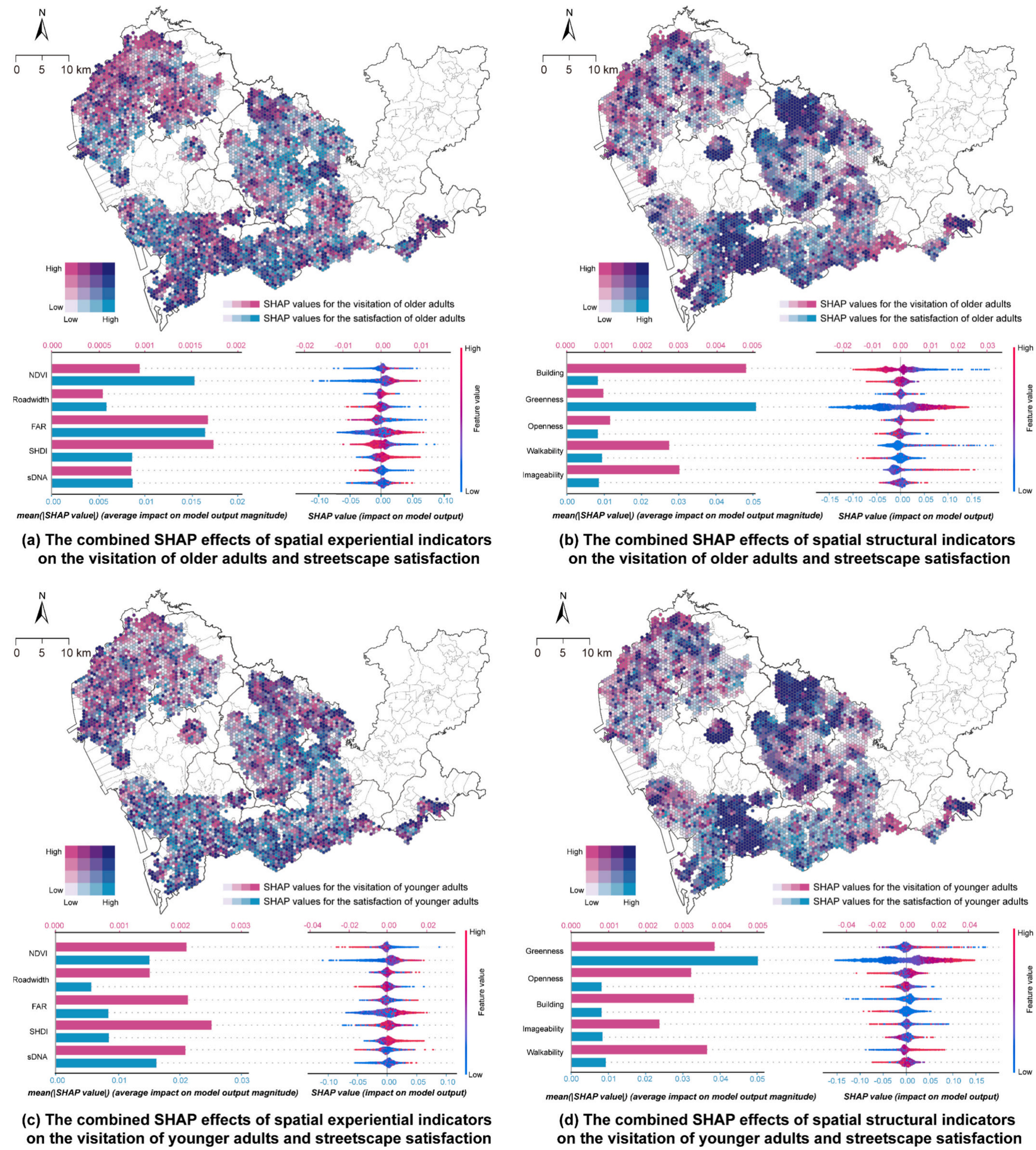
5.1. Using new technologies to identify spatial intergeneration segregations

Previous studies have used SVI to survey static built environment features like green coverage, enclosure, and density, while dynamic elements such as pedestrians and vehicles have received less attention due to their temporal variability and the high cost of traditional data collection. However, recent studies using object-tracking techniques on SVI have shown strong correlations with field measurements, offering a scalable approach for pedestrian monitoring (Chen et al., 2020).

Building on this foundation, we developed a novel approach to identify pedestrian age groups from SVI. We first trained deep learning models using existing annotated datasets (e.g., RAP v2, PETA) and subsequently refined the model using a self-constructed and labeled dataset based on SVI in residential areas. The results showed that models incorporating our custom dataset achieved higher classification accuracy. By integrating DeepLab v3+ with EfficientNet, we successfully classified pedestrian age groups in public spaces across residential neighborhoods in Shenzhen.

In addition, this study leverages SVI and deep learning within a unified analytical framework to conduct large-scale assessments of age-based perceptual preferences toward urban space. This framework enables the simultaneous capture of perception data from both younger and older adults under identical spatial conditions, thereby minimizing the bias that may arise from environmental variability across different observation sites. This approach addresses the methodological limitations of separate group assessments and provides a novel technical pathway for more accurately identifying intergenerational differences in spatial perception.

According to (Giles-Corti et al., 2005), individuals are more likely to walk through spaces perceived as attractive. Other studies have similarly emphasized that analyzing spatial behaviors can help uncover the relationships between residents and their surrounding environments (Garrido-Valenzuela et al., 2023). However, empirical analyses reveal



(a) The combined SHAP effects of spatial experiential indicators on the visitation of older adults and streetscape satisfaction

(b) The combined SHAP effects of spatial structural indicators on the visitation of older adults and streetscape satisfaction

(c) The combined SHAP effects of spatial experiential indicators on the visitation of younger adults and streetscape satisfaction

(d) The combined SHAP effects of spatial structural indicators on the visitation of younger adults and streetscape satisfaction

Fig. 9. GeoShapley-based analysis of the nonlinear and combinatorial effects of spatial indicators on visitation and streetscape satisfaction across age groups.

that spatial preferences and actual behaviors are not always aligned, particularly in non-central urban areas and industrial zones, where intergenerational differences in preference become pronounced. For example, in the eastern industrial parks of Bao'an District, younger adults exhibit high visitation frequency and satisfaction levels, whereas older adults show low visitation rates and inconsistent satisfaction assessments. This divergence between preference and behavior suggests that the mechanisms of spatial attraction may differ across age groups, challenging the explanatory adequacy of the classic "attraction–visitation" paradigm. By incorporating age attributes into the analysis, this study complements Gehl's framework and offers a more comprehensive understanding of the heterogeneity and underlying drivers of intergenerational spatial behavior. These intergenerational spatial patterns are particularly pronounced in Shenzhen due to its rapid internal migration and stark job-housing separation, where younger adults concentrate near employment centers while older adults remain in peripheral communities. This context-specific amplification raises important considerations regarding the generalizability of our findings to cities with more stable demographic structures.

5.2. Beyond lip service: gaps between spatial preference and travel behavior across generations

This study draws on a "spatial cognition–behavior trajectory" framework and integrates insights from ART and the P–E Fit model to explore the phenomenon of misalignment between stated spatial preferences and actual behaviors across different age groups. Based on a perceptual-preference online questionnaire, we identified a clear intergenerational disparity in the extent of this disconnect. Among older adults, this "lip service" effect is particularly evident: despite expressing negative evaluations of street environments in peripheral urban areas, many continued to frequent these locations. In contrast, younger adults exhibited a stronger alignment between perception and action, suggesting a greater tendency to adjust spatial choices in accordance with personal preferences.

By further analyzing the impact of experiential and structural indicators on both groups, we uncovered patterns of synergy or divergence between spatial perception and actual visitation behaviors, offering a novel interpretive framework for understanding intergenerational spatial differentiation. For younger adults, the coherence between spatial perception and behavior is largely associated with factors linked to urban vitality—such as high development density and mixed land use. This finding aligns with the work of Puhakka et al. (2015), which highlights younger adults' preference for diverse and socially engaging environments, and confirms that such preferences are more likely to be translated into concrete spatial behaviors.

In contrast, older adults showed a clear disconnect between perception and behavior. No environmental indicator consistently influenced both aspects for this group. This "lip service" pattern challenges earlier findings that highlight environmental friendliness as key to older adults' spatial engagement (Van Hoof et al., 2021). Our results suggest that better environmental quality alone does not lead to greater use of space. Instead, their spatial behaviors appear constrained by multiple overlapping mechanisms. Glass and Balfour (2009) identified four key sources of older adults' heightened vulnerability to neighborhood environments: longer duration of residential exposure, increased biological and psychological vulnerability, shrinking spatial life space, and greater reliance on proximate community resources. These structural constraints may explain why older adults continue visiting peripheral areas despite negative evaluations. Habitual routines established over decades (Meijering et al., 2024), residential proximity limiting alternative choices, established social networks concentrated in familiar locations, and constrained mobility capital (Feng, 2017) collectively override subjective environmental preferences in determining actual spatial engagement. This finding reveals a fundamental paradox in classical P-E Fit theory: while the framework predicts that older adults would actively avoid high environmental press contexts, our evidence demonstrates continued visitation despite low satisfaction. This inconsistency suggests that non-environmental factors including habitual routines, social networks, residential proximity, and lack of accessible alternatives may override subjective environmental evaluations in shaping older adults' spatial behavior, thereby extending P-E Fit theory beyond its original person-environment compatibility assumptions.

Our study identifies key environmental features that enhance perceptual inclusivity across age groups. Elements such as NDVI, greenness, SHDI, and FAR positively influence spatial perception for both younger and older adults, offering restorative environments that meet diverse psychological needs and support varying abilities and preferences. These shared perceptual drivers provide a strong foundation for designing intergenerationally inclusive public spaces. However, whether this perceptual consensus leads to shared spatial behaviors remains uncertain. Given older adults' tendency toward "lip service," a key challenge in street planning is translating cognitive alignment into actual intergenerational engagement.

5.3. Planning recommendations to reduce spatial intergenerational segregation

Based on the in-depth analysis of spatial mismatch and intergenerational differentiation in this study, we propose the following planning recommendations. Informed by the spatial justice literature and recent geospatial assessments of age-friendly environments in European contexts (Świąder et al., 2025), our analysis of spatial mismatch and intergenerational differentiation suggests planning recommendations that acknowledge the foundational importance of co-production methodologies central to the WHO age-friendly framework (WHO, 2007).

First, the study highlights key environmental elements that can help align spatial preferences with actual behaviors among both younger and older adults. Urban planners should focus on improving green infrastructure such as parks and street greenery, which our findings reveal as shared perceptual drivers (NDVI, greenness, SHDI). Functional mix requires calibration: high intensity mixing attracts younger adults but generates preference behavior decoupling among older adults. Road width uniquely promotes visitation across both generations by accommodating diverse mobility modes. These patterns challenge Gehl's attraction visitation paradigm, showing perceived attractiveness does not uniformly predict spatial behavior across age groups. Environments that are too uniform or excessively dense may hinder accessibility and inclusivity. Importantly, road width emerged as the only factor promoting visitation across both age groups, underscoring the need for a layered street network. At the neighborhood level, micro-circulation systems with a three to five minute walking radius can support older adults' mobility. At the *meso* scale, ten to fifteen minute living circles with wider streets and mixed-use environments can cater to younger adults' social and exploratory needs. At the macro scale, road networks should connect seamlessly with public transit to ensure broader accessibility and spatial equity.

Second, for spatial features preferred by younger adults such as high-intensity functional mixing and spatial diversity, planning strategies should adopt a more inclusive design approach. While these environments attract younger users, they may deter older adults. In high-visitation zones such as transport hubs, industrial parks, and commercial centers, a "spatial memory preservation" strategy is recommended. This involves retaining familiar spatial elements such as traditional street names, iconic façades, and neighborhood textures to strengthen older adults' sense of recognition and belonging while easing navigation. Additionally, intergenerational-friendly micro-spaces can be incorporated into dynamic areas. Within transport hubs, planners could create 5 by 8 m alcoves featuring heritage photo walls paired with digital wayfinding screens, tiered seating at 45 cm and 50 cm heights accommodating different user needs, and traditional street furniture styles. Such spaces enable older adults to maintain spatial recognition while meeting younger adults' expectations for contemporary functionality. By integrating memory continuity with contemporary function, these mixed-use environments can foster more inclusive public spaces (Kim, 2019; Wen et al., 2018). These planning interventions must be understood as mechanisms for advancing spatial justice by addressing the structural factors that generate unequal spatial outcomes, including housing affordability, transportation equity, and the uneven distribution of urban amenities (Buffel et al., 2024; Greenfield, 2018).

Third, for spatial features that support the needs of older adults such as imageability and perceived safety, it is important to enhance urban vitality and functional diversity while maintaining environmental recognizability, especially in non-central areas. Traditional imageability, which relies on point-based landmarks, may not fully support older adults' spatial cognition and may fall short of meeting younger users' expectations for interactivity and social engagement. To address this, we recommend expanding imageability through concrete interventions: wayfinding signage at 80 m intervals with pictographic symbols, thematic paving patterns demarcating neighborhood boundaries, community murals narrating local histories at key nodes, and consistent street furniture creating recognizable spatial sequences. These layered cues enable older adults to construct cognitive maps while providing younger users with legible, engaging environments. This approach creates a multi-level memory network that enables older adults to navigate beyond familiar surroundings while also fostering vibrant environments that engage younger users.

5.4. Limitations and further work

This study has several limitations. First, SVI is subject to seasonal variability, whereas travel behavior changes dynamically across times of day and seasons. Although we employed large volumes of SVI data to estimate pedestrian distributions across residential areas, such data may overlook finer temporal patterns, such as morning versus evening differences. Future studies should incorporate more time-sensitive methods to capture these variations. Second, while deep learning techniques enabled identification of younger and older adults in SVI, age classification remains coarse. More detailed datasets, including middle-aged adults and children, could enhance the precision of cross-age spatial behavior analysis. Third, integrating multi-source data such as mobile signaling could help distinguish residents from visitors, offering deeper insight into group-specific spatial behaviors. This distinction is particularly important for urban planning efforts seeking to balance local needs with tourism development.

6. Conclusions

This study systematically investigated the phenomenon of “preference-behavior inconsistency” in urban street spaces, referring to the spatial mismatch between subjective satisfaction and actual visitation among younger and older adults in Shenzhen. It adopted an innovative computer vision framework that integrates multi-source big data with an online questionnaire designed under the theoretical lens of ART and the P–E Fit model.

The main findings are as follows:

First, we developed a pedestrian age recognition model based on DINO and T2T-ViT architectures, which enabled accurate identification of younger and older adults in street view imagery. This approach overcomes the limitations of traditional survey methods in terms of sample size and spatial coverage, offering robust technical support for large-scale studies on intergenerational spatial behavior.

Second, the results revealed pronounced intergenerational spatial differentiation. Young adults exhibited highly clustered spatial activity patterns, concentrated around transportation hubs and industrial parks. In contrast, older adults showed a dispersed, polycentric pattern, with relatively low activity density in central urban areas. These patterns reflect fundamental differences in residential choice and daily mobility behavior across age groups.

Third, the spatial distribution of perceptual differences was strongly aligned with urban functional zones. Young adults rated the aesthetic and vibrancy of central areas more positively, but gave lower ratings to their perceived safety and affluence compared to older adults. In non-core areas, young adults were also more sensitive to perceptions of monotony and environmental pressure.

Fourth, the study uncovered distinct intergenerational patterns of preference-behavior mismatch. In non-central areas, both groups expressed relatively low satisfaction, yet exhibited divergent visitation behaviors. This finding challenges the universality of the traditional “attraction–visitation” paradigm.

Fifth, using GeoShapley analysis, we explored the driving factors of intergenerational spatial differentiation. Young adults showed a tendency toward preference-behavior alignment, as indicators like FAR, SHDI, and greenness promoted both satisfaction and visitation. In contrast, older adults exhibited clear preference-behavior inconsistency, with no factor consistently influencing both perception and behavior. Green infrastructure and spatial diversity enhanced perceptual satisfaction for both groups, while road width was the only variable that positively influenced actual visitation across both age cohorts.

These findings extend existing environmental behavior theories while challenging their conventional assumptions. They also provide comprehensive empirical evidence to support the design of cognitively and behaviorally inclusive street spaces that foster intergenerational integration.

This study systematically investigated preference-behavior inconsistency in urban street spaces by examining the spatial mismatch between subjective satisfaction and actual visitation among younger and older adults in Shenzhen. We adopted an innovative computer vision framework integrating multi-source big data with an online questionnaire grounded in ART and the P-E Fit model, developing a pedestrian age recognition model based on DINO and T2T-ViT architectures that enabled large-scale identification of intergenerational spatial patterns.

Our analysis revealed pronounced intergenerational spatial differentiation driven by divergent urban engagement logics. Younger adults exhibited clustered activity patterns around transportation hubs and industrial parks with preference behavior alignment where environmental attractiveness predicts visitation. Older adults demonstrated dispersed distributions reflecting behaviors constrained by habitual routines, residential proximity, and social networks rather than subjective evaluations. Critically, we uncovered distinct preference-behavior mismatch patterns in non-central areas where both groups expressed low satisfaction but exhibited divergent visitation behaviors, fundamentally challenging the traditional attraction-visitation paradigm. GeoShapley analysis revealed that younger adults demonstrated preference behavior alignment through synergistic effects of FAR, SHDI, and greenness. Critically, older adults exhibited systematic decoupling with no factors consistently influencing both perception and behavior, a pattern explained by structural constraints including shrinking life space, constrained mobility capital, and reliance on proximate community resources that override subjective preferences in determining actual spatial engagement. Green infrastructure and spatial diversity enhanced satisfaction across age groups, while road width emerged as the sole variable positively influencing visitation for both cohorts.

These findings extend existing environmental behavior theories while challenging their conventional assumptions, providing empirical evidence to support cognitively and behaviorally inclusive street design that fosters intergenerational integration. B By revealing systematic decoupling between perception and behavior among older adults, our study demonstrates that structural mechanisms (mobility limitations, residential inertia) and psychological mechanisms (habitual routines, social embeddedness) collectively shape spatial behavior beyond traditional person environment compatibility frameworks. This finding calls for age differentiated planning approaches addressing both environmental quality and the life course contingencies mediating environment behavior relationships across demographic cohorts.

CRediT authorship contribution statement

Jin Rui: Writing – review & editing, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Wenjing Gong:** Writing – original draft, Visualization, Investigation, Formal analysis, Conceptualization.

Declaration of competing interest

The authors have declared no conflict of interest.

Appendix A. Figures

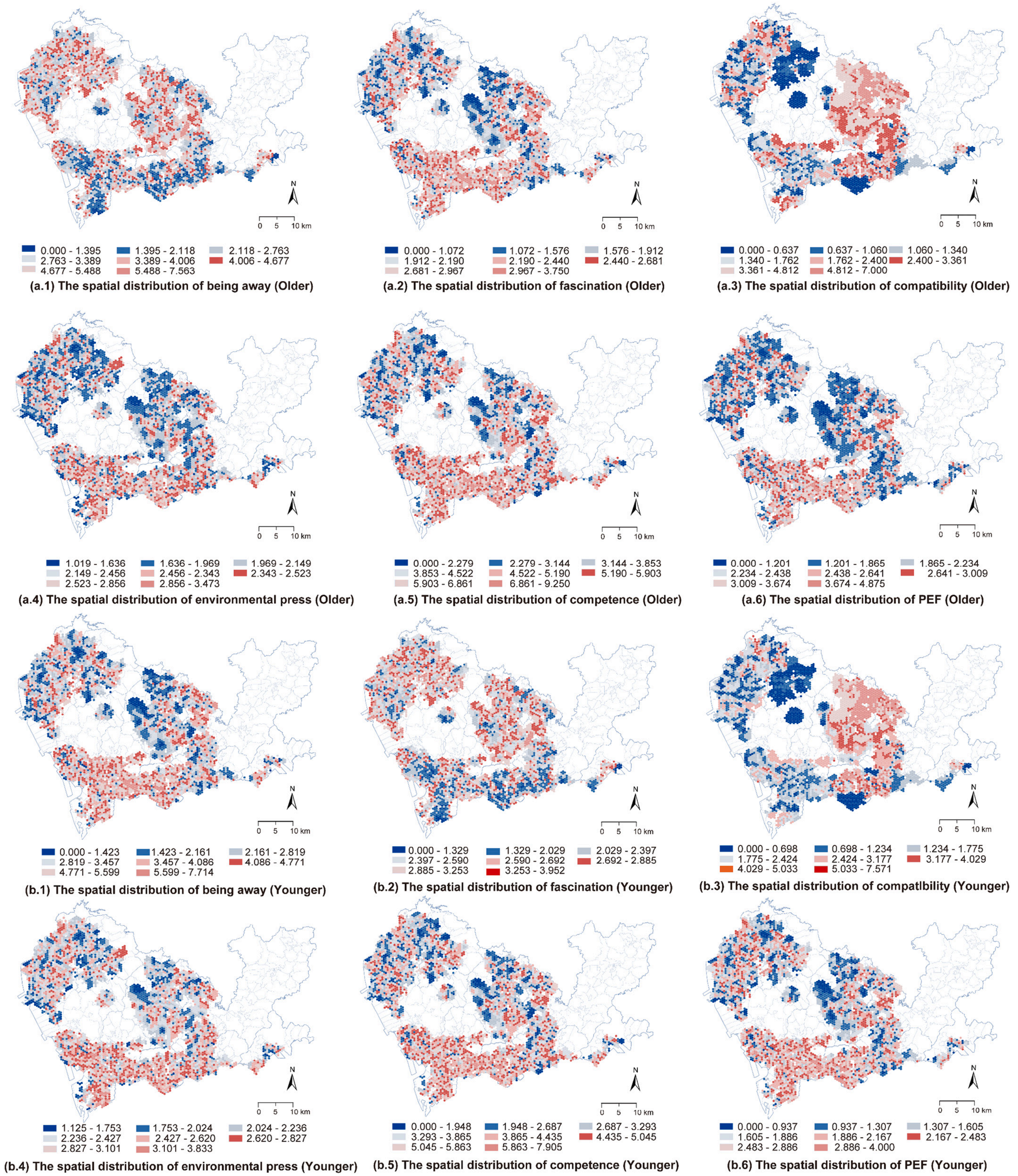


Fig. A1. Spatial distribution of perceptual and environmental dimensions across older and younger populations.

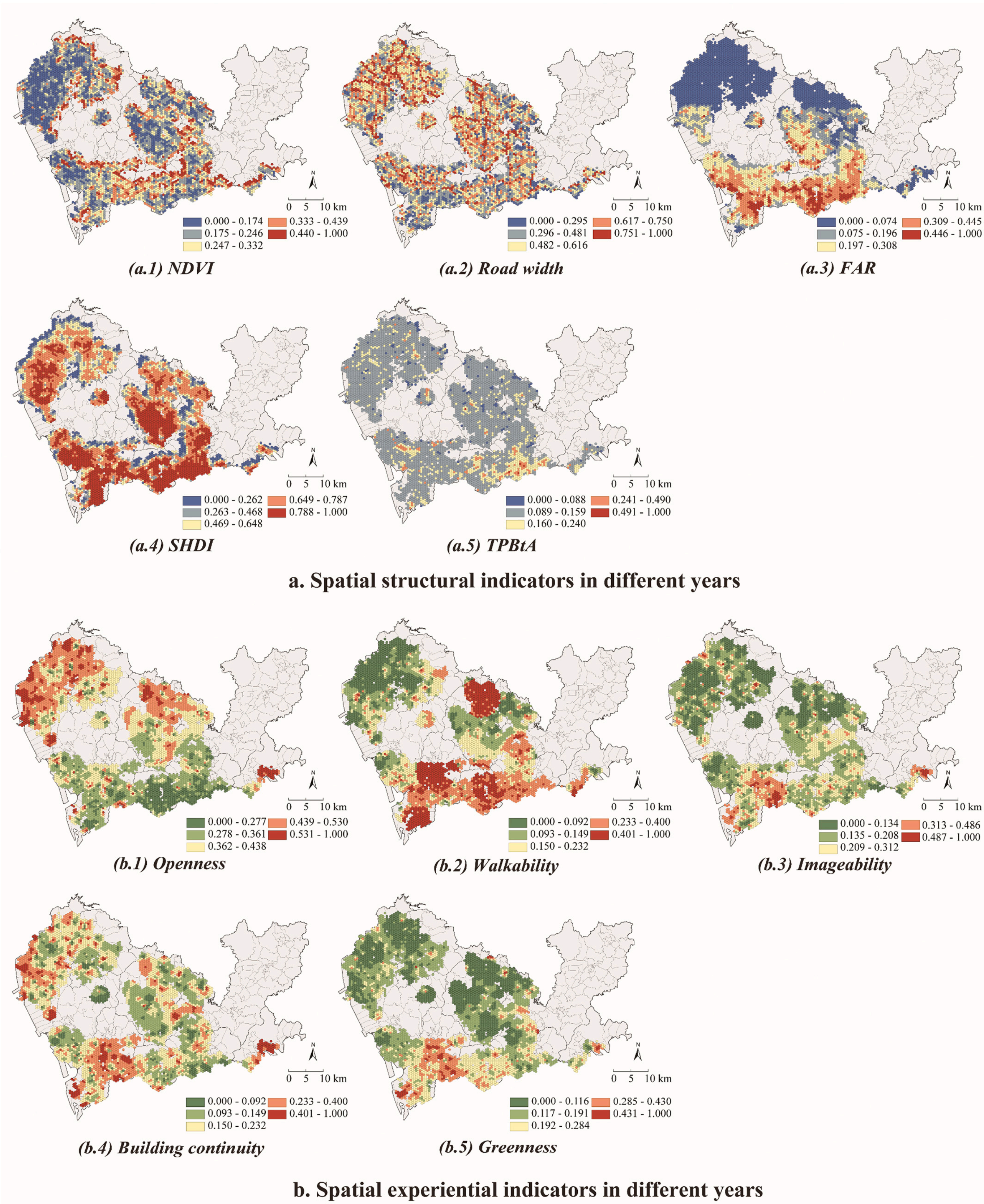


Fig. A2. Spatial distribution of structural and experiential indicators across different years.

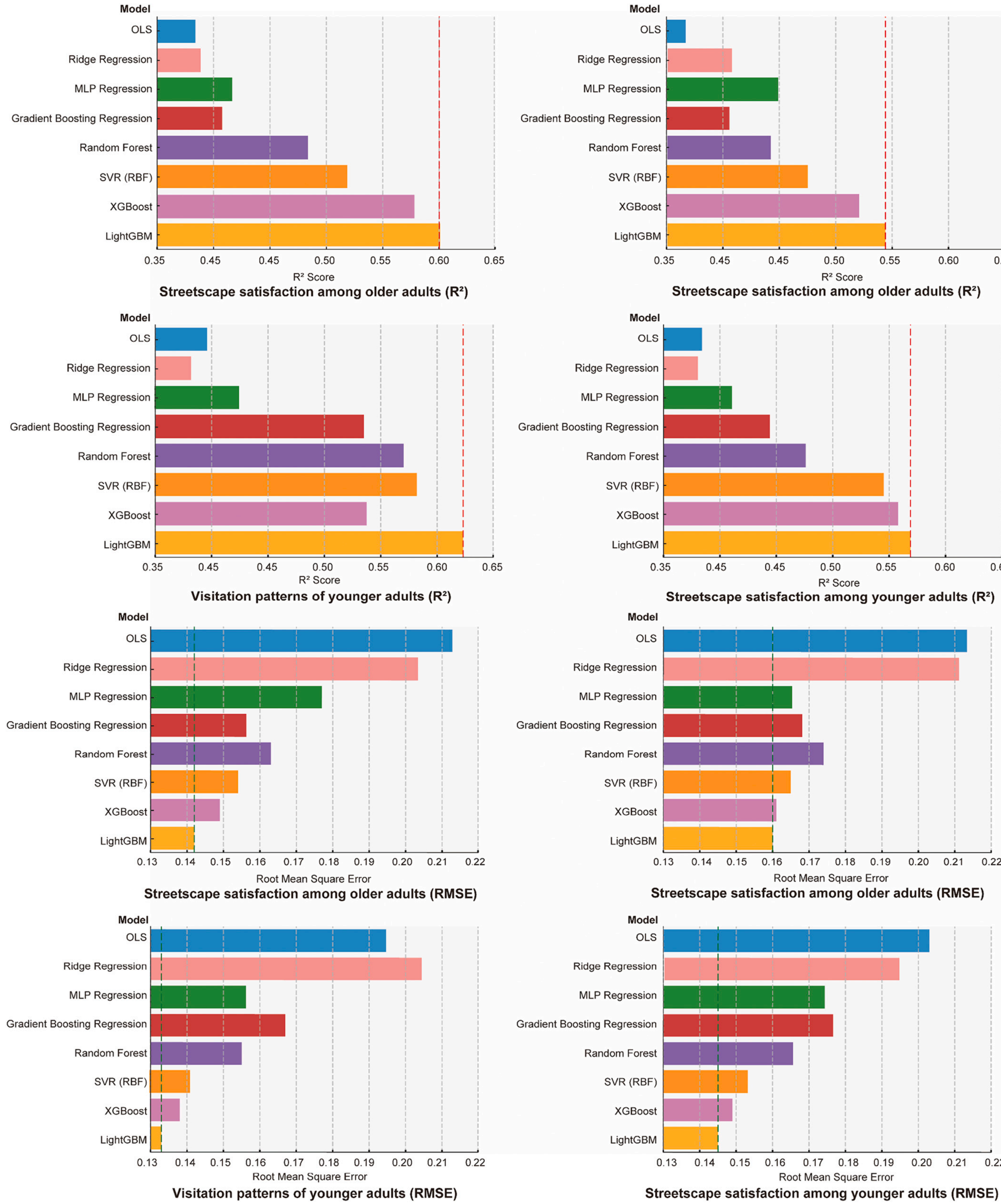


Fig. A3. Model performance comparison across age groups and outcomes using R^2 and RMSE metrics.

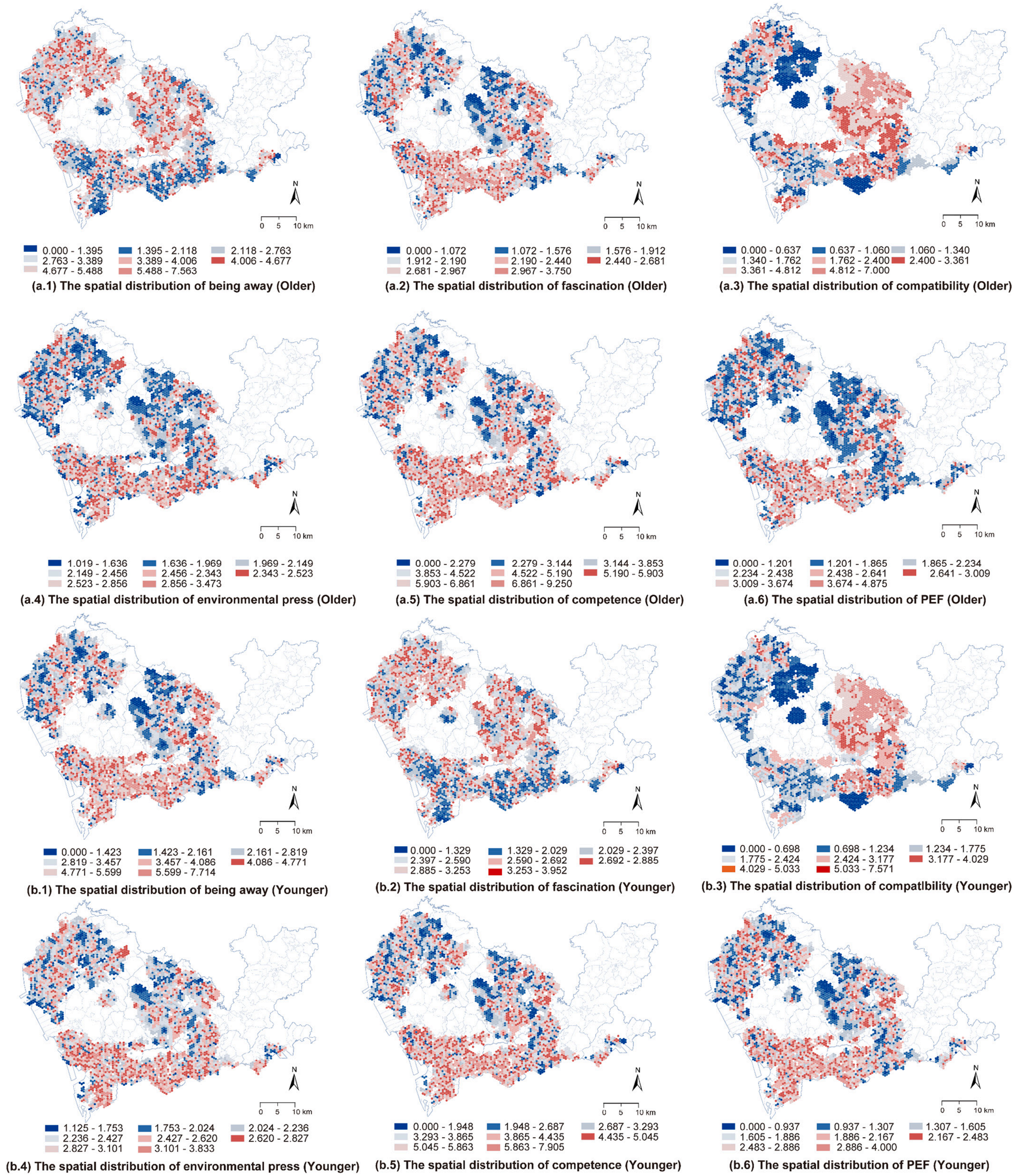


Fig. A4. Spatial distribution of perceived environmental qualities among older and younger adults based on ART and P-E Fit theories.

Appendix B. Model performance and hyperparameters for LightGBM models

Table A1
Optimized hyperparameters and performance for LightGBM models.

Parameter	Older Adults Occurrence	Older Adults Satisfaction	Younger Adults Occurrence	Younger Adults Satisfaction
n_estimators	520	640	580	600
learning_rate	0.032	0.018	0.036	0.025
max_depth	6	8	7	9
min_child_weight	4.2	5.0	3.8	4.5
subsample	0.82	0.87	0.78	0.8
colsample_bytree	0.76	0.73	0.81	0.78
reg_alpha (L1)	0.1	0.25	0.05	0.2
reg_lambda (L2)	0.85	1.0	0.9	1.1
min_split_gain	0.01	0.02	0.015	0.025
random_state	42	42	42	42
cross-validation folds	5	5	5	5
R^2	0.601	0.544	0.623	0.569
BRMSE	0.142	0.161	0.133	0.15

Appendix C. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cities.2025.106750.

Data availability

Data will be made available on request.

References

Abdul Latiff, A. R., & Mohd, S. (2023). Transport, mobility and the wellbeing of older adults: An exploration of private chauffeuring and companionship services in Malaysia. *International Journal of Environmental Research and Public Health, 20*, 2720. https://doi.org/10.3390/ijerph20032720

Ajzen, I. (1991). The theory of planned behavior. In *, 50. Organizational behavior and human decision processes, theories of cognitive self-regulation* (pp. 179–211). https://doi.org/10.1016/0749-5978(91)90020-T

Andersson, M., Larsson, J. P., & Wernberg, J. (2018). Urban preferences, amenities and age: Exploring the spatial distribution of age in Stockholm from 1991 to 2011. *Regional Science Policy & Practice, 10*(4), 367–382.

Bafatakis, C., Duives, D., & Daamen, W. (2015). *Determining a pedestrian route choice model through a photo survey*.

Berman, M. G., Jonides, J., & Kaplan, S. (2008). The cognitive benefits of interacting with nature. *Psychological Science, 19*(12), 1207–1212.

Brandt, M. (2021). In M. Kaplan, L. L. Thang, M. Sánchez, & J. Hoffman (Eds.), *Intergenerational contact zones. Place-based strategies for promoting social inclusion and belonging*. New York and London: Routledge. march 2020.(Paperback) ISBN 9780367189037,(Hardback) ISBN 9780367189020, E-book-ISBN 9780429199097. (Paperback)£ 39.99 (54.36)and(Hardback)£120.00(157.27), Taylor & Francis.

Buffel, T., Doran, P., & Yarker, S. (2024). *Reimagining age-friendly communities: Urban ageing and spatial justice* (1st ed.). Bristol University Press. https://doi.org/10.2307/jj.11102872

Capaldi, C. A., Dopko, R. L., & Zelenski, J. M. (2014). The relationship between nature connectedness and happiness: A meta-analysis. *Frontiers in Psychology, 5*, 92737.

Caron, M., Touvron, H., Misra, I., Jégou, H., Mairal, J., Bojanowski, P., & Joulin, A. (2021). Emerging properties in self-supervised vision transformers. In *Proceedings of the IEEE/CVF international conference on computer vision* (pp. 9650–9660).

Chen, L., Lu, Y., Sheng, Q., Ye, Y., Wang, R., & Liu, Y. (2020). Estimating pedestrian volume using street view images: A large-scale validation test. *Computers, Environment and Urban Systems, 81*, Article 101481.

Chen, L.-C., Zhu, Y., Papandreou, G., Schroff, F., & Adam, H. (2018). Encoder-decoder with atrous separable convolution for semantic image segmentation. In *Proceedings of the European conference on computer vision (ECCV)* (pp. 801–818).

Chen, Y., Huang, X., & White, M. (2024). A study on street walkability for older adults with different mobility abilities combining street view image recognition and deep learning-the case of Chengxianjie community in Nanjing (China). *Computers, Environment and Urban Systems, 112*, Article 102151.

Chen, Y., Yu, B., Shu, B., Yang, L., & Wang, R. (2023). Exploring the spatiotemporal patterns and correlates of urban vitality: Temporal and spatial heterogeneity. *Sustainable Cities and Society, 91*, Article 104440.

De Vos, J., Derudder, B., Van Acker, V., & Witlox, F. (2012). Reducing car use: Changing attitudes or relocating? The influence of residential dissonance on travel behavior. *Journal of Transport Geography, 22*, 1–9.

Edwards, J. R., Caplan, R. D., & Harrison, R. V. (1998). Person-environment fit theory: Conceptual foundations, empirical evidence, and directions for future research. In *, 28. Theories of organizational stress* (pp. 28–67).

Ewing, R., & Handy, S. (2009). Measuring the unmeasurable: Urban design qualities related to walkability. *Journal of Urban Design, 14*(1), 65–84.

Fan, Y., Wong, I. A., Zhang, G., Lin, Z., & Wu, L. (2024). A multiwave study on tourist well-being: The role of attention restoration, psychological-need and social-sharing satisfaction. *Tourism Management Perspectives, 51*, Article 101234.

Feng, J. (2017). The influence of built environment on travel behavior of the elderly in urban China. *Transportation Research Part D: Transport and Environment, 52*, 619–633.

Gaglione, F., Gargiulo, C., & Zucaro, F. (2022). Where can the elderly walk? A spatial multi-criteria method to increase urban pedestrian accessibility. *Cities, 127*, Article 103724.

Garrido-Valenzuela, F., Cats, O., & van Cranenburgh, S. (2023). Where are the people? Counting people in millions of street-level images to explore associations between people's urban density and urban characteristics. *Computers, Environment and Urban Systems, 102*, Article 101971.

Gehl, J. (1987). *Life between buildings: Using public space*. Island Press.

Giles-Corti, B., Broomhall, M. H., Knuiman, M., Collins, C., Douglas, K., Ng, K., … Donovan, R. J. (2005). Increasing walking: How important is distance to, attractiveness, and size of public open space? *American Journal of Preventive Medicine, 28*(2), 169–176.

Glass, T. A., & Balfour, J. L. (2009). Neighborhoods, aging, and functional limitations. In *Neighborhoods and health*. Oxford University Press. https://doi.org/10.1093/acprof:oso/9780195138382.003.0014.

Gong, W., Rui, J., & Li, T. (2024). Deciphering urban bike-sharing patterns: An in-depth analysis of natural environment and visual quality in New York's Citi bike system. *Journal of Transport Geography, 115*, Article 103799. https://doi.org/10.1016/j.jtrangeo.2024.103799

Greenfield, E. A. (2018). Age-friendly initiatives, social inequalities, and spatial justice. *The Hastings Center Report, 48*(Suppl. 3), S41–S45. https://doi.org/10.1002/hast.912

Guo, Z., & Loo, B. P. (2013). Pedestrian environment and route choice: Evidence from new York City and Hong Kong. *Journal of Transport Geography, 28*, 124–136.

Guzman, L. A., Arellana, J., & Castro, W. F. (2022). Desirable streets for pedestrians: Using a street-level index to assess walkability. *Transportation Research Part D: Transport and Environment, 111*, Article 103462.

Handy, S., Cao, X., & Mokhtarian, P. L. (2006). Self-selection in the relationship between the built environment and walking: Empirical evidence from northern California. *Journal of the American Planning Association, 72*(1), 55–74.

Holland, C., Clark, A., Katz, J., & Peace, S. (2007). *Social interactions in urban public places*. Policy Press.

Hu, S., Zhang, Z., Ge, D., Lin, X., & Lu, Y. (2024). Residential differentiation characteristics based on "socio-spatial" coupling: A case study of Zhengzhou. *Applied Geography, 166*, Article 103269.

Hu, X., Cao, K., Huang, B., Li, X., & Wu, R. (2025). Walkability of greenways from the perspective of the elderly: A case study of Huangpu River waterfront greenway. *International Journal of Applied Earth Observation and Geoinformation, 136*, Article 104322.

Kaplan, S., Kaplan, R., & Wendt, J. S. (1972). Rated preference and complexity for natural and urban visual material. *Perception & Psychophysics, 12*(4), 354–356.

Ke, G., Meng, Q., Finley, T., Wang, T., Chen, W., Ma, W., Ye, Q., & Liu, T.-Y. (2017). Lightgbm: A highly efficient gradient boosting decision tree. In *Advances in neural information processing systems* (p. 30).

Kim, D. (2019). The transportation safety of elderly pedestrians: Modeling contributing factors to elderly pedestrian collisions. *Accident Analysis & Prevention, 131*, 268–274.

Kirasic, K. C. (2000). Age differences in adults' spatial abilities, learning environmental layout, and wayfinding behavior. *Spatial Cognition and Computation, 2*, 117–134.

Kollmuss, A., & Agyeman, J. (2002). Mind the gap: Why do people act environmentally and what are the barriers to pro-environmental behavior? *Environmental Education Research, 8*, 239–260. https://doi.org/10.1080/13504620220145401

Koohsari, M. J., Karakiewicz, J. A., & Kaczynski, A. T. (2013). Public open space and walking: The role of proximity, perceptual qualities of the surrounding built environment, and street configuration. *Environment and Behavior, 45*(6), 706–736.

Lewicka, M. (2008). Place attachment, place identity, and place memory: Restoring the forgotten city past. *Journal of Environmental Psychology, 28*(3), 209–231.

Li, Z. (2024). Geoshapley: A game theory approach to measuring spatial effects in machine learning models. *Annals of the American Association of Geographers, 114*(7), 1365–1385.

Liu, D., Wang, R., Grekousis, G., Liu, Y., & Lu, Y. (2023). Detecting older pedestrians and aging-friendly walkability using computer vision technology and street view imagery. *Computers, Environment and Urban Systems, 105*, Article 102027.

Lundberg, S. M., & Lee, S.-I. (2017). A unified approach to interpreting model predictions. *Advances in Neural Information Processing Systems, 30*.

Ma, H., Zhang, Y., Liu, P., Zhang, F., & Zhu, P. (2024). How does spatial structure affect psychological restoration? A method based on graph neural networks and street view imagery. *Landscape and Urban Planning, 251*, Article 105171.

Ma, J., Dong, G., Chen, Y., & Zhang, W. (2018). Does satisfactory neighbourhood environment lead to a satisfying life? An investigation of the association between neighbourhood environment and life satisfaction in Beijing. *Cities, 74*, 229–239.

Mahmoudi Farahani, L. (2016). The value of the sense of community and neighbouring. *Housing, Theory and Society, 33*(3), 357–376.

Manzo, L., & Devine-Wright, P. (2013). *Place attachment: Advances in theory, methods and applications*. Routledge.

Marston, H. R., Shore, L., Stoops, L., & Turner, R. S. (2022). *Transgenerational technology and interactions for the 21st century: Perspectives and narratives*.

Mehrabian, A., & Russell, J. A. (1974). *An approach to environmental psychology*. the MIT press.

Meijering, L., Osborne, T., van Doorne, M., & Weitkamp, G. (2024). Seasonal differences in mobility and activity space in later life: A case study of older adults in the northern Netherlands. *Mobilities, 19*, 736–755. https://doi.org/10.1080/17450101.2023.2289453

Mouratidis, K., & Yiannakou, A. (2022). What makes cities livable? Determinants of neighborhood satisfaction and neighborhood happiness in different contexts. *Land Use Policy, 112*, Article 105855.

Mukherjee, J., & Kadali, B. R. (2022). A comprehensive review of trip generation models based on land use characteristics. *Transportation Research Part D: Transport and Environment, 109*, Article 103340.

Nelischer, C., & Loukaitou-Sideris, A. (2023). Intergenerational public space design and policy: A review of the literature. *Journal of Planning Literature, 38*(1), 19–32.

Plouffe, L., & Kalache, A. (2010). Towards global age-friendly cities: Determining urban features that promote active aging. *Journal of Urban Health, 87*, 733–739. https://doi.org/10.1007/s11524-010-9466-0

Puhakka, R., Poikolainen, J., & Karisto, A. (2015). Spatial practises and preferences of older and younger people: Findings from the Finnish studies. *Journal of Social Work Practice, 29*(1), 69–83.

Ringland, J., Bohm, M., & Baek, S.-R. (2019). Characterization of food cultivation along roadside transects with Google street view imagery and deep learning. *Computers and Electronics in Agriculture, 158*, 36–50. https://doi.org/10.1016/j.compag.2019.01.014

Rui, J., & Xu, Y. (2024). Beyond built environment: Unveiling the interplay of streetscape perceptions and cycling behavior. *Sustainable Cities and Society, 109*, Article 105525.

Samus, A., Freeman, C., van Heezik, Y., Krumme, K., & Dickinson, K. J. (2022). How do urban green spaces increase well-being? The role of perceived wildness and nature connectedness. *Journal of Environmental Psychology, 82*, Article 101850.

Sarkar, C., Webster, C., Pryor, M., Tang, D., Melbourne, S., Zhang, X., & Jianzheng, L. (2015). Exploring associations between urban green, street design and walking: Results from the greater London boroughs. *Landscape and Urban Planning, 143*, 112–125.

Schwanen, T., & Mokhtarian, P. L. (2005). What affects commute mode choice: Neighborhood physical structure or preferences toward neighborhoods? *Journal of Transport Geography, 13*(1), 83–99.

Sen, Z., Ke, Z., Xiaoyang, L., Jian, Z., Yan, L., & Lian, Z. (2022). Characterisation of elderly daily travel behaviour in Tianjin using a space–time cube. *Environment and Planning B: Urban Analytics and City Science, 49*(2), 603–618.

Sheeran, P. (2002). Intention—Behavior relations: a conceptual and empirical review. *European Review of Social Psychology, 12*, 1–36. https://doi.org/10.1080/14792772143000003

Świąder, M., Aslanoğlu, R., Chrobak, G. J., Ivan, L., Perek-Białas, J. M., Dikken, J., van Hoof, J., & Kazak, J. K. (2025). Shaping age-friendly cities and communities: a geospatial approach to the assessment of four cities in Europe. *Cities, 166*, Article 106247. https://doi.org/10.1016/j.cities.2025.106247

Tuomola, E.-M., Keskinen, K. E., Rantanen, T., & Portegijs, E. (2024). Associations between walking limitations and reported activity destinations among older adults. *European Journal of Ageing, 21*, 16. https://doi.org/10.1007/s10433-024-00813-1

Van Hoof, J., Marston, H. R., Kazak, J. K., & Buffel, T. (2021). Ten questions concerning age-friendly cities and communities and the built environment. *Building and Environment, 199*, Article 107922.

Wang, R., Yuan, Y., Liu, Y., Zhang, J., Liu, P., Lu, Y., & Yao, Y. (2019). Using street view data and machine learning to assess how perception of neighborhood safety influences urban residents' mental health. *Health & Place, 59*, Article 102186.

Wei, H., Hauer, R. J., & Guo, S. (2021). Daytime dynamic of spontaneous expressions of pedestrians in an urban forest park. *Urban Forestry & Urban Greening, 65*, Article 127326.

Wen, C., Albert, C., & Von Haaren, C. (2018). The elderly in green spaces: Exploring requirements and preferences concerning nature-based recreation. *Sustainable Cities and Society, 38*, 582–593.

Wendel, G., Loukaitou-Sideris, A., Nelischer, C., & Bastar, G. (2022). "We should all feel welcome to the park": Intergenerational public space and universal design in disinvested communities. *The Journal of Public Space, 7*(2), 135–154.

WHO. (2007). Global age-friendly cities: a guide [WWW Document]. URL https://www.who.int/publications/i/item/9789241547307 (accessed 11.11.25).

Yamada, K., Murotani, K., Mano, M., Lim, Y., & Yoshimatsu, J. (2023). Age-friendly approach is necessary to prevent depopulation: Resident architectural designers and constructors' evaluation of the age-friendliness of Japanese municipalities. *International Journal of Environmental Research and Public Health, 20*, 6626. https://doi.org/10.3390/ijerph20176626

Yang, Y., Wang, Q., Wu, D., Hang, T., Ding, H., Wu, Y., & Liu, Q. (2024). Constructing child-friendly cities: Comprehensive evaluation of street-level child-friendliness using the method of empathy-based stories, street view images, and deep learning. *Cities, 154*, Article 105385.

Yin, L., Cheng, Q., Wang, Z., & Shao, Z. (2015). Big data'for pedestrian volume: Exploring the use of Google street view images for pedestrian counts. *Applied Geography, 63*, 337–345.

Yuan, L., Chen, Y., Wang, T., Yu, W., Shi, Y., Jiang, Z.-H., … Yan, S. (2021). Tokens-to-token vit: Training vision transformers from scratch on imagenet. *Proceedings of the IEEE/CVF international conference on computer vision*, 558–567.

Zhang, Y., & Wang, J. (2025). Bidirectional spatial mobility and intergenerational social mobility in contemporary China: The role of escalator regions. *Eurasian Geography and Economics*, 1–27.

Ziganshina, L. E., Garaeva, A. F., Talipova, L. I., Khairullin, R. N., Dikken, J., & van Hoof, J. (2025). Measuring the age-friendliness of cities in the Russian Federation: The translation, validation and application of the age-friendly cities and communities questionnaire in the city of Kazan. *Heliyon, 11*, Article e41100. https://doi.org/10.1016/j.heliyon.2024.e41100