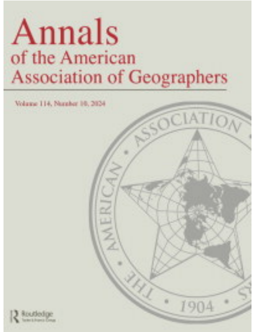

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Unveiling the Neighborhood Effect Averaging Problem: The Role of Daily Mobility in Shaping Built-Environment Quality Exposure

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Equal exposure to quality-built environments fosters livable, inclusive cities. The neighborhood effect averaging problem (NEAP) suggests that daily mobility plays a crucial role in shaping environmental exposure. This study aims to unveil the NEAP in built-environment quality exposure. Street-view image data and mobile phone signaling data are coupled to measure built-environment quality in people's residential space and activity space. Subsequently, a conditional process analysis model is employed to investigate how daily mobility, income, and built-environment quality in residential space influence built-environment quality in activity space. The results indicate that (1) there is a significant disparity in built-environment quality exposure, although the disparity in activity space is smaller than that in residence; (2) income exerts a dual influence on built-environment quality in activity space through direct and indirect pathways, and the pathways could be moderated by high mobility; and (3) neighborhood effect averaging is evident at the individual level and manifests as a derived phenomenon associated with income groups. The findings provide insights for better serving environmental equality. *Key Words: built-environment quality, daily mobility, mobile phone signaling data, neighborhood effect averaging problem (NEAP), street-view images.*

The quality of the built environment is crucial to livable cities. There is much evidence linking built-environment quality (BEQ) to human health, crime rate, and so on (He, Páez, and Liu 2017; R. Wang et al. 2019; Zhang, Li, and Chan 2020; T. T. Nguyen et al. 2021; Su, Li, and Qiu 2023). Moreover, the disparity in BEQ exposure evokes spatial inequality issues, as it is largely shaped by socioeconomic and racial inequalities (Ludwig et al. 2012). Using residential neighborhoods as the spatial or contextual areas for assessing people's environmental exposure cannot fully reveal the disparity in such exposure. Kwan (2012) articulated the uncertain geographic context problem (UGCoP), which indicates that people in the same neighborhood could be exposed to different spatial contexts. Despite shared residence-based exposure, people's divergent daily mobility patterns yield varying activity-space-based exposure (Kwan 2018a). Compared to residence-based exposure, Kwan (2018b) found that activity-space-based exposure might converge toward the average exposure of the whole population, encapsulated as the neighborhood effect averaging problem (NEAP). Kim and Kwan (2021) further revealed that for individuals with low residence-based exposure but high daily mobility, their activity-space-based exposure tends to average upward, whereas low-mobility individuals might suffer double inequality (i.e., they experience little downward averaging even if they are exposed to high levels of environmental risk). For example, a person who lives in a neighborhood with poor air quality and conducts daily activities (work, leisure) in the surrounding areas of the neighborhood suffers from double inequality: poor air quality in both residential space and activity space.

Whereas the residence-based disparity in BEQ exposure has been studied, the activity-space-based disparity has been overlooked (Zhang et al. 2018;

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R. Wang et al. 2019; Larkin et al. 2021; Z. Wang, Ito, and Biljecki 2024). Moreover, past studies show considerable disagreement on the role of daily mobility. The NEAP indicates that high daily mobility alleviates environmental inequality by upward and downward averaging. In contrast, B. Wang et al. (2021) and J. Wu et al. (2023) proposed the neighborhood effect polarization problem (NEPP), which describes a phenomenon that the overall trend of activity-space-based exposure is more polarized than residence-based exposure. The NEPP indicates that high mobility cannot alleviate but even intensifies environmental inequality. Although the NEPP might suggest a meaningful phenomenon, the two NEPP empirical studies seem to have some methodological limitations. In fact, the NEAP is grounded in the spatial distribution of the whole city, where the participants' residential environments vary considerably. The observation of the NEPP is largely the result of using data collected from only one subdistrict in the entire study area (where participants' residence-based environments are very similar, whereas their mobility-based exposures vary considerably due to their daily activities and travel in the entire study area). The presence of the NEAP and NEPP in varied environmental exposures and contexts thus warrants further investigation. Further, the complex interplay among residence-based exposure, activity-space-based exposure, daily mobility patterns, and socioeconomic factors (e.g., income) has not been estimated (J. Wang et al. 2024). Income could influence people's residential location choices (Alonso 1962; Mills 1967; Muth 1969), which consequently influence residence-based exposure. Income could also influence people's daily mobility patterns (Morency et al. 2011; Moro et al. 2021) and hence result in varying activity-space-based exposure.

These knowledge gaps impede us from fully understanding the intricate interactions between BEQ exposure and spatial outcomes, as well as from designing a more inclusive urban environment. Thus, it is necessary to consider how individuals experience varying BEQ in both their residences and activity spaces. It is never an easy task, though. On the one hand, the lack of auditing methods for large-scale applications limits us from identifying spatial disparity in BEQ exposure. Traditional audits of BEQ rely on field surveys, which are difficult to conduct at a large spatial scale (Jackson 2003; Z. Huang and Du 2015). Fortunately, emerging solutions using street-view images (SVIs) and deep learning algorithms provide alternatives. Salesses, Schechtner, and Hidalgo (2013) pitched that differences in BEQ are usually conspicuous as the beauty, safety, and liveliness of the built environment are visible. Therefore, SVIs can largely capture disparity in BEQ exposure. Porzi et al. (2015) and Dubey et al. (2016) proposed that convolutional neural networks (CNNs) can be employed to rate SVIs, thereby assessing BEQ. Zhang et al. (2018) and Z. Wang, Ito, and Biljecki (2024) applied similar methodologies to assess BEQ in the aspects of beauty, safety, liveliness, and so on, indicating large-scale application potential. On the other hand, the activity-space-based approach requires individual-level daily activity data, which can capture a wide range of daily mobility levels. Although some studies have used portable Global Positioning System (GPS) devices, mobile sensors, and travel diaries to record the daily activity locations of small samples of participants (Song and Kwan 2023; Yu and Kwan 2024), it is a challenge to conduct such data collection at a large spatial scale. Mobile phone signaling data provide an alternative for analyzing individuals' daily activities, and many studies have demonstrated the feasibility of using mobile phone signaling data to identify the locations of daily activity space (Rao and Minakakis 2003).

This article aimed to examine the NEAP in BEQ exposure, thereby enhancing our understanding of activity-space-based disparity and the underlying mechanisms. First, more than 1 million SVIs in Guangzhou (China) were collected to assess the BEQ of the whole city. Second, mobile phone signaling data were used to identify 1.66 million individuals' daily activity locations and daily mobility patterns. Third, BEQ in people's residential space (BEQ-RS) and BEQ in people's daily activity space (BEQ-AS) were measured. Finally, BEQ-RS and BEQ-AS were compared to assess the NEAP phenomenon, and a conditional process analysis model was employed to estimate the complex interplay among the BEQ-RS, BEQ-AS, daily mobility, and income.

Theoretical Framework

With the Chinese housing market reform, housing prices have dramatically increased in the megacities in China since the 1990s (Chen, Guo, and Wu

2011). Disparity in housing affordability has led to a significant disparity in residence-based exposure. Low-income groups mostly have few choices but to live in informal housing (e.g., urban villages, indemnificatory housing), whereas high-income groups live in commercial housing and gated communities (Liu et al. 2010; Li and Wu 2013). Due to imbalances in economic development and accumulation (Soja 2013; Harvey 2017, 2018), commercial housing neighborhoods have better BEQ and informal housing neighborhoods have inferior ones. Therefore, we infer that income might be a significant factor influencing BEQ-RS.

Although having identical BEQ-RS, people's divergent daily mobility patterns yield varying BEQ-AS (Kwan 2018a). The NEAP suggests that people's daily mobility patterns are also crucial factors influencing their BEQ exposure (Kwan 2018b). Moreover, according to the Alonso–Mills–Muth (AMM) model (Alonso 1962; Mills 1967; Muth 1969), people seek to balance housing costs and daily mobility costs to maximize their utility. For example, Chiarazzo et al. (2014), based on empirical findings from Taranto (Italy), found that environmental quality would increase housing price. People are willing to sacrifice the environmental quality of their residential space (lower housing price), however, for better opportunities to travel into the central business district (higher environmental quality). Therefore, people's income can influence their BEQ-AS by altering their BEQ-RS, and it can also interact with people's daily mobility to influence their BEQ-AS. In addition, some studies support that mobility patterns differ across age and gender groups, which could consequently influence the environmental quality of the activity spaces of people in these groups. As people age, their physical abilities deteriorate, resulting in a reduction in their activity space radius (Morency et al. 2011). Therefore, the elderly who live in poor environmental quality neighborhoods are more likely to face a double disadvantage. Whereas females tend to devote more time to daily household-related travels (e.g., shopping and chauffeuring children to school), their work commutes are shorter (Fan 2017). This could result in females' daily activities being largely centered on their residential surroundings, making it difficult for them to avoid the environmental risks associated with their residential neighborhoods.

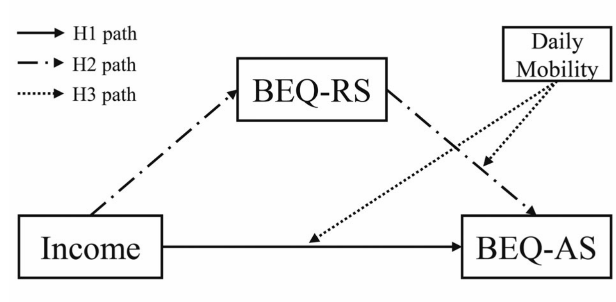

Figure 1. A theoretical framework for explaining how income, built-environment quality of residential space (BEQ-RS), and daily mobility influence built-environment quality of activity space (BEQ-AS).

Based on the preceding analysis, a theoretical framework was proposed for examining the NEAP phenomenon in people's BEQ exposure, by exploring the complex interplay among BEQ-RS, BEQ-AS, daily mobility, and income (Figure 1). It has three hypotheses: Income can influence BEQ-AS (H1), the effect of income on BEQ-AS is mediated by BEQ-RS (H2), and daily mobility can moderate the paths of H1 and H2 (H3). If both H1 and H2 hold, a consistent relationship between BEQ exposure and income can be observed. Furthermore, if H3 also holds, the existence of the NEAP in BEQ exposure across different income groups can be observed. Although the NEAP is an individual-level phenomenon, if H1, H2, and H3 hold, it should also manifest as a derived phenomenon associated with income groups.

The conditional process analysis model, also known as the moderated mediation model, is well suited to implement this framework (Hayes and Rockwood 2020). Specifically, the total effect of income on BEQ-AS can be decomposed into a direct effect and an indirect effect in the conditional process analysis model. BEQ-RS plays a mediation role. The direct and indirect effects are both moderated by daily mobility. Additionally, gender and age should be included as confounders to control for their potential influence on the variations in people's daily activity patterns.

Study Area, Data Set, and Measurements

To examine the NEAP phenomenon in BEQ exposure, 1,655,834 users' mobile phone signaling data and 1,005,180 SVI data in Guangzhou were collected. Figure 2 provides a visual interpretation of the

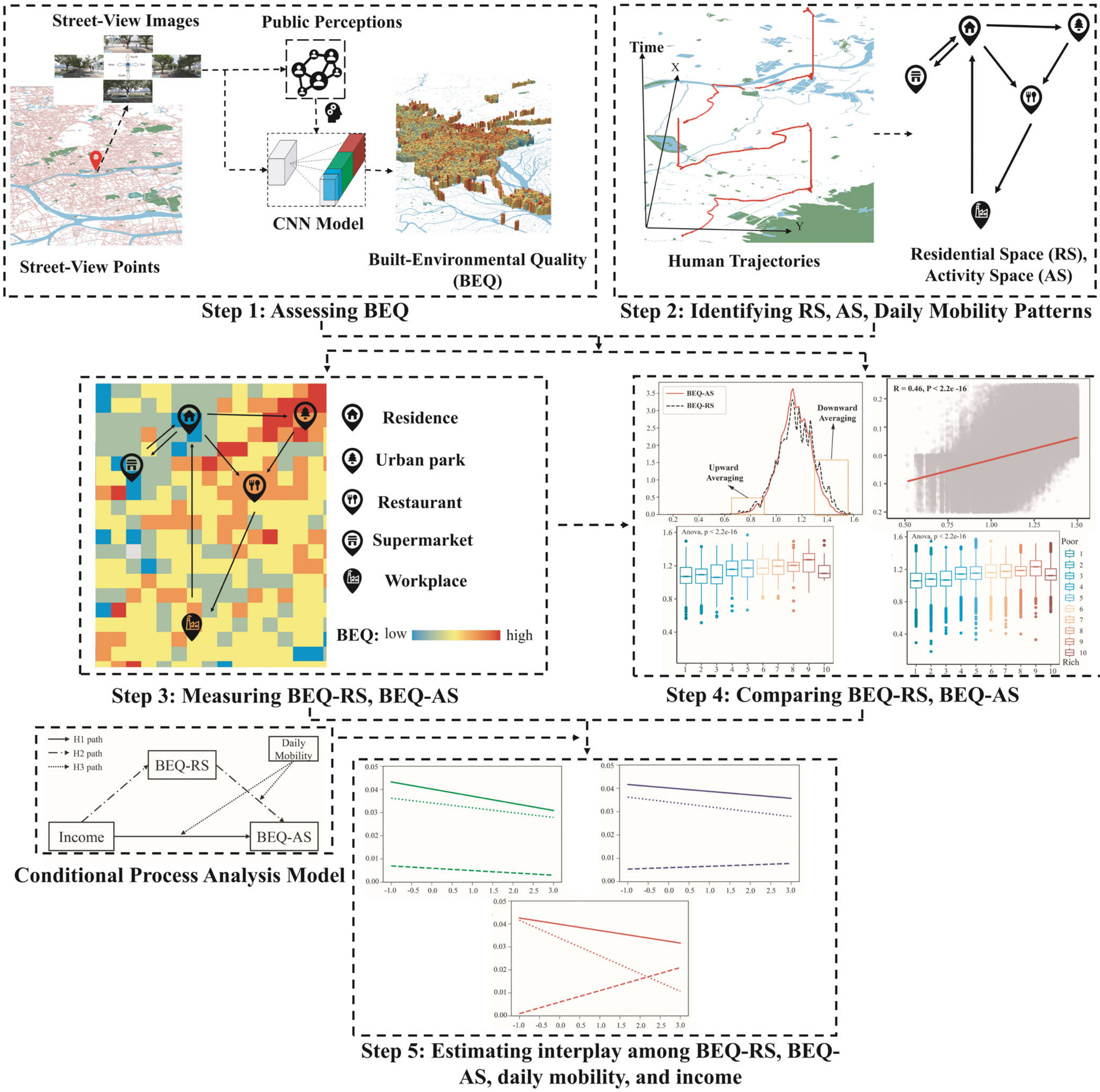

Figure 2. Outline of technical flow. *Note:* CNN = convolutional neural network.

technical flow outline. In Step 1, SVI data and CNN techniques were used to assess BEQ. In Step 2, human trajectories were derived from mobile phone signaling data and used to identify RS, AS, and daily mobility patterns. In Step 3, BEQ-RS and BEQ-AS were measured. In Step 4, BEQ-RS and BEQ-AS were compared. In Step 5, a conditional process analysis model was used to investigate the interplay among BEQ-RS, BEQ-AS, daily mobility, and income.

Study Area

This study was conducted in Guangzhou, the capital city of Guangdong Province, one of China's megacities (Figure 3). According to census data from the Guangzhou Statistics Bureau, it has a resident population of 18.7 million and an urbanization rate of over 85 percent. To integrate the data from multiple sources, Guangzhou was divided into $500 \times 500\,\mathrm{m}^2$

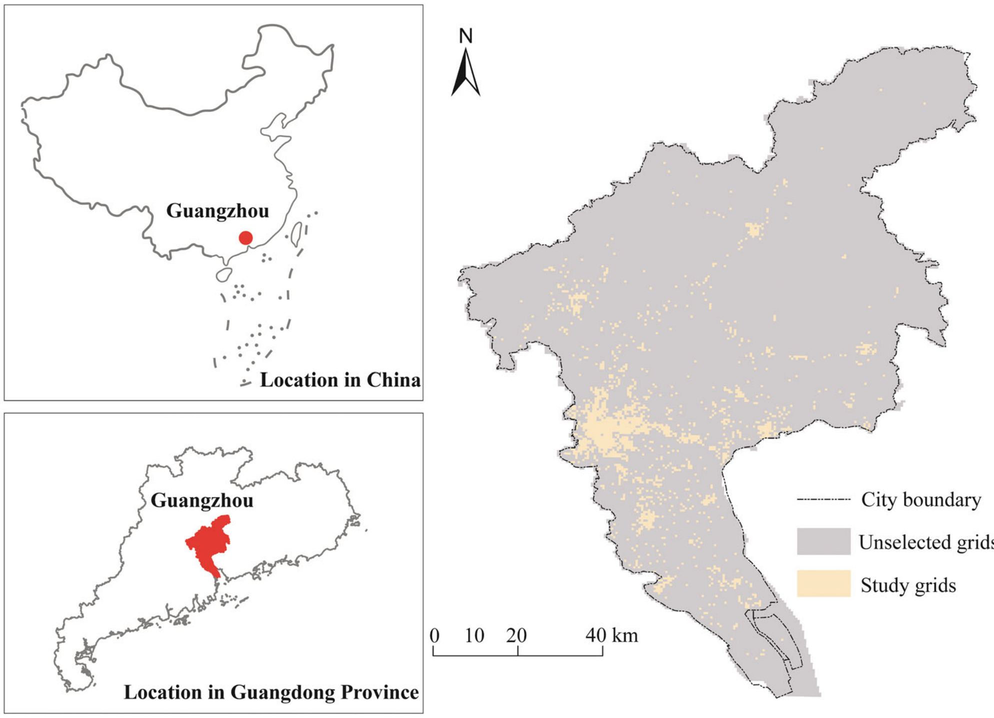

Figure 3. Location of Guangzhou in Guangdong, China, and study grids.

grid cells, maintaining a consistent spatial scale at the neighborhood level (Khodakarami et al. 2023). There are 30,308 grids in total, and 6,813 grids in the built-up area in Guangzhou were selected as the study area. It includes the central district of Guangzhou and the surrounding satellite areas.

Data Set

Our data set includes mobile phone signaling data, SVI data, public rating data on BEQ, and housing rent data. The mobile phone signaling data were provided by a local mobile phone operator. The data consist of personal information (gender, age), coordinates of activity locations, and staying time at each location in October 2020 (thirty-one-days) in Guangzhou. The data have undergone a cleaning and anonymization process to ensure privacy and confidentiality. The subsequent data analysis was performed exclusively on a secure platform that allows for basic spatial and statistical analysis while restricting direct viewing of users' age, gender, and geographic coordinates of residential and activity spaces. Users staying in the study area over ten-days were selected, and there are 1,655,834 valid users in total. There are nearly 17 million daily activity locations. The age levels 1 through 12 indicate ages eighteen and below, nineteen through twenty-four, twenty-five through twenty-nine, thirty through thirty-four, thirty-five through thirty-nine, forty through forty-four, forty-five through forty-nine, fifty through fifty-four, fifty-five through fifty-nine, sixty to sixty-four, sixty-five through sixty-nine, and over sixty-nine, respectively. A dummy variable was also processed for the gender field: 0 for females and 1 for males. Referring to previous studies measuring the economic level of mobile phone users (Moro et al. 2021; Xu et al. 2018, 2019), housing rent data were spatially matched to the users' residences, and the rent of the grids where the users live was used as an approximate measure of their income level.

SVI data have been widely used to extract neighborhood environmental characteristics, assess the built-environment quality, and investigate their relationship with health outcomes (Porzi et al. 2015; Q. C. Nguyen et al. 2018; R. Wang et al. 2019; T. T. Nguyen et al. 2021; Chen et al. 2023). SVI data used in this study were collected via the public application programming interface (API) of Baidu Map in 2020. Street-view points were extracted from the road networks of Guangzhou (every 50 m marks a street-view point), and these points were used to obtain 1,005,180 SVIs in the built-up areas. A street-view point is associated with four SVIs in four directions (i.e., north, east, south, and west), and a grid cell has 147.5 SVIs on average.

Public rating data on BEQ were collected by an online survey. Through a self-developed online platform, 2,791 volunteers from all over China participated in rating the collected SVIs. Each participant was asked to make a binary choice to select a preferred one from a pair of SVIs. Any pair of SVIs is randomly selected from the pool of total images. Each of the four dimensions of beauty, liveliness, safety, and uncleanliness was rated by participants. In other words, the participants were asked to answer the following four questions (in Chinese): Between these two images, which one displays the more beautiful scene? Which one has more liveliness? Which one conveys a safer scene? Which one appears more cluttered or messy? A total of 50,170 valid votes were collected, covering 8,602 SVIs. Of those, 7,587 images received at least three votes, and the votes were converted into scores for each SVI by the "strength of schedule" method (Park and Newman 2005). The scores ranged from 0 to 1, where a score closer to 1 means more beautiful, livelier, safer, and less clean, and a score closer to 0 denotes the opposite meaning.

The 2020 Guangzhou Housing Rent Reference Price, published by the Guangzhou Municipal Bureau of Housing and Urban-Rural Development, provides information on housing rents for neighborhoods in the built-up areas of Guangzhou. The mean value of the rents of neighborhoods in each grid was used to represent the rent level of that grid. The Jenks natural break method (Jenks 1967) was used to divide the rents into ten levels. Levels 1 through 10 indicate the monthly housing rent of 2 to 9, 10 to 14, 15to 22, 23 to 31, 32 to 39, 40 to 47, 48 to 55, 56 to 67, 68 to 84, and 85 to 105 CNY per square meter, respectively.

Measurements

Assessment of BEQ. Based on the works of Porzi et al. (2015), Salesses, Schechtner, and Hidalgo (2013), and L. Wang et al. (2022), SVI data and CNN techniques were used to assess BEQ in aspects of beauty, liveliness, safety, and uncleanliness. The four variables were selected based on the four spatial functional perspectives of physicality, economy, social security, and social governance. Beauty reflects the physical design of the built environment, corresponding to the city beautiful movement (Wilson 1964). Liveliness reflects the economic function of built environment (W. Wu et al. 2016). Safety reflects the social security function of built environment, corresponding to "eyes on the street" (Jacobs 1961). Uncleanliness reflects the social governance function of built environment, based on the Chinese national civilized cities movement. The first three variables (i.e., beauty, liveliness, and safety) were derived from the MIT Place Pulse 2.0 data set (see https://paperswithcode.com/dataset/place-pulse −2–0; Dubey et al. 2016). We proposed the last variable based on the distinctive context of city governance in China, aiming to evaluate the performance of the national civilized cities movement. Through the image convolution operation, a deep-structured feedforward neural network is built to recognize the graphic features of each SVI. Thus, connections between the indexes of BEQ and the graphic features of the SVI are constructed. This study fine-tuned Inception v3 (Szegedy et al. 2016) in the framework of Keras = 2.10.0. The input layer of the model is $512 \times 512 \times 3$-pixel SVIs; the output layer consists of four dimensions (i.e., beauty, liveliness, safety, and uncleanliness). The training and test data set ratio was 0.8:0.2. The overall root mean square error of the model in the test data set is 0.0855. The mean scores of multiple SVIs were computed and normalized for each grid. The loss function (objective function) used is the Huber Loss, with the specific formula as follows:

$$Loss = Huber_{beauty} + Huber_{liveliness} + Huber_{safety} + Huber_{uncleanliness} \tag{1}$$

$$Huber = \begin{cases} 0.5 \times (y - f(x))^2, if \ |y - f(x)| < 0 \\ |y - f(x)| - 0.5, \ otherwise \end{cases} \tag{2}$$

where $Huber_{beauty}$, $Huber_{liveliness}$, $Huber_{safety}$, and $Huber\ _{uncleanliness}$ correspond to the Huber functions of the four output dimensions, respectively. y represents the true label value, and $f(x)$ represents the predicted value from the model. In this study, the RMSprop algorithm was used to optimize the gradient of the Loss function to iteratively update the model's weights. See Supplemental Material A for the model-specific settings and training process.

Measurements of BEQ-AS and BEQ-RS. Each mobile phone user's BEQ-AS was calculated using a time-weighted exposure approach (Lu et al. 2021). A compensatory formulation was used to aggregate the four dimensions. Beauty, safety, and liveliness are positive dimensions, and uncleanliness is a negative dimension. The specific formula is as follows:

$$\text{BEQ-AS} = \sum_{\mathrm{i}} \frac{\mathrm{beauty_i} \times \mathrm{t_i}}{T} + \sum_{\mathrm{i}} \frac{\mathrm{liveliness_i} \times \mathrm{t_i}}{T} + \sum_{\mathrm{i}} \frac{\mathrm{safety_i} \times \mathrm{t_i}}{T} - \sum_{\mathrm{i}} \frac{\mathrm{uncleanliness_i} \times \mathrm{t_i}}{\mathrm{T}} \tag{3}$$

$$\text{BEQ-RS} = \mathrm{residence_{beauty}} + \mathrm{residence_{liveliness}} + \mathrm{residence_{safety}} - \mathrm{residence_{uncleanliness}} \tag{4}$$

For Equation 3, $beauty_i$ is the beauty-dimensional score of BEQ at activity location i, and notations are similar for $liveliness_i$, $safety_i$, and $uncleanliness_i$. t_i is the staying time at activity location i, T denotes the total time spent in Guangzhou in October 2020. For Equation 4, $residence_{beauty}$, $residence_{liveliness}$, $residence_{safety}$, and $residence_{uncleanliness}$ are the beauty-, liveliness-, safety-, and uncleanliness-dimensional scores of BEQ in residential space. Note that a multiplicative equivalence method has also been employed for data aggregation. We have found a high degree of correlation between the variables obtained from the two aggregation methods, and their correlations with other study variables are also largely analogous, as detailed in Supplemental Material B.

Measurements of Daily Mobility Patterns. Daily mobility patterns in this article were simplified as intracity mobility degrees. Mobility across cities was not considered. According to previous literature (Yoo et al. 2021), mobility is primarily associated with three variables: activity distance away from home (AD), the number of activity locations (NA), and the activity of time spent outside the home (AT). Therefore, this article calculated AD per day, NA per month, and AT per day to represent three dimensions of mobility degrees.

The Conditional Process Analysis Model. The process is carried out as follows: First, Equation 5 is developed to examine the effect of income on BEQ-AS (H1). Second, Equations 6 and 7 are developed to assess whether the path of H1 is mediated by BEQ-RS (H2), and whether the paths of H1 and H2 are moderated by mobility (H3).

$$\text{BEQ-AS} = \mathrm{c_1} \times \mathrm{income_{level}} + \mathrm{c_2} \times \mathrm{age} + \mathrm{c_3} \times \mathrm{gender} + \mathrm{c_0} + \mathrm{e_1} \tag{5}$$

$$\text{BEQ-RS} = \mathrm{a_1} \times \mathrm{income_{level}} + \mathrm{a_2} \times \mathrm{age} + \mathrm{a_3} \times \mathrm{gender} + \mathrm{a_0} + \mathrm{e_2} \tag{6}$$

$$\text{BEQ-AS} = \mathrm{c_1'} \times \mathrm{income_{level}} + \mathrm{c_2'} \times \mathrm{age} + \mathrm{c_3'} \times \mathrm{gender} + \mathrm{b_1} \times \text{BEQ-RS} + \mathrm{b_2} \times \mathrm{mobility} + \mathrm{b_3} \times \mathrm{income_{level}} \times \mathrm{mobility} + \mathrm{b_4} \times \text{BEQ-RS} \times \mathrm{mobility} + \mathrm{c_0'} + \mathrm{e_3} \tag{7}$$

where $income_{level}$, *age*, *gender*, and *mobility* refer to an individual's income level, age, gender, and mobility (represented by AD, NA, and AT), respectively. To test the significance of the mediated process, it is necessary to show that the regression coefficient $a_1 \times b_1$ is significant or that both a_1 and b_1 are significant (Wen and Ye 2014). To examine whether the hypothesized mediated process is moderated, it is necessary to show that there is a significant difference in the mediating effect when the moderating variable values are high and low, or the index of moderated mediation (IMM, $a_1 \times b_4$) is significant (Hayes 2015). The methods to test this model include the stepwise method, the Sobel method, and the bootstrap method. The bootstrap method has the highest level of statistical rigor and robustness, according to previous literature (MacKinnon, Lockwood, and Williams 2004). In this article, the stepwise method was initially employed to test the model. Subsequently, the bootstrap method was used for robustness and sensitivity analysis, employing a pull-back sampling approach with 10,000 times. A 95 percent bias-corrected confidence band was established, and if the confidence band does not include 0, the significance test is considered successful. The model estimation was conducted using the PROCESS V3.3 developed by Hayes (2022).

Results

Disparities in BEQ-RS and BEQ-AS Across Income Groups

In this subsection, the BEQ-RS and BEQ-AS were compared across income groups. We preliminarily analyze whether income influences BEQ-RS and BEQ-AS, and whether daily mobility can alleviate the effect. As shown in Figure 4, disparities in BEQ-RS and BEQ-AS across income groups are both significant (analysis of variance test, $p < 0.01$). Particularly, people's BEQ-RS and BEQ-AS increase with their income levels, suggesting that people with higher income levels are exposed to better BEQ. Moreover, the disparity in BEQ-RS across income groups is much greater than that in BEQ-AS. We infer that daily mobility might give people more opportunities to access diverse activity spaces. As a result, poor groups could experience better BEQ-AS, whereas rich groups could also encounter poorer BEQ-AS.

This finding is largely consistent across the four dimensions of BEQ. The disparity in BEQ-AS sees an obvious reduction compared to that in BEQ-RS. Specifically, Figure 5 shows that high-income groups (income levels 8, 9, and 10) have the highest BEQ-RS and BEQ-AS in the dimensions of beauty and the lowest BEQ-RS and BEQ-AS in the dimension of uncleanliness. The BEQ-RS and BEQ-AS of high-income groups are not the highest in the dimensions of liveliness and safety, however, especially lower in BEQ-RS (Figure 5A). We inferred that high-income groups tend to live in neighborhoods that are beautiful and clean, yet quiet and less crowded. For middle-income groups (income levels 4, 5, 6, and 7), their BEQ-RS and BEQ-AS are similar to those of high-income groups and even exceed those of high-income groups in the dimensions of liveliness and safety. Low-income groups (income levels 1, 2, and 3) suffer from the lowest BEQ-RS and BEQ-AS and are far below other groups in all dimensions. Compared to the disparity in BEQ-RS, though, the disparity in BEQ-AS is reduced. Therefore, our results indicate that the NEAP is related to income groups.

It is worth noting that daily mobility does not just benefit low-income groups; the BEQ-RS of high-income groups is lower in the dimensions of liveliness and safety, but their BEQ-AS averages upward. Moreover, although daily mobility can alleviate the disparity in the four dimensions of BEQ, it cannot reverse the order of that (i.e., the BEQ-AS of the poor groups is always lower than that of the rich groups in all dimensions).

Comparisons of Individuals' BEQ-RS and BEQ-AS

J. Huang and Kwan (2022) proposed three methods for identifying the NEAP by comparing individuals' BEQ-AS and BEQ-RS. The methods consist of probability density function (PDF) comparison,

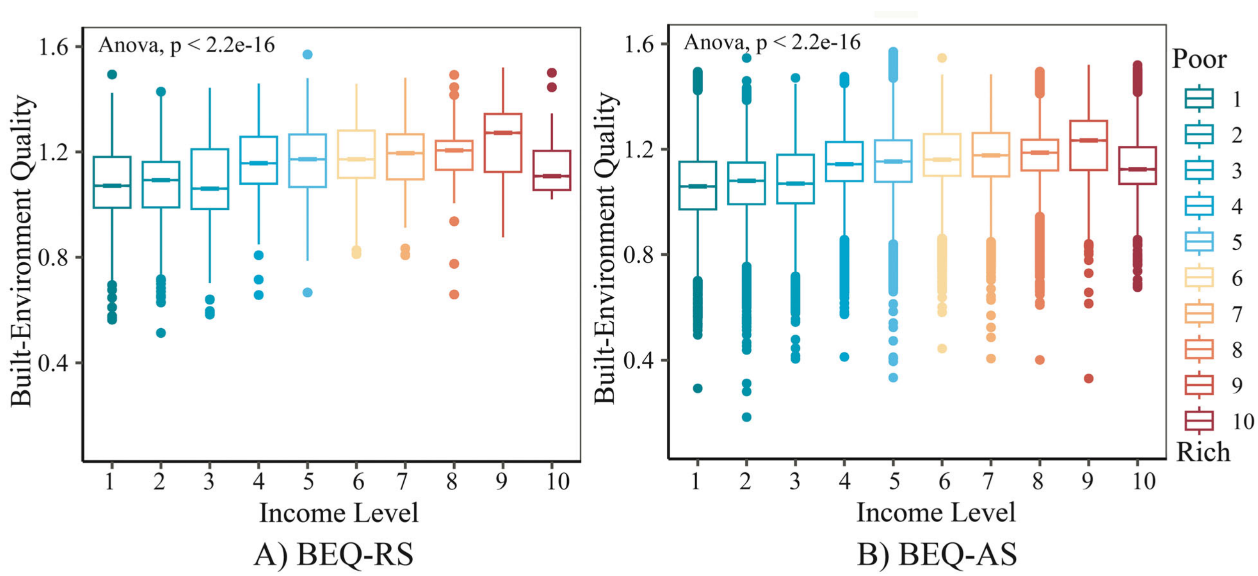

Figure 4. Disparities in built-environment quality of residential space (BEQ-RS) and built-environment quality of activity space (BEQ-AS) across income groups. *Note:* ANOVA = analysis of variance.

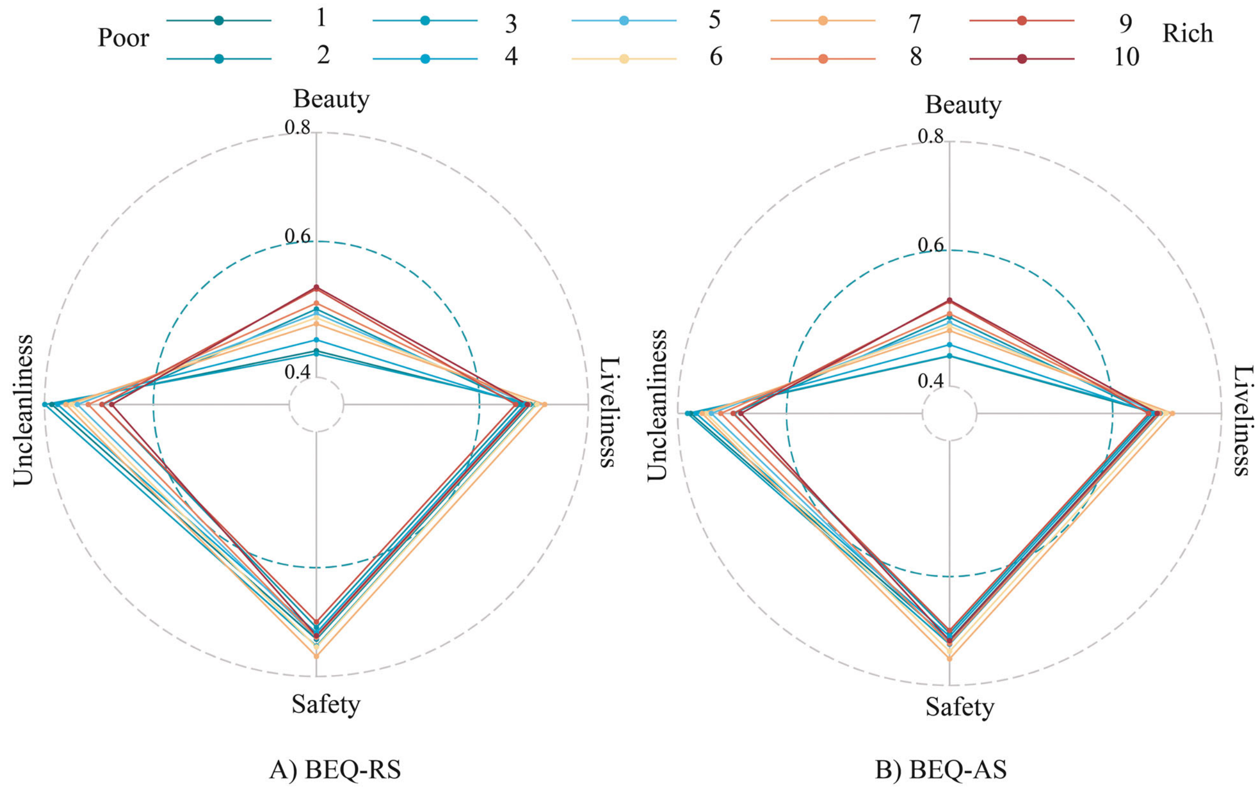

Figure 5. Differences in the mean of built-environment quality of residential space (BEQ-RS) and built-environment quality of activity space (BEQ-AS; four dimensions) across income groups.

paired-sample t tests of BEQ-AS and BEQ-RS, and correlation analysis of BEQ-RS and the difference between BEQ-RS and BEQ-AS. As shown in Figure 6A, the PDF of BEQ-AS is less deviated than that of BEQ-RS. Table 1 shows that the pairwise difference (0.01) is significant at the 99 percent confidence level, and the standard deviation of BEQ-RS (0.143) is greater than that of BEQ-AS (0.126). Furthermore, Figure 6B presents a positive and significant correlation ($p < 0.01$) between BEQ-RS and the difference between BEQ-RS and BEQ-AS ($r = 0.46$), indicating that individuals with higher BEQ-RS have relatively lower BEQ-AS and vice versa.

Our results indicate that, after considering daily mobility, the BEQ experienced by individuals tends to converge. This finding is consistent across the three methods of identifying the NEAP. Our research strongly supports the existence of the NEAP in BEQ exposure, whereas the NEPP is not evident. Moreover, it has been shown that the extent of downward averaging is greater than that of upward averaging, indicating that the NEAP influences the BEQ-AS of different groups in different ways.

Interplay Among BEQ-RS, BEQ-AS, Daily Mobility, and Income

The preceding results indicate that there are significant disparities in both BEQ-RS and BEQ-AS across income groups. Moreover, the NEAP occurs in BEQ exposure, meaning that daily mobility seems to alleviate the disparities. This subsection focuses on verifying the paths of the theoretical framework. Table 2 presents correlations between study variables. There is a significant and positive correlation between income level and BEQ-AS ($r = 0.299$), as is the correlation between income level and BEQ-RS ($r = 0.276$) and the correlation between BEQ-RS and BEQ-AS ($r = 0.918$). These correlations are consistent with the hypotheses and expectations of the theoretical framework.

Table 3 presents the results of the conditional process analysis model. The regression result of Model 1 indicates that the effect of income on BEQ-AS is still significant after controlling for age and gender, $c_1 = 0.316$, $p < 0.01$, retaining H1. The regression result of Model 2 shows that income significantly predicts BEQ-RS, $a_1 = 0.297$, $p < 0.01$. The regression results of Models 3, 4, and 5 provide evidence that BEQ-RS has a significant and consistent

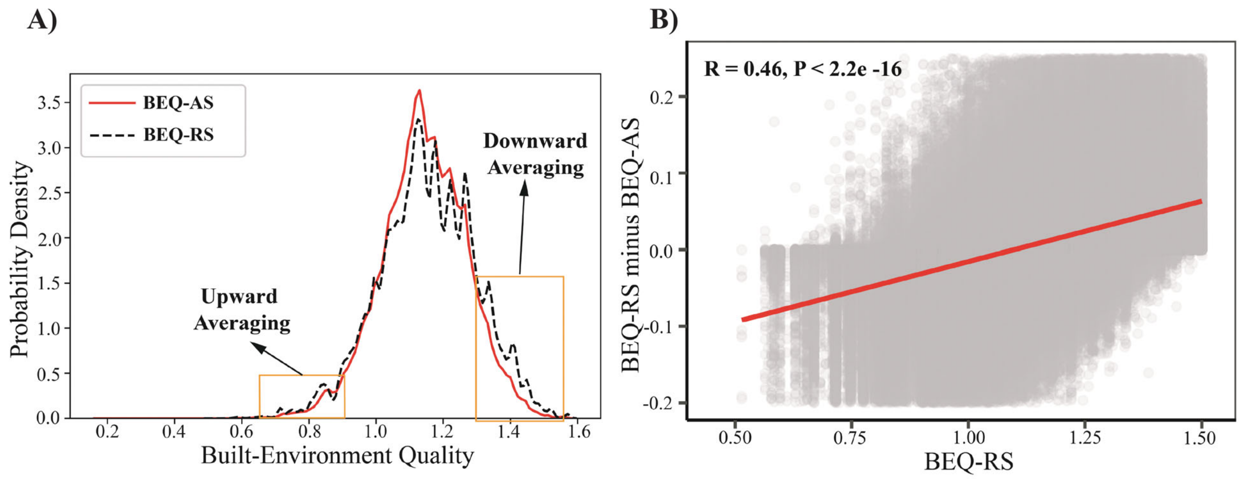

Figure 6. Two methods for identifying the neighborhood effect averaging problem. (A) Probability density function. (B) Correlation analysis of built-environment quality of residential space (BEQ-RS) and the difference between BEQ-RS and built-environment quality of activity space (BEQ-AS).

Table 1. Descriptive statistics of built-environment quality of residential space (BEQ-RS) and built-environment quality of activity space (BEQ-AS)

	M	*SD*
BEQ-RS	1.153	0.143
BEQ-AS	1.143	0.126
Difference	0.010***	—

***$p < 0.01$.

effect on BEQ-AS, $b_1 = 0.115$ (Model 3), $b_1 = 0.115$ (Model 4), and $b_1 = 0.114$ (Model 5), with p values all less than 0.01. In addition, $c'_1 = 0.006$ (Model 3), $c'_1 = 0.006$ (Model 4), and $c'_1 = 0.006$ (Model 5), with p values all less than 0.01. a_1, b_1, and c'_1 are all significant and consistent in Models 3, 4, and 5; thus BEQ-RS plays a partly mediating role in the effect of income on BEQ-AS, retaining H2.

The interaction between income and mobility in Models 3, 4, and 5 is significant, and the interaction between BEQ-RS and mobility can also significantly predict BEQ-AS: $b_3 = -0.001$ (Model 3), $b_3 = 0.001$ (Model 4), and $b_3 = 0.005$ (Model 5), with all p values less than 0.05; $b_4 = -0.007$ (Model 3), $b_4 = -0.007$ (Model 4), $b_4 = -0.026$ (Model 5), with all p values less than 0.01. These results suggest that, regardless of the specific measurements employed to represent mobility, the indirect effect of income on BEQ-AS is negatively moderated by mobility. The direct effect of income on BEQ-AS, however, is influenced in different directions depending on the measurements of mobility, and thus H3 is partially retained.

To conduct a sensitivity analysis, the bootstrap method was used to compare the effect of income on BEQ-AS, when mobility is high and low. In the conditional process analysis model, one standard deviation above and below the mean is usually considered the high value and the low value, respectively. Thus, the moderated mediation effect can be evaluated by comparing the difference between the mediating effects when the moderating variable values are one standard deviation above and below the mean (Edwards and Lambert 2007). Moreover, the moderating variable must be centered to ensure accuracy (i.e., the mean should be converted to 0). In this article, the Z-score method was used to centralize mobility variables. As a result, in the converted mobility variables, 0 equals the mean, 1 equals one standard deviation above the mean, and −1 equals one standard deviation below the mean.

As shown in Table 4, when converted mobility is 1, the indirect effect of income on BEQ-AS is 0.0360, 0.0360, and 0.0414, corresponding to mobility represented by AD, NA, and AT. When converted mobility is −1, the indirect effect is 0.0320, 0.0320, and 0.0263, respectively; and the difference is −0.0040, −0.0040, and −0.0152, respectively. The bootstrap confidence band of the difference is [–0.0041, −0.0039], [–0.0041, −0.0039], and [–0.0153, −0.0151], respectively. The confidence band consistently does not contain 0, no matter what mobility measurement is used. This indicates that the effects of income on BEQ-AS under the two scenarios are significantly different. Thus, the higher the daily

Table 2. Descriptive statistics and correlation analysis of study variables

		Income	BEQ-RS	BEQ-AS	Mobility			Age	Gender
					AD	NA	AT		
Income		1.000	—	—	—	—	—	—	—
BEQ-RS		0.276***	1.000	—	—	—	—	—	—
BEQ-AS		0.299***	0.918***	1.000	—	—	—	—	—
Mobility	AD	−0.115**	−0.033***	−0.068***	1.000	—	—	—	—
	NA	−0.016**	0.009*	−0.017***	0.738***	1.000	—	—	—
	AT	−0.015**	0.007**	−0.058***	0.310***	0.340***	1.000	—	—
Age		0.035***	0.049**	0.0518**	−0.041***	−0.011***	−0.062***	1.000	—
Gender		−0.038*	−0.023*	−0.036**	0.058**	0.074**	0.019**	−0.022**	1.000
M		5.023	1.153	1.143	3532	11.320	316	3.860	0.610
SD		2.070	0.143	0.126	3462	8.114	214	2.488	0.488

Note: The sample number (*N*) is 1,655,834 and the correlation coefficients refer to Pearson correlation. BEQ-RS = built-environment quality of residential space; BEQ-AS = built-environment quality of activity space; AD = distance away from home; NA = number of activity locations; AT = activity of time spent outside the home.
$^{*}p < 0.1$.
$^{**}p < 0.05$.
$^{***}p < 0.01$.

Table 3. Result summary of conditional process analysis model

	Model 1	Model 2	Model 3	Model 4	Model 5
Income	0.316***(c_1)	0.297***(a_1)	0.006***(c'_1)	0.006***(c'_1)	0.006***(c'_1)
BEQ-RS	—	—	0.115***(b_1)	0.115***(b_1)	0.114***(b_1)
Mobility	—	—	−0.005**(b_2)	−0.003**(b_2)	−0.009**(b_2)
Mobility × Income	—	—	−0.001*(b_3)	0.001***(b_3)	0.005**(b_3)
Mobility × BEQ-RS	—	—	−0.007***(b_4)	−0.007***(b_4)	−0.026***(b_4)
Age	0.047***(c_2)	0.017***(a_2)	< 0.001**(c'_2)	< 0.001**(c'_2)	< 0.001**(c'_2)
Gender	−0.024**(c_3)	−0.026**(a_3)	−0.003***(c'_3)	−0.003***(c'_3)	−0.003***(c'_3)
R^2	0.104	0.092	0.857	0.855	0.894

Note: Model 1 corresponds to Equation 5, Model 2 corresponds to Equation 6, and Models 3, 4, and 5 correspond to Equation 7, but mobility is denoted by distance away from home (AD), number of activity locations (NA), and activity of time spent outside the home (AT), respectively. To ensure the accuracy of the conditional process analysis model, variables with interaction terms (i.e., the income level, built-environment quality of residential space [BEQ-RS], mobility) have been centralized and standardized by Z-score method.
$^{*}p < 0.1$.
$^{**}p < 0.05$.
$^{***}p < 0.01$.

mobility degree, the weaker the indirect effect of income on BEQ-AS. In addition, the IMM is −0.0019, −0.0020, and −0.0076, respectively. The bootstrap confidence band of IMM also consistently excludes 0. Therefore, our results are robust.

The Extent to Which Daily Mobility Influences the Effect of Income on BEQ-AS

This subsection focuses on estimating the extent to which daily mobility influences the effect of income on BEQ-AS. Variations in the direct effect, the indirect effect, and the total effect of income on BEQ-AS under different mobility degrees were compared. Figure 7 illustrates that as mobility increases, there is a consistent and significant decrease in the indirect effect and total effect of income on BEQ-AS, whereas variation in the direct effect depends on the measurement of mobility. Compared to mobility at the mean level, a one-standard-deviation increase in AD (i.e., an increase in activity distance away from home by 3.5 km per day) leads to a 6.1 percent reduction in the indirect effect, a 7.7 percent reduction in the total effect, and a 16.7 percent reduction in the direct effect. Similarly, a one-standard-deviation increase in NA (i.e., an increase in the number of activity locations by 8.1 per month)

Table 4. The bootstrap test result of the conditional process analysis model

Converted mobility		Indirect effect	Bootstrap *SE*	Bootstrap LLCI	Bootstrap ULCI
Mobility-AD	−1 (M − *SD*)	0.0360	0.0001	0.0358	0.0362
	0 (M)	0.0340	0.0001	0.0338	0.0342
	1 (M + *SD*)	0.0320	0.0001	0.0319	0.0323
	Difference	−0.0040	0.0000	−0.0041	−0.0039
	IMM	−0.0019	0.0000	−0.0020	−0.0019
Mobility-NA	−1 (M − *SD*)	0.0360	0.0001	0.0358	0.0362
	0 (M)	0.0340	0.0001	0.0338	0.0342
	1 (M + *SD*)	0.0320	0.0001	0.0319	0.0322
	Difference	−0.0040	0.0000	−0.0041	−0.0039
	IMM	−0.0020	0.0000	−0.0020	−0.0020
Mobility-AT	−1 (M − *SD*)	0.0414	0.0001	0.0412	0.0417
	0 (M)	0.0339	0.0001	0.0337	0.0340
	1 (M + *SD*)	0.0263	0.0001	0.0261	0.0264
	Difference	−0.0152	0.0001	−0.0153	−0.0151
	IMM	−0.0076	0.0000	−0.0076	−0.0075

Note: Difference denotes the variation in the indirect effect between two scenarios (i.e., moderator is one standard deviation above and below the mean). *SE* = standard error; LLCI = lower level of confidence interval; ULCI = upper level of confidence interval; AD = distance away from home; NA = number of activity locations; AT = activity of time spent outside the home. IMM = index of moderated mediation. Bootstrap uses 95 percent confidence band.

results in a 6.1 percent reduction in the indirect effect and a 3.7 percent reduction in the total effect, and the direct effect increases by 10 percent. Finally, a one-standard-deviation increase in AT (i.e., an increase in activity time away from home by 3.6 hours per day) results in a 22.8 percent reduction in indirect effect and a 6.8 percent reduction in total effect, whereas direct effect increased by 83.3 percent.

Our results indicate that the largest reduction in the indirect effect of income on BEQ-AS occurs by increasing the AT. It is important to note, however, that the direct effect of income on BEQ-AS also exhibits a substantial increase. As a result, there is a relatively moderate reduction in the total effect. The largest reduction in the total effect of income on BEQ-AS is achieved by increasing the AD. Additionally, as depicted in Figure 7, the effect of income on BEQ-AS is primarily manifested through the indirect effect. This implies that income mainly alters BEQ-RS, which in turn significantly influences BEQ-AS. The principal mechanism of mobility alleviating the effect of income on BEQ-AS is weakening the indirect effect.

Figure 8 illustrates the extent of mobility needed to fully offset the indirect effect of income on BEQ-AS. For the AD and NA, daily mobility needs to increase to nearly thirteen standard deviations above the mean (i.e., activity distance is 43.5 km per day or the number of activity locations is 116.8 per month). In this scenario, the indirect effect of income on BEQ-AS is not statistically significant anymore (i.e., the lower 95 percent confidence band contains 0). The actual highest AD and NA in our data, however, are only 21.6 km and 99, respectively. For the AT, daily mobility needs to increase to nearly 4.5 standard deviations above the mean (i.e., activity time is 21.3 hours per day), which is also unrealistic. Therefore, it is difficult to completely offset the effect of income on BEQ-AS.

Discussion and Conclusion

Dominated by the prevailing view that you are where you live (Sampson, Morenoff, and Gannon-Rowley 2002; Tammaru et al. 2020), past studies and interventions mainly focused on people's residential space. The NEAP proposes that people's residence-based exposure and activity-space-based exposure are divergent (Kwan 2018a, 2018b). BEQ exposure is widely associated with spatial outcomes (e.g., health outcomes, crime rate), but its related studies have also ignored the role of people's daily mobility (He, Páez, and Liu 2017; R. Wang et al. 2019; Zhang, Li, and Chan 2020; Su, Li, and Qiu 2023). To bridge this gap, this study revealed the NEAP in BEQ exposure. Specifically, SVIs and mobile phone signaling data were integrated to assess BEQ in people's residential space (BEQ-RS) and

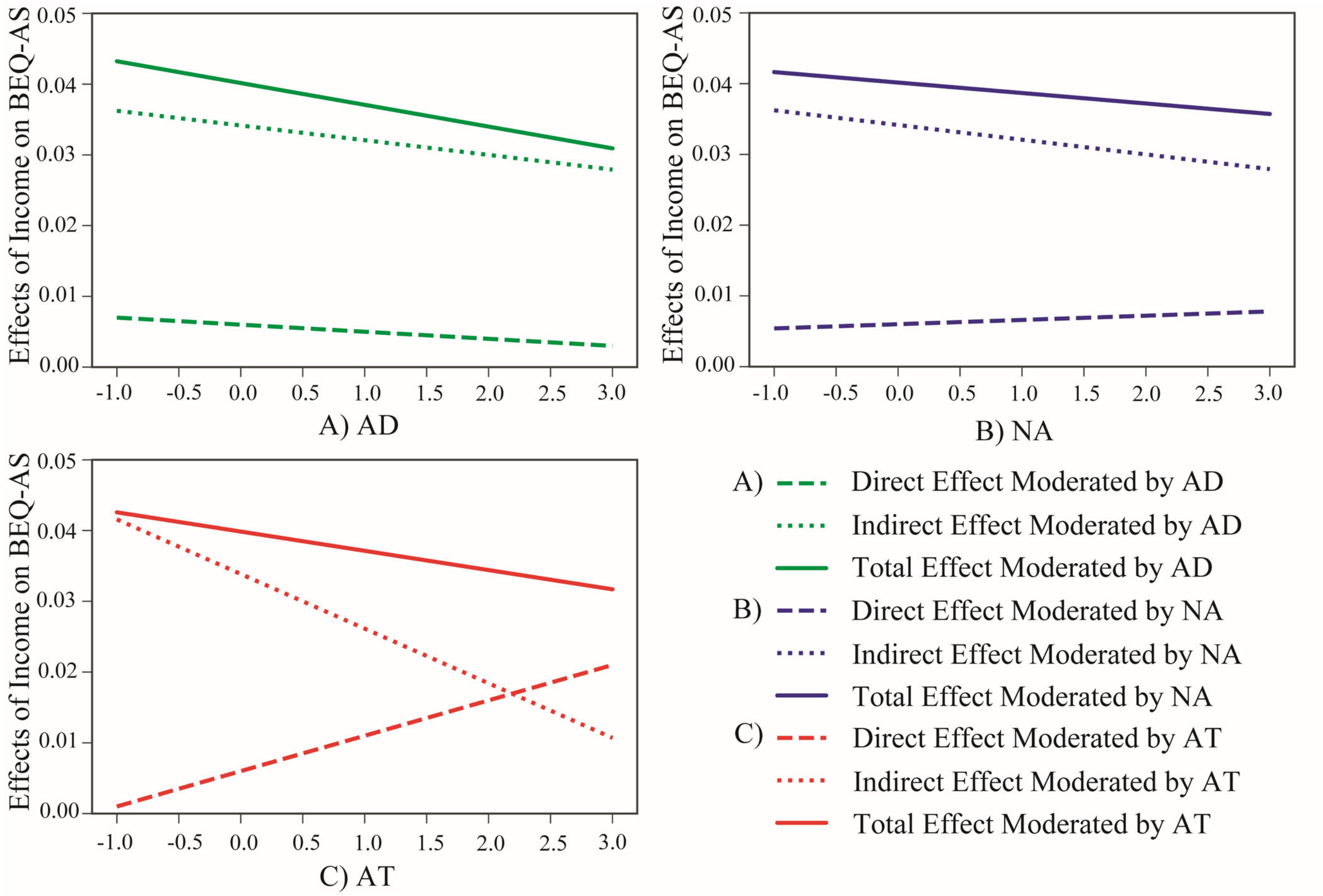

Figure 7. Visual representation of the direct, indirect, and total effect of income on built-environment quality of activity space (BEQ-AS) versus the mobility degree. *Note:* AD = distance away from home; NA = number of activity locations; AT = activity of time spent outside the home.

BEQ in people's activity space (BEQ-AS). Subsequently, the complex interplay among BEQ-RS, BEQ-AS, daily mobility, and income was explored. The main findings are as follows.

There Is a Significant Disparity in BEQ Exposure and the Disparity in BEQ-AS is Smaller Than That in BEQ-RS

Income has a considerable effect on BEQ exposure, for both BEQ-RS and BEQ-AS. The finding of the disparity in BEQ-RS aligns with the work of Salesses, Schechtner, and Hidalgo (2013). Moreover, the disparity in BEQ-AS has been revealed in this article. Compared to BEQ-RS, the disparity in BEQ-AS is much smaller. The effect of income on BEQ-RS corroborates the spatial inequality in China resulting from the housing reform. Since the 1990s, housing prices in China's megacities have seen a dramatic increase after the housing market reform (Chen, Guo, and Wu 2011). Disparities in housing affordability have led to a certain extent of disparities in BEQ-RS. High-income groups chose commercial housing neighborhoods, whereas low-income groups had to choose informal housing neighborhoods (e.g., urban villages, public housing neighborhoods; Liu et al. 2010; Li and Wu 2013). With the uneven development and accumulation driven by profit seeking, commercial housing neighborhoods tend to have better BEQ, whereas informal housing neighborhoods have poor BEQ. Meanwhile, the Guangzhou government is keen to develop public transportation (Institute for Transportation and Development Policy 2020), which is relatively accessible to all groups. A developed mobility system provides all groups with more opportunities for accessing diverse daily activity spaces that are quite different from their residential spaces. As a result, we saw that the disparity in BEQ-AS is significantly smaller than that in BEQ-RS.

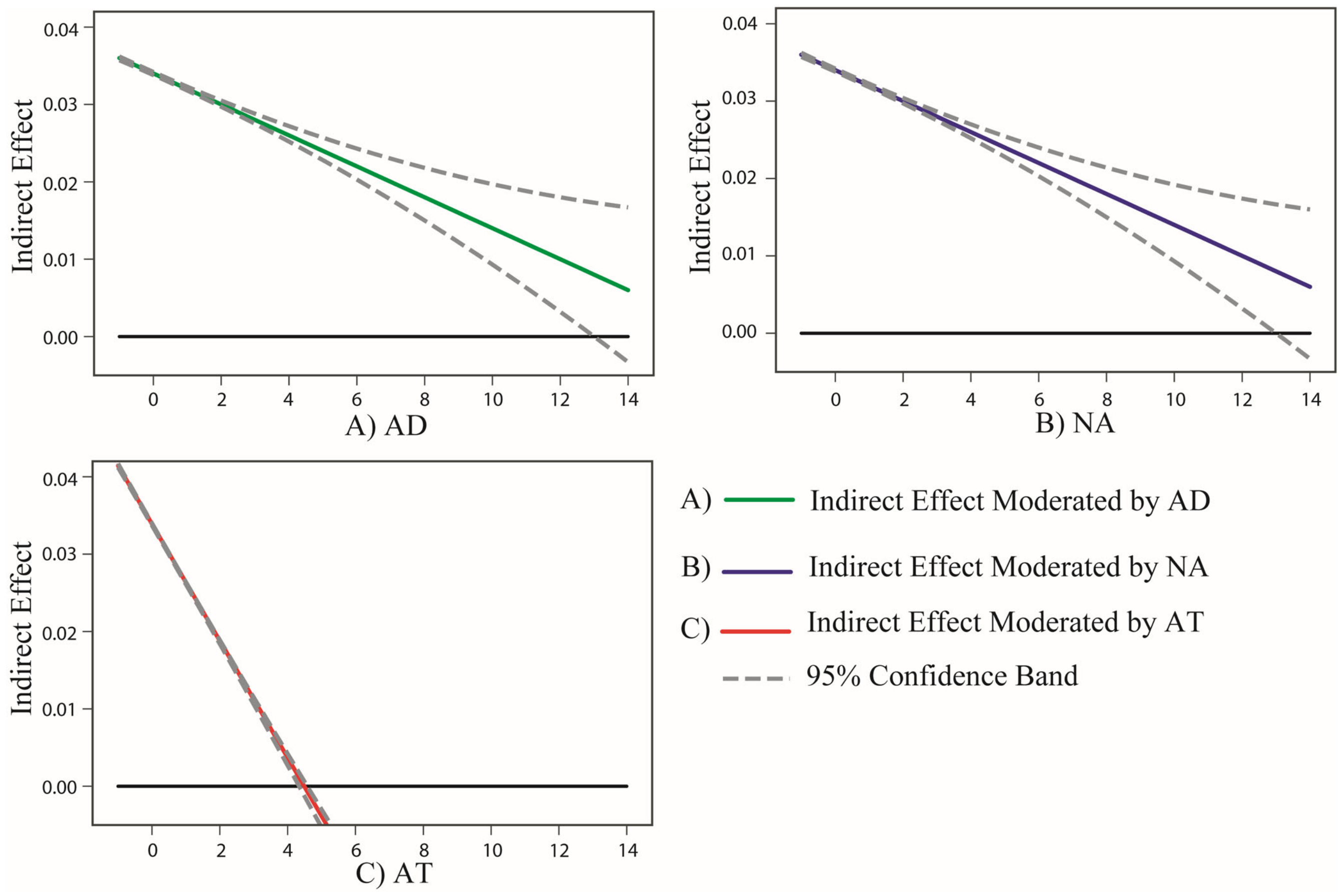

Figure 8. Visual representation of the indirect effect of income on built-environment quality of activity space (BEQ-AS) versus the mobility degree, with 95 percent confidence band. *Note:* AD = distance away from home; NA = number of activity locations; AT = activity of time spent outside the home.

The NEAP Is Evident in BEQ Exposure and the NEPP Is Not Supported

After using large samples to capture a wide range of daily mobility degrees and spatial contexts, the NEAP was still observed but the NEPP was not supported. Our result is consistent with the works of Kim and Kwan (2021), J. Huang and Kwan (2022), Cai and Kwan (2024), and J. Wang et al. (2024), but is opposite to the studies by B. Wang et al. (2021) and J. Wu et al. (2023). In two empirical studies supporting the NEPP, the authors used a small sample size from a subdistrict in an entire city and the participants actually shared a similar residential context. The standard deviation of residence-based exposures is naturally smaller than that of activity-based exposure, as residence-based calculations did not capture environmental exposures from other spaces in the entire study area. The polarization phenomenon occurred simply because the participants encountered different spaces in their daily lives. In conclusion, the NEPP studies ignored the spatial comparability between residence-based exposure and activity-based exposure. Therefore, we infer that the NEAP indicates the common occurrence that daily mobility provides all individuals with more opportunities for accessing diverse daily activity spaces. The conclusions of the NEPP are subject to methodological limitations (i.e., the lack of spatial representativeness in the obtained samples of residential contexts).

In addition, the correlation between BEQ-RS and BEQ-AS is very high ($r = 0.918$). The R^2 increases significantly when BEQ-RS is included in the conditional process analysis model. Such findings indicate that residential environmental exposures exert a profound influence on individuals' overall environmental exposure profiles. For BEQ exposure, residence-based data might also yield relatively reasonable conclusions if mobility data are not available. Nonetheless, residence-based studies tend to overlook some individual-level bias because individuals have varying mobility levels. Mobility data can help us identify and give voice to doubly disadvantaged groups.

Income Exerts a Dual Influence on BEQ-AS Through Direct and Indirect Pathways, and the Pathways Could Be Moderated by High Mobility

The complex interplay among BEQ-RS, BEQ-AS, daily mobility, and income is investigated by the conditional process analysis model. The results show that income exerts a dual influence on BEQ-AS, through direct and indirect effects. Directly, individuals' ability to access good BEQ-AS is constrained by their income. Indirectly, income determines BEQ-RS, subsequently influencing BEQ-AS. Moreover, the results also show that both direct and indirect effects could be moderated by high daily mobility. It indicates that the NEAP is an individual-level phenomenon, and also manifests as a derived phenomenon associated with income groups. This is primarily because BEQ exposure and income have a consistent association, and daily mobility can reduce disparity in BEQ exposure.

According to our estimate, compared to the mean level, an activity distance increase of 3.5 km per day leads to a 7.7 percent reduction in the effect of income on BEQ-AS. An increase in activity numbers of 8.1 per month reduces the effect of income on BEQ-AS by 3.7 percent. An activity time increase of 3.6 hours per day results in a 6.8 percent reduction in the effect of income on BEQ-AS.

Implications

The findings of this article provide some practicable insights into promoting spatial equality. First, it is imperative to improve the BEQ of neighborhoods where low-income groups live because people's BEQ-AS is largely influenced by BEQ-RS. Policymakers and urban planners should mitigate residential segregation and adopt a spatial planning strategy of cross-locating indemnificatory housing and commercial housing. Second, according to the classical analytical model of urban spatial structure, people seek to balance housing costs and mobility costs to maximize their utility (Alonso 1962; Mills 1967; Muth 1969). Thus, income can also interact with daily mobility to influence BEQ-AS. Although the disparity in BEQ-AS can be significantly alleviated by improving people's daily mobility, this strategy has not received sufficient attention. High mobility can help low-income groups escape from the poor BEQ-RS. Public transport planning should be more responsive to the needs of low-income groups. It should prioritize serving areas covered by the subway and bus, where low-income groups live in clusters. Moreover, policymakers should be aware that a low-income-friendly transport system can reduce double inequality in BEQ exposure. This is because low-income groups who have limited mobility cannot benefit from the upward averaging of the NEAP.

Limitations and Future Work

This study has some limitations that require further research. First, SVIs are all shot on roads and hence only roughly reflect the condition of the built environment. Second, based on the assumption that income highly determines people's housing prices, housing rent has been used to infer people's income levels. It might, however, cause some bias. Third, we measured the BEQ-AS using the time-weighted exposure approach, which assumed that different spatial contexts had equal importance to people. This assumption might break down, so temporal contexts should be examined in future studies. Fourth, this study used traditional linear regressions to implement the theoretical framework. The results, though, found a high correlation between BEQ-RS and BEQ-AS, which could cause the coefficients of other explanatory variables to be underestimated. In future research, other methods should be explored to address and account for this issue. Last, this study found that increasing activity numbers and activity time can significantly reduce the indirect effect and the total effect of income on BEQ-AS, but also increase the direct effect. Thus, the direct effect's specific form remains for future research.

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