ISSN: 3007-9640 DOI: https://doi.org/10.70114/acmsr.2026.9.1.P112

Nonlinear Effects of Built Environment on Commuting Distances Across Diverse Urban Communities

Jiandong Peng [1, a], Qiuyu Wan [1, b], Weiming Zhang [2, c] and Xuexin Yan [3, d] *

[1] School of Urban Design, Wuhan University, Wuhan, China

[2] Wuhan Natural Resources Conservation and Utilization Center, Wuhan, China

[3] State Key Laboratory of Information Engineering in Surveying, Mapping and Remote Sensing, Wuhan University, Wuhan, China

[a] 00006790@whu.edu.cn, [b] 2022282090078@whu.edu.cn,

[c] ming616968880@163.com, [d] yan.xuexin902@whu.edu.cn

Abstract: Residents of informal settlements often experience disproportionate commuting burdens, yet how these vary across community types and built environments remains unclear. Using cell phone signaling data from Wuhan, China, this study investigates commuting disparities across urban villages, old plant area, and general neighborhoods with a Gradient Boosting Decision Tree (GBDT) model. We examine the nonlinear effects of built environment attributes at residential and employment locations on commuting distance. Results indicate that urban village residents experience the greatest commuting burden, characterized by both longer average and more extreme commutes. Although built environment effects differ across community types, workplace distance to the city center consistently emerges as the dominant determinant. The results further reveal substantial nonlinear and community-specific effects, suggesting that identical built environment characteristics may produce contrasting commuting outcomes. These findings support place-sensitive planning strategies for reducing commuting inequality and promoting healthier, more equitable urban environments.

Keywords: informal communities; transportation equity; commuting distance; built environment; nonlinear correlation

1. Introduction

Global urbanization has significantly increased commuting distances, causing traffic congestion and environmental degradation [1], [2] .The built environment is widely recognized as a crucial determinant of commuting distance, and its optimization has become an important planning strategy ([3], [4]; [5]). However, existing research predominantly focuses on the city scale [6], [7], while detailed examinations of commuting distance variations across diverse settings remain limited, particularly for residents of incommodity housing communities.

Residents in informal settlements typically have shorter commuting distances than those in commodity housing communities, driven by limited transportation resources and financial constraints that hinder expensive motor vehicle travel [8]. In China, urban villages and old plant area serve as archetypal incommodity housing communities, which often lack sufficient transport infrastructure due to historical or geographical constraints [9], [10]. Furthermore, affordable housing in these areas accommodates low-income migrants, prompting them to reside close to workplaces to avoid financially challenging long-distance commutes [11] . Despite current attention on informal community mobility, a research gap remains concerning the specifics of commuting distances within these settings.

Studies employing the 5D framework—density, diversity, design, distance to public transportation, and destination accessibility—show that high-intensity mixed-use developments significantly reduce commuting distances [12]; [13], [14]. However, given the structural differences between informal and commodity housing communities, whether these city-scale findings apply to informal settings requires further validation. Existing studies also focus primarily on residential rather than

ISSN: 3007-9640 DOI: https://doi.org/10.70114/acmsr.2026.9.1.P112
employment locations [4], [15]. Moreover, recent evidence reveals a non-linear relationship between the built environment and commuting distance, challenging traditional linear assumptions ([5], [16].

To address these gaps, this study utilizes cell phone signaling data from Wuhan, China. Combining these data with a GBDT model and integrating the spatial distribution of urban villages, old plant area, and general neighborhoods, we explore built environment impacts on commuting distances in informal settlements across the work-life spectrum, contrasting them with formal ones. This study offers a dual contribution. First, it scrutinizes commuting characteristics and their nonlinear built environment associations in informal settlements, contrasting them with formal settings to fill a literature void on built environment-commuting interplays. Second, by analyzing commuting patterns and built environment associations across formal and informal communities, we devise targeted strategies to optimize the built environment, thereby reducing commuting distances and promoting sustainable urban development.

2. Literature Review

Residents in different neighborhoods exhibit distinct spatio-temporal commuting patterns, which studies primarily attribute to income differences [17], [18]. Surveys in the United States show that commercial housing residents generally have higher incomes, greater car ownership, and greater reliance on motor vehicles than residents of low-income neighborhoods [19]. Similarly, studies of Kenyan slums and Chinese urban villages report lower car ownership and a stronger preference for living near workplaces, resulting in shorter commuting distances [11], [20]. Although commercial housing residents typically commute farther, they experience shorter travel times because of greater mobility [10]. In China, traditional Danwei (work-unit) compounds minimized commuting distances through integrated job-housing provision and non-motorized travel [9]. However, market-oriented housing reforms after the 1980s relocated many secondary industries to suburban areas, changing the composition of Danwei residents and reshaping commuting patterns (Zhang et al., 2021; Hu et al., 2022). Despite extensive research on commuting behavior, comparisons of commuting characteristics among urban village, Danwei, and commercial housing residents remain limited.

The built environment is commonly characterized using the 5D framework—density, diversity, design, distance to transit, and destination accessibility [12]. Higher population density improves proximity to employment, while mixed land use promotes jobs–housing balance, both contributing to shorter commuting distances, although mixed land use may also increase traffic congestion (Zhao, 2013; (Bezirgani and Lachapelle, 2021; Böcker et al., 2017; Shen et al., 2020). Higher intersection density improves accessibility and further reduces commuting distances [5], [27], [28]. Greater destination accessibility generally shortens commuting distances, while polycentric urban structures may further reduce travel by distributing employment opportunities, although existing evidence remains mixed [29], [30]. Most studies, however, focus on residential rather than workplace built environments [4], [31].

Traditional studies typically employ linear models, including ordinary least squares (OLS), geographically weighted regression (GWR), and Bayesian methods, to examine built environment effects on commuting [32], [33]. Although effective, these models struggle to capture nonlinear relationships. Recent studies have therefore adopted machine learning methods, particularly GBDTmodels, to address this limitation [34], [35]. Applications in Wuhan and Stavanger demonstrate that GBDT effectively identifies nonlinear effects, threshold effects, and the relative importance of explanatory variables, providing valuable support for planning decisions under resource constraints [36]; [33]. Nevertheless, despite the growing use of machine learning, understanding of how the built environment nonlinearly influences commuting distances across different urban settlement types remains limited.

Several research gaps remain. Existing studies often overlook spatio-temporal commuting pattern variations between formal and informal communities and their relationship with the built environment. Moreover, built environment effects at both residential and workplaces remain underexplored, while

ISSN: 3007-9640 DOI: https://doi.org/10.70114/acmsr.2026.9.1.P112
reliance on linear models limits capturing nonlinear relationships. To address these gaps, this study employs cell phone signaling data from Wuhan, China, to examine commuting distances across informal settlements—including urban villages and old plant area—and formal communities. Using a GBDT model, it investigates nonlinear built environment effects from both residential and workplace perspectives across settlement types, providing evidence for sustainable urban development.

3. Research Design

3.1 Research Area

Wuhan, China, was selected as the study area (Figure 1). The study covers the central urban area within the Third Ring Road and the surrounding Urban Development Zone. Previous studies commonly used Traffic Analysis Zones (TAZs) or communities as analytical units [37], [38] but these are unsuitable for highly localized urban villages and old plant area. Taking advantage of the spatial precision of cell phone signaling data, this study adopts a 1 km × 1 km grid as the analytical unit. Grids with more than 50% coverage of urban villages or old plant area were classified accordingly, enabling a fine-grained comparison of commuting distances and their relationships with the built environment across community types.

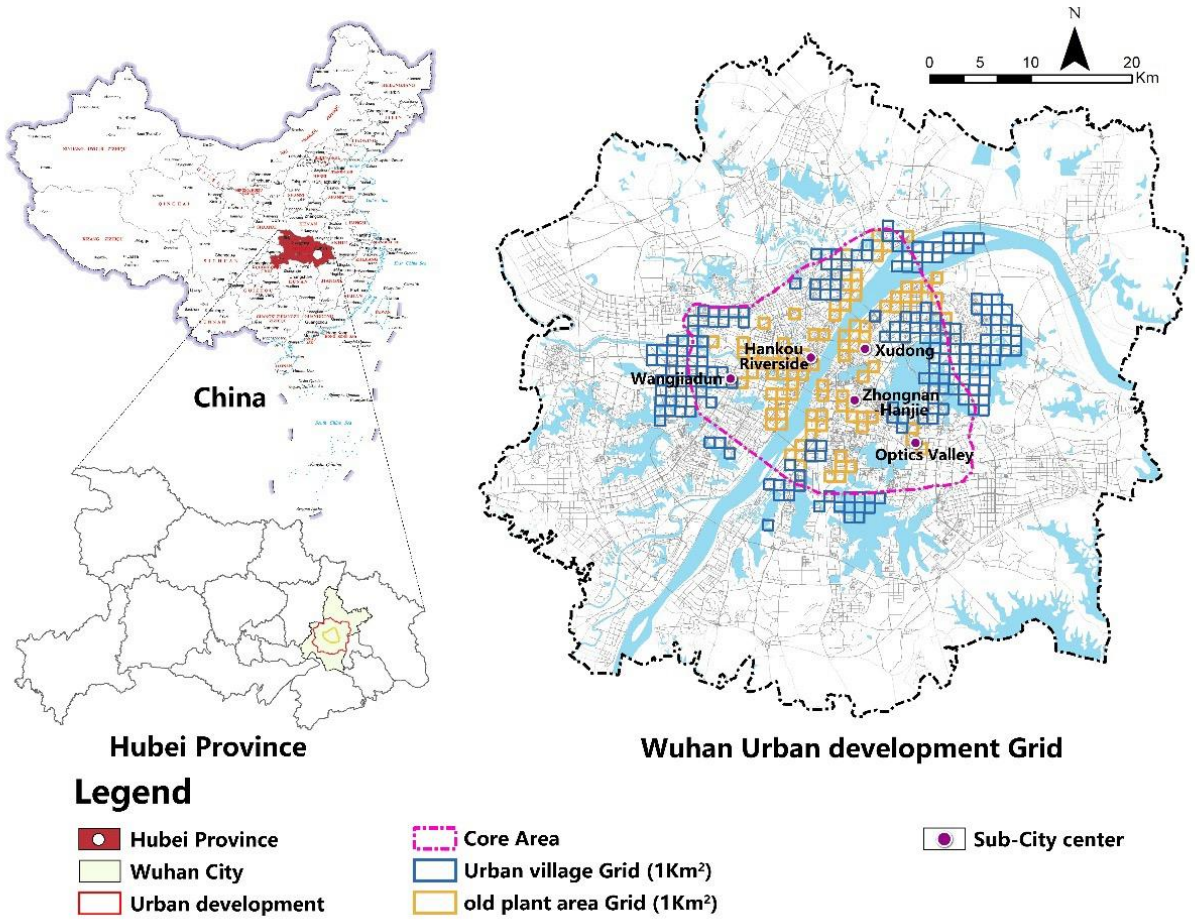

Fig 1. Research area

3.2 Data

Mobile phone signaling data for Wuhan in June 2021 were obtained from China Unicom and included user IDs, demographic attributes, geographic coordinates, and location types. Location

ISSN: 3007-9640 DOI: https://doi.org/10.70114/acmsr.2026.9.1.P112
records and timestamps were used to identify residents' homes and workplaces. Residents were assigned to 1 km × 1 km grids according to their residential locations and classified into urban villages, old plant area, or commodity housing communities. Commuting distances were calculated from home and workplace coordinates, while built environment variables were derived for both residential and workplace grids. The analysis was limited to employed individuals aged 18–60, yielding 68,252 commuting records from urban villages, 101,099 from old plant area, and 777,522 from commodity housing communities.

To investigate the relationships between residential and workplace built environments and commuting distances across urban villages, old plant area, and commodity housing communities, this study develops an indicator system based on the 5D framework [12], including density, diversity, design, destination accessibility, and public transportation accessibility. Average house prices are used as a proxy for residents' income levels [39], [40]. All built environment data were collected in 2021. Resident and employment population densities were sourced from mobile phone signaling records; building vector data for calculating floor area ratios were obtained via water injection software; land use data was supplied by the Wuhan Urban Planning and Design Institute; information on various amenities was acquired through the Amap API data service; and housing price data was sourced from Lianjia.com, a prominent real estate transaction platform in China. Indicator definitions and data sources are provided in Table 1.

Table 1. Definition and descriptive statistics of variables

Variable	Description	Mean			Std dev.		
		urban villages	old plant area	commodity housing communities	urban villages	old plant area	commodity housing communities
Residential density	Number of resident population in the grid (persons/km2)	4303.78	7308.15	5170.88	2779.14	3768.58	4151.79
Employment density	Number of employed population in the grid (persons/km2)	1118.05	3031.53	1705.72	712.61	2278.06	1884.28
FAR	Floor area ratio in the grid	4.58	4.10	4.16	2.56	2.71	3.00
Land use mix	Calculations using land use entropy in the grid	0.60	0.57	0.61	0.15	0.10	0.19
Facility mixture	Mix of facilities on the grid	0.94	0.82	0.98	0.29	0.25	0.36
Number of intersections	Number of intersections in the grid	8.66	9.21	6.72	4.76	4.65	5.45
Distance to city center	Distance of grid center from city center (km)	6.15	3.65	8.38	2.88	2.38	6.25
Distance to sub-city center	Distance of grid center from sub-city center (km)	2.46	1.75	3.26	1.59	1.00	2.82
Number of companies	Number of companies in the grid	520.35	159.85	921.51	629.93	158.87	1409.86
Number of shopping facilities	Number of shopping facilities in the grid	182.42	101.39	203.16	144.52	78.47	217.01

ISSN: 3007-9640 DOI: https://doi.org/10.70114/acmsr.2026.9.1.P112

Number of metro stations	Number of metro stations in the grid	1.55	1.24	1.72	2.08	1.74	2.81
Number of bus stops	Number of bus stops in the grid	2.38	2.55	2.56	2.48	2.35	2.85
Housing Prices	Average transaction price of dwellings on the grid (1000yuan/m^2)	12.81	13.60	13.89	6.27	6.52	7.82

3.3 Method

To explore the nonlinear effects of residential and workplace built environments on commuting distances, this study employs the GBDTmodel. Unlike traditional linear models, GBDT relaxes linear assumptions, enabling the identification of nonlinear effects, threshold effects, and the relative importance of independent variables (Friedman, 2001; Ding et al., 2018b; Ding and Cao, 2019). Following [44], the GBDT model is expressed as:

$$F(x) = \sum_{m=1}^{M} f_m(x) = \sum_{m=1}^{M} \beta_m h(x; a_m)$$

Here, x represents the explanatory variables, i.e., the features of the built environment at residential and workplaces. $F(x)$ is the approximate function of the response variable y (commuting distance), which is the cumulative result of the outputs of a series of decision trees. Moreover, M denotes the total number of decision trees, m is the index variable for the current decision tree (ranging from 1 to M), a_m epresents the average split position and terminal node parameter for each decision tree $h(x; a_m)$ to characterize the structure of the decision tree, and β_m is the weight of the mth tree estimated by minimizing a specified loss function. The computation method for minimizing the loss function can be expressed as:

$$F(x) = F_{m-}(x) + \emptyset \times \beta_m h(x; a_m), \quad 0 < \emptyset \leq 1$$

A five-fold cross-validation procedure was employed to determine the optimal learning rate, tree complexity, and number of trees [42]. The model was implemented using the “gbm” package in R.

4. Results

4.1 Descriptive Analysis

Figure 2 illustrates the distribution of commuting distances across the three community types. Residents of old plant area exhibit the shortest average commuting distance (7.83 km), consistent with previous findings [9]. Average commuting distances are 8.25 km for commodity housing communities and 8.81 km for urban villages, indicating that urban village residents have the longest commuting distance among the three community types.

ISSN: 3007-9640 DOI: https://doi.org/10.70114/acmsr.2026.9.1.P112

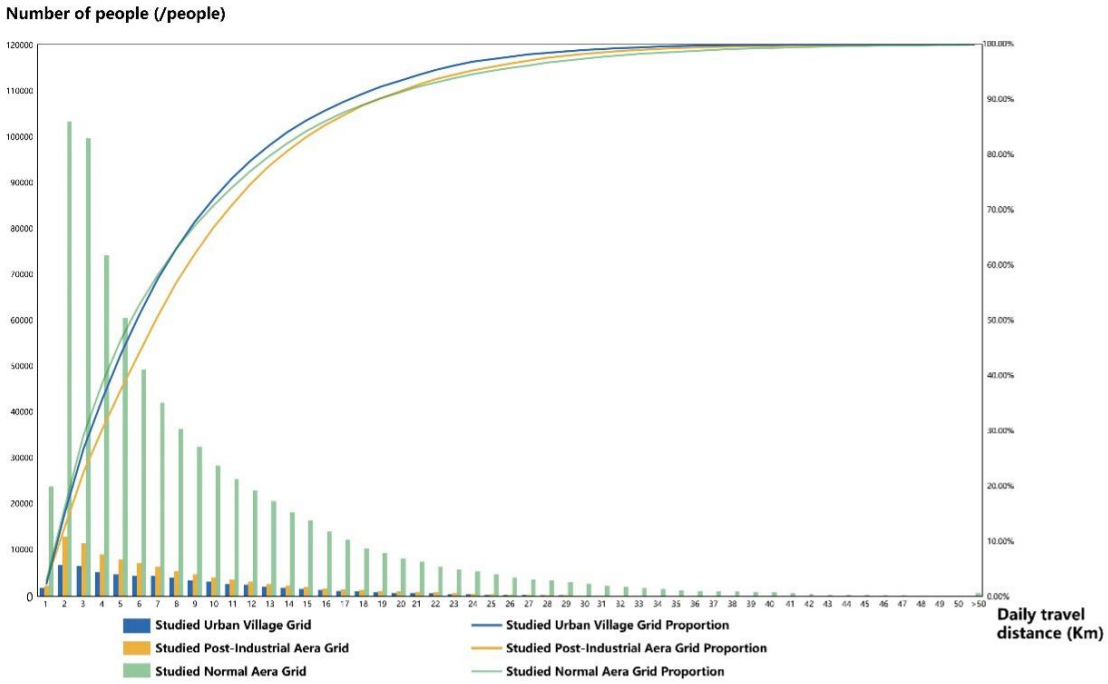

Figure 2: Distribution of commuting distances in different communities

Figure 3–5 presents the Origin-Destination (OD) distribution of commuting trips across urban villages, old plant area, and commodity housing communities. Trips originating from urban villages and old plant area are predominantly concentrated within the same district, with relatively few crossing the Yangtze or Han rivers. In contrast, commodity housing communities exhibit a higher frequency of inter-district commuting. Despite having the shortest average commuting distance, old plant area have a lower proportion of commutes within 5 km (43.89%) than commodity housing communities (46.53%), while urban villages have the lowest proportion (37.47%). Conversely, urban village residents have the highest proportion of commutes exceeding 10 km (33.09%), compared with 29.15% for commodity housing communities and 27.91% for old plant area.

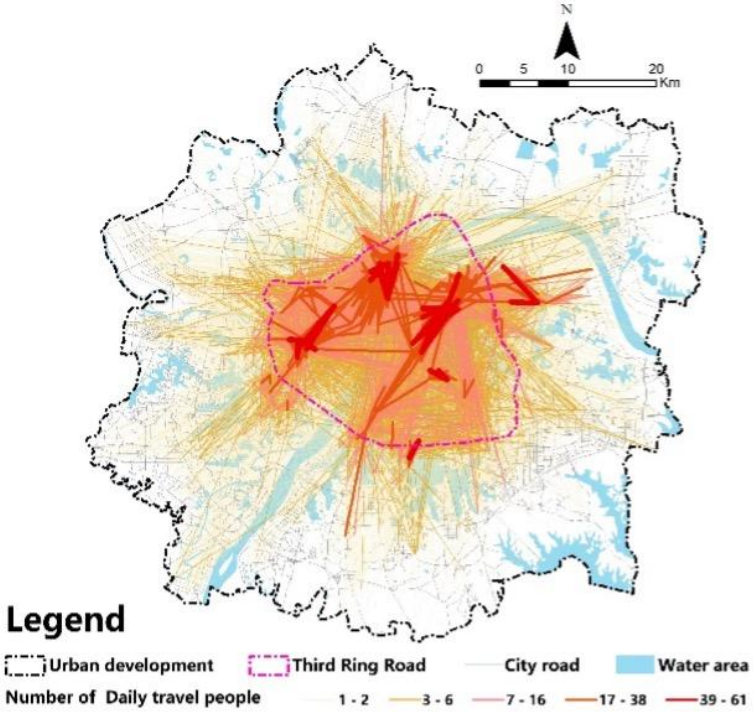

Figure 3: Urban village commuting OD

ISSN: 3007-9640 DOI: https://doi.org/10.70114/acmsr.2026.9.1.P112

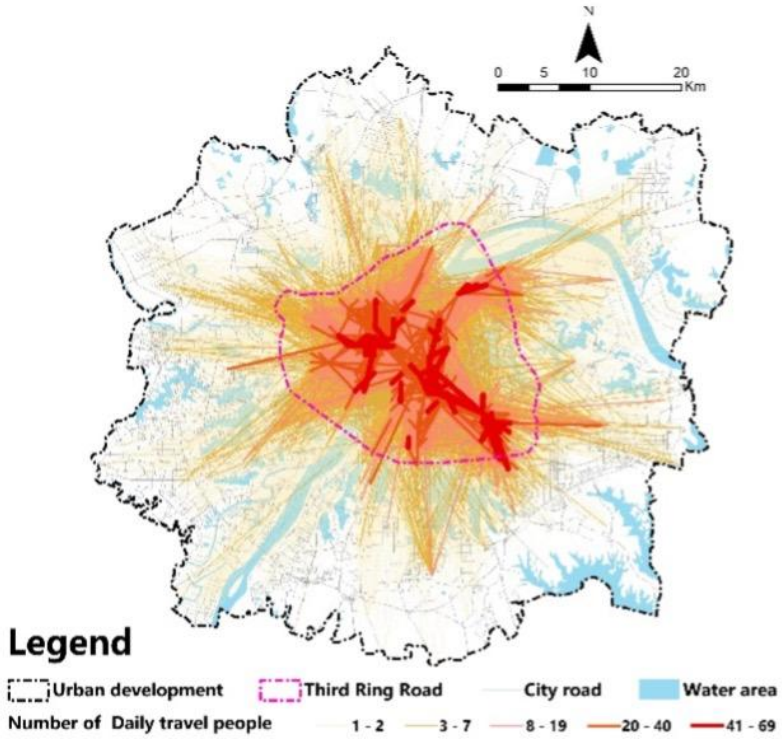

Figure 4: Old plant area commuting OD

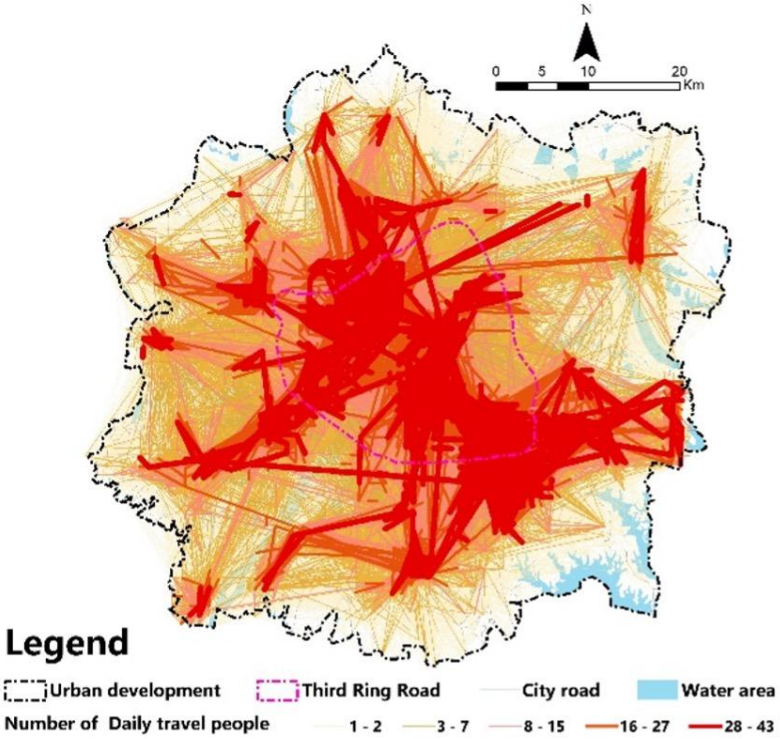

Figure 5: Commodity housing communities commuting OD

4.2 The Relative Importance of The Built Environment of The Workplace And Residence on Commuting Distance

Figure 6 illustrates the relative importance of built environment variables affecting commuting distances across urban villages, old plant area, and general neighborhoods, with noticeable differences between residential and workplaces. Among all variables, workplace distance to the city center has

ISSN: 3007-9640 DOI: https://doi.org/10.70114/acmsr.2026.9.1.P112
the greatest relative importance across all community types, consistent with previous findings [2]. Its relative importance is highest in old plant area (60.24%), followed by urban villages (36.49%) and general neighborhoods (32.10%).

For urban village residents, the second most influential variable is the number of shopping facilities within the residential vicinity (6.17%). This reflects the limited availability of shopping facilities in urban villages, where greater local accessibility reduces commuting detours. Employment population density at the workplace is the third most influential variable (5.16%), as higher employment density provides more job opportunities near residences, thereby reducing commuting distances.

For old plant area, the population density of residents at the workplace is the second most influential factor (4.41%), as higher residential density limits nearby employment opportunities, thereby increasing commuting distances. Workplace housing prices rank third (3.82%). Because most old plant area are located in central urban areas, higher workplace housing prices generally correspond to shorter commuting distances.

For general neighborhoods, the distance from the residence to the city center is the second most influential variable (13.07%), with greater distances associated with longer commuting distances. Workplace housing prices rank third (9.21%), with a substantially greater impact than in old plant area. Unlike old plant area, limited land availability in city centers prevents many residents of general neighborhoods from living centrally, thereby increasing the influence of workplace housing prices on commuting distances.

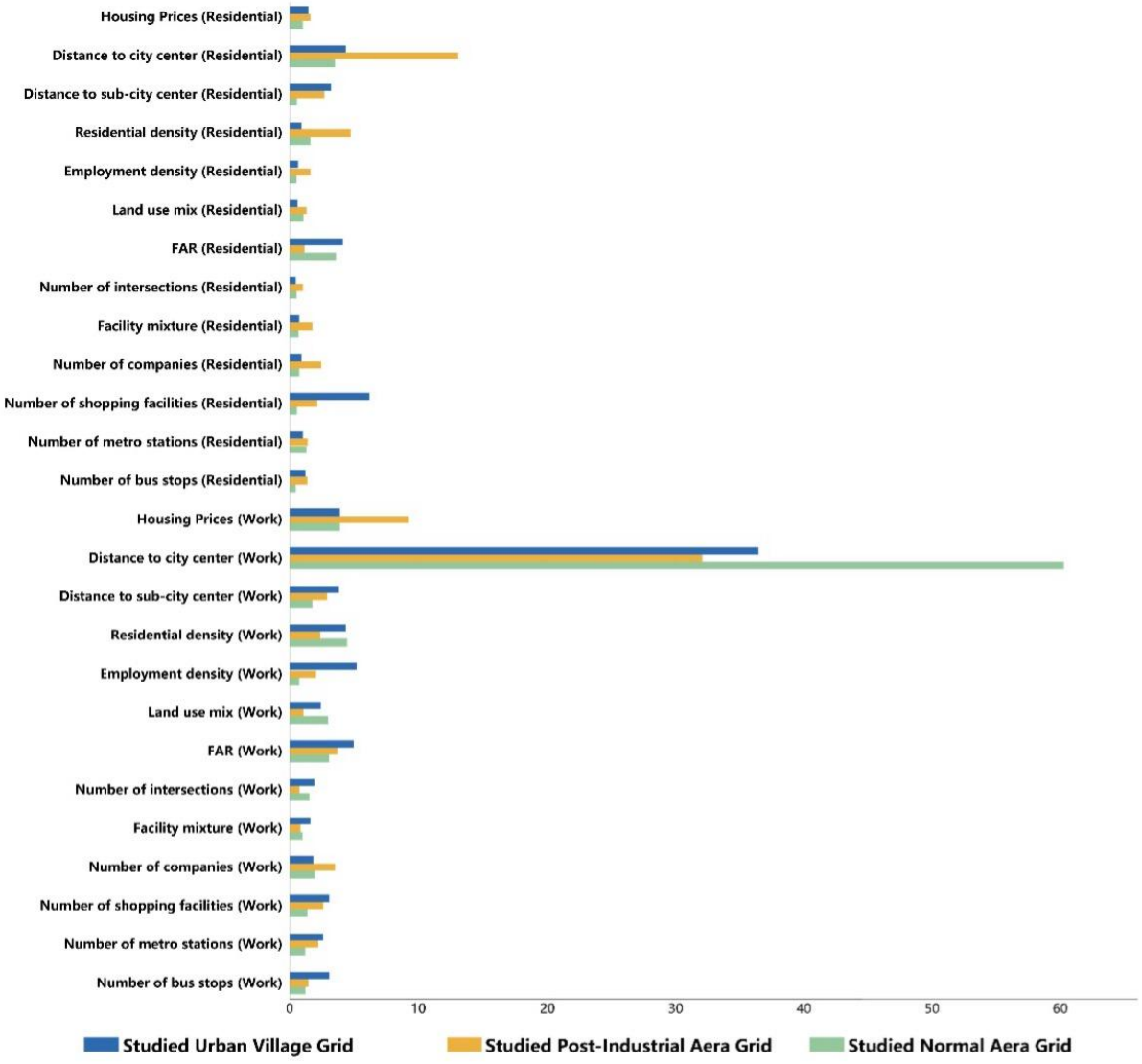

Figure 6: Relative significance of built environment in influencing commuting distance

ISSN: 3007-9640 DOI: https://doi.org/10.70114/acmsr.2026.9.1.P112

4.3 Nonlinear Impact of the Built Environment of Work And Residence on Commuting Distance

The partial dependence plots derived from the GBDTmodel (Figure 7) illustrate that nearly all built environment variables exhibit distinct nonlinear relationships with commuting distances, varying notably across urban villages, old plant area, and general neighborhoods. To compare these distinctions, eight variables with significant influence are selected for detailed analysis.

For distance from workplace to city center under 10 km, the impact on commuting distances across urban villages, old plant area, and general neighborhoods is relatively weak; beyond this threshold, a near-linear amplification effect is observed. Similarly, for distance from residence to city center under 10 km, the influence remains limited. As residential distance increases to approximately 15 km, commuting distances peak at around 12 km for urban villages and 9 km for old plant area, followed by a plateau and subsequent decline. In contrast, commuting distances in general neighborhoods increase continuously, reaching approximately 20 km at 25 km, with an approximately linear pattern thereafter.

The number of shopping facilities has a negative effect on commuting distances for urban village residents. As the number increases from 0 to around 60, commuting distance decreases from approximately 10 km to 6 km, and further to about 4 km at 70 facilities, after which the effect becomes negligible. This reflects the role of local commercial accessibility in reducing commuting detours in urban villages. In contrast, a positive effect is observed in old plant areas and general neighborhoods. For old plant areas, the effect peaks at approximately 11 km, corresponding to the spatial concentration of commercial facilities, while general neighborhoods exhibit a more dispersed spatial pattern, leading to a broader and more sustained influence on commuting distances.

Significant disparities are observed in the impact of housing prices on commuting distances across the three community types. Given that higher-priced areas are predominantly located in city centers, including Wuhan's historical old plant area, higher housing prices are associated with shorter commuting distances in these areas. Specifically, as housing prices increase from RMB 11,000 to RMB 18,000 per square meter, commuting distances for old plant area residents decrease from 11 km to 6 km. In contrast, workplace housing prices exhibit a more complex nonlinear effect for urban villages and general neighborhoods. For general neighborhoods, the effect is more dispersed across space, with a peak influence around RMB 20,000 per square meter. Urban villages, located near Wuhan's third ring road, show a similar nonlinear pattern, but with a narrower range of sensitivity to price changes.

FAR exhibit significant disparities in their effects on commuting distances across community types at both employment and residential ends. At the employment end, for general neighborhoods, FAR exert a positive effect, with commuting distances increasing from 7.6 km to 8.5 km (0–5) and rising nearly linearly to 13 km at higher values (up to 10). In contrast, at the residential end, FAR have a negative effect on general neighborhoods, reducing commuting distances from 11 km to 8.8 km (0–3) before stabilizing.For informal communities (urban villages and old plant area), the employment-end plot ratio reduces commuting distances, from 17.5 km to 7.8 km and from 12.5 km to 7 km, respectively, as values increase from 0 to 5. At the residential end, however, increasing FAR from 0 to 2 leads to higher commuting distances, rising from 7.5 km to 8.5 km in urban villages and from 7 km to 7.6 km in old plant area, with peak effects reaching 9.5 km and 8.4 km, respectively.

Similarly, employment population density and the distance from the workplace to the urban sub-center exhibit pronounced nonlinear effects on commuting distances. For employment population density, the strongest response occurs between 0 and 2,000 individuals, while the effect persists beyond this threshold with diminishing marginal effects. This influence is most pronounced for urban villages, followed by old plant area, and weakest for general neighborhoods. Regarding the distance from the workplace to the urban sub-center, commuting distances increase across all three community types as the distance extends from 0 to 7 km. Beyond this threshold, the effect continues to increase for urban villages, peaking at approximately 11 km, whereas it remains relatively stable for old plant area and general neighborhoods.

ISSN: 3007-9640 DOI: https://doi.org/10.70114/acmsr.2026.9.1.P112

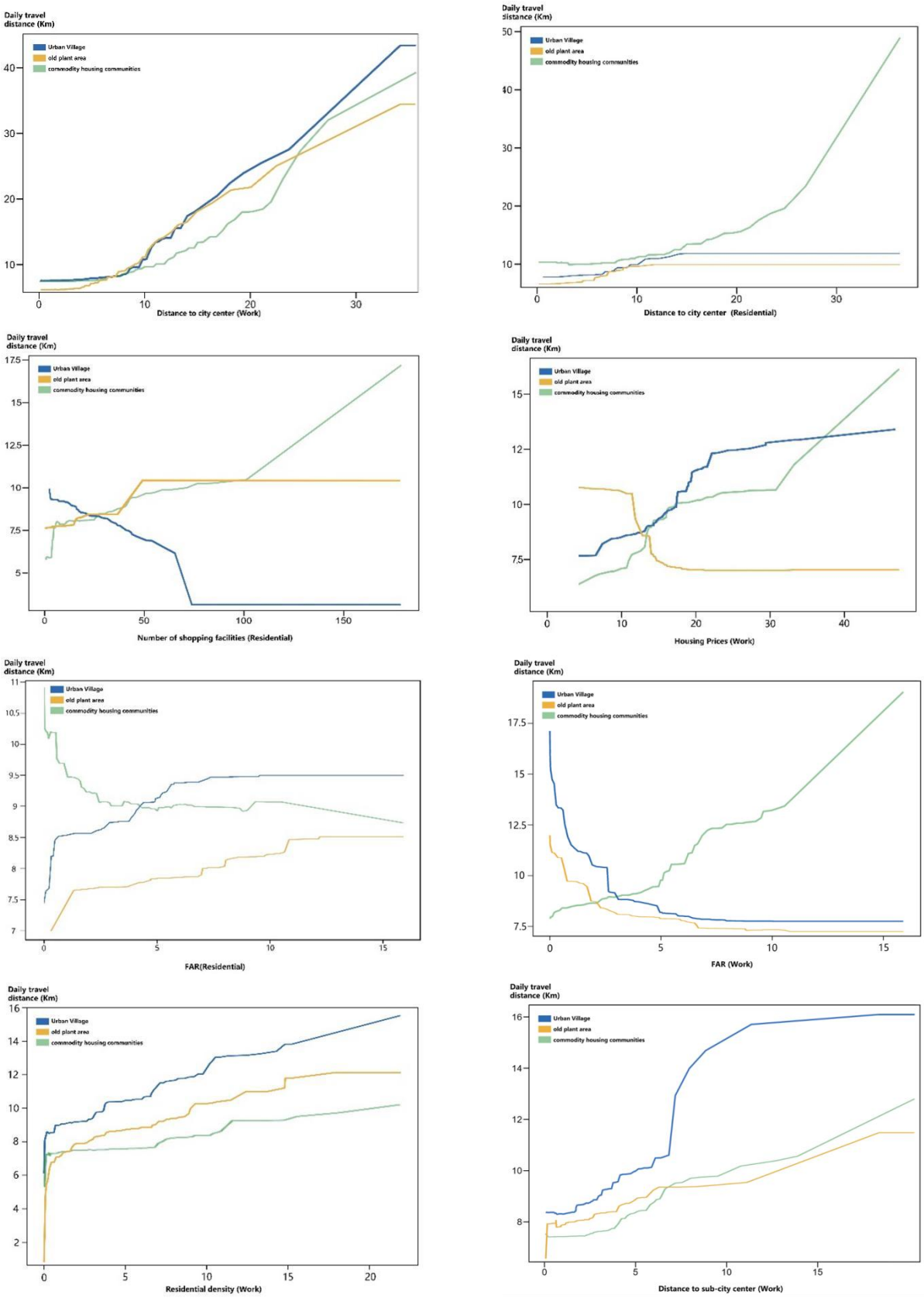

Figure 7: Nonlinear relationship of built environment with commuting distance

ISSN: 3007-9640 DOI: https://doi.org/10.70114/acmsr.2026.9.1.P112

5. Discussion and Conclusion

The escalation of commuting distances resulting from rapid global urban sprawl poses a significant challenge to sustainable urban development worldwide. Mitigating the adverse impacts of urban sprawl by shortening commuting distances has become a common challenge worldwide. While numerous studies have explored the relationship between the built environment and commuting distance [3], [5], the commuting characteristics of residents in informal settlements, such as urban villages and old plant area, and their relationship with the built environment remain unclear. Given the greater commuting pressures faced by residents of informal settlements, addressing these knowledge gaps is essential for developing sustainable urban planning strategies. Leveraging cell phone signaling data from Wuhan, China, this study examines the commuting patterns of residents in urban villages and old plant area. Using the GBDTmodel, it further investigates the nonlinear effects of the built environment on commuting distances by comparing informal settlements with general neighborhoods. The study yields several noteworthy findings.

Firstly, residents in old plant area exhibit the shortest commuting distances, consistent with previous studies (Wang and Chai, 2009; Zhang et al., 2021). This can be attributed to China's historical unitary system, under which residential areas were developed close to workplaces. In contrast to previous findings [9], [21] , residents of urban villages exhibit the longest average commuting distances, likely reflecting the relocation of industries from Wuhan's city center to suburban areas. Urban village residents also record the lowest proportion of short-distance commuting (within 5 km, 37.47%) and the highest proportion of long-distance commuting (over 10 km, 33.09%), indicating greater commuting pressures and travel burdens.

Second, the analysis of relative importance indicates that the distance from the workplace to the city center is the most influential variable affecting commuting distances across all three community types. This reaffirms previous research highlighting the central role of the city center in urban employment and its profound influence on commuting distances [2]. For urban villages, the number of shopping facilities at residential locations and employment density at workplaces emerge as key determinants. The scarcity of shopping facilities increases commuting detours, while higher employment density provides more nearby job opportunities, reducing commuting distances. In old plant area, residential density and housing prices at the workplace are the second and third most influential factors. Higher residential density at workplaces may increase commuting distances, whereas higher workplace housing prices—typically associated with central urban locations—correspond with shorter commuting distances. In general neighborhoods, the distance from residential areas to the city center and workplace housing prices also play important roles. Consistent with previous studies [4] , greater residential distance from the city center is associated with longer commuting distances, while high housing prices in city centers limit residential opportunities and consequently increase commuting distances.

Third, this study confirms that the effects of the built environment on commuting distances are highly nonlinear, consistent with previous studies [33], [45] . More importantly, these nonlinear effects vary substantially across community types. For example, the influence of workplace distance to the city center is limited to the first 10 km for urban villages and old plant area but persists almost linearly for general neighborhoods beyond 25 km. These findings suggest that identical built environment factors may operate through different mechanisms across community types.

Fourth, unlike city-wide analyses [5], this study confirms that the same built environment element may exert opposite effects on commuting distances across different community types. Shopping facilities provide a representative example: within a range of 0–70, they reduce commuting distances in urban villages; conversely, within a range of 0–50, they increase commuting distances in old plant area and general neighborhoods. Beyond 100 facilities, the effect in general neighborhoods becomes nearly linear. These contrasting effects reflect the different characteristics of the three community types. Urban villages generally lack adequate commercial facilities, so increasing shopping facilities near residences or workplaces helps reduce commuting detours. In contrast, old plant area and general

ISSN: 3007-9640 DOI: https://doi.org/10.70114/acmsr.2026.9.1.P112
neighborhoods are relatively well served by shopping facilities, where excessive shopping facilities may intensify traffic congestion and consequently increase commuting distances.

Finally, this study demonstrates that the same built environment factor may exert distinct effects at residential and employment locations. In general neighborhoods, higher residential FAR reduce commuting distances, consistent with previous studies [4], [46], whereas higher employment-end FAR increase commuting distances, contrary to prevailing research [47]. This difference is likely attributable to the concentration of high-intensity commercial development in city centers with limited residential space. In contrast, for urban villages and old plant area, higher residential FAR increase commuting distances because homogeneous land use and limited local employment opportunities force residents to seek employment elsewhere, whereas higher employment-end FAR reduce commuting distances by concentrating employment opportunities.

These findings provide important implications for urban planning aimed at reducing commuting distances and improving transportation equity in informal settlements such as urban villages and old plant area. First, given the pronounced long-distance commuting of urban village residents, urban renewal should prioritize the introduction of employment opportunities compatible with local labor characteristics. Second, because workplace distance to the city center is the dominant determinant of commuting distance across all community types, promoting a polycentric urban structure is essential to mitigate urban sprawl and relieve congestion in central areas. Community-specific interventions are also required, including improving shopping accessibility in urban villages, optimizing residential density in employment areas of old plant area, and coordinating the spatial distribution of general neighborhoods with the city center. Third, the identified nonlinear relationships suggest that planning interventions should account for threshold effects. For example, establishing new employment centers approximately 10 km from the city center may effectively reduce commuting distances. Finally, because the effects of built environment factors vary across community types and between residential and employment locations, planning strategies should be tailored accordingly. For general neighborhoods, increasing residential-end FAR while reducing employment-end FAR may shorten commuting distances, whereas the opposite strategy appears more effective for urban villages and old plant area.

While this study examines the commuting characteristics of different community types and their relationship with the built environment, providing insights for refining measures to reduce commuting distances, several limitations remain. First, relying solely on cross-sectional data precludes investigating temporal commuting dynamics during urban expansion. Second, using house prices as an economic proxy omits key individual attributes (e.g., gender, age, occupation) [48], [49] which future research should capture via small-scale surveys. Finally, while machine learning offers superior predictive accuracy over linear regression, it cannot establish causality. Future studies should employ rigorous designs to clarify causal mechanisms and better guide planning practice.

Acknowledgements

Funding: This work was supported by the Wuhan Pilot Construction of a Strong Transportation Country Science and Technology Joint Research Project (Grant Nos. 2024-2-2, 2024-2-3).

6. Reference

[1] L. Hu, T. Sun, and L. Wang, “Evolving urban spatial structure and commuting patterns: A case study of Beijing, China,” Transp. Res. D Transp. Environ., vol. 59, pp. 11–22, Mar. 2018, doi: 10.1016/j.trd.2017.12.007.

[2] H. Yang, Y. Lu, J. Wang, Y. Zheng, Z. Ruan, and J. Peng, “Understanding post-pandemic metro commuting ridership by considering the built environment: A quasi-natural experiment in Wuhan, China,” Sustain. Cities Soc., vol. 96, p. 104626, Sep. 2023, doi: 10.1016/J.SCS.2023.104626.

ISSN: 3007-9640 DOI: https://doi.org/10.70114/acmsr.2026.9.1.P112
[3] K. Manaugh, L. F. Miranda-Moreno, and A. M. El-Geneidy, "The effect of neighbourhood characteristics, accessibility, home-work location, and demographics on commuting distances," Transportation (Amst)., vol. 37, no. 4, pp. 627–646, Jul. 2010, doi: 10.1007/s11116-010-9275-z.

[4] X. Yan, J. Zhou, F. Sheng, and Q. Niu, "Influences of Built Environment at Residential and Work Locations on Commuting Distance: Evidence from Wuhan, China," ISPRS Int. J. Geoinf., vol. 11, no. 2, Feb. 2022, doi: 10.3390/ijgi11020124.

[5] B. Sun, A. Ermagun, and B. Dan, "Built environmental impacts on commuting mode choice and distance: Evidence from Shanghai," Transp. Res. D Transp. Environ., vol. 52, pp. 441–453, May 2017, doi: 10.1016/j.trd.2016.06.001.

[6] C. Ding, S. Mishra, G. Lu, J. Yang, and C. Liu, "Influences of built environment characteristics and individual factors on commuting distance: A multilevel mixture hazard modeling approach," Transp. Res. D Transp. Environ., vol. 51, pp. 314–325, Mar. 2017, doi: 10.1016/j.trd.2017.02.002.

[7] H. Rüger, N. Stawarz, T. Skora, and B. M. Wiernik, "Longitudinal relationship between long-distance commuting willingness and behavior: Evidence from European data," J. Environ. Psychol., vol. 77, Oct. 2021, doi: 10.1016/j.jenvp.2021.101667.

[8] M. Chikaraishi, A. Jana, R. Bardhan, V. Varghese, and A. Fujiwara, "A framework to analyze capability and travel in formal and informal urban settings: A case from Mumbai," J. Transp. Geogr., vol. 65, pp. 101–110, Dec. 2017, doi: 10.1016/j.jtrangeo.2017.09.001.

[9] D. Wang and Y. Chai, "The jobs-housing relationship and commuting in Beijing, China: the legacy of Danwei," J. Transp. Geogr., vol. 17, no. 1, pp. 30–38, Jan. 2009, doi: 10.1016/j.jtrangeo.2008.04.005.

[10] W. Zhang and C. Li, "Varying mobility adaptation to COVID-19 of residents in urban villages and commodity housing communities: A quasi-experimental analysis in Shenzhen, China," Cities, vol. 145, Feb. 2024, doi: 10.1016/j.cities.2023.104711.

[11] L. Yu, B. Xie, and E. H. W. Chan, "Exploring impacts of the built environment on transit travel: Distance, time and mode choice, for urban villages in Shenzhen, China," Transp. Res. E Logist. Transp. Rev., vol. 132, pp. 57–71, Dec. 2019, doi: 10.1016/j.tre.2019.11.004.

[12] R. Ewing and R. Cervero, "Travel and the built environment," Journal of the American Planning Association, vol. 76, no. 3, pp. 265–294, Jun. 2010, doi: 10.1080/01944361003766766.

[13] H. Yang, Z. Ruan, W. Li, H. Zhu, J. Zhao, and J. Peng, "The Impact of Built Environment Factors on Elderly People's Mobility Characteristics by Metro System Considering Spatial Heterogeneity," ISPRS Int. J. Geoinf., vol. 11, no. 5, May 2022, doi: 10.3390/ijgi11050315.

[14] J. Hong, Q. Shen, and L. Zhang, "How do built-environment factors affect travel behavior? A spatial analysis at different geographic scales," Transportation (Amst)., vol. 41, no. 3, pp. 419–440, May 2014, doi: 10.1007/s11116-013-9462-9.

[15] H. Yang et al., "Examining non-linear associations between built environments around workplace and adults' walking behaviour in Shanghai, China," Transp. Res. Part A Policy Pract., vol. 155, pp. 234–246, Jan. 2022, doi: 10.1016/j.tra.2021.11.017.

[16] J. Chica-Olmo, C. Rodríguez-López, and P. Chillón, "Effect of distance from home to school and spatial dependence between homes on mode of commuting to school," J. Transp. Geogr., vol. 72, pp. 1–12, Oct. 2018, doi: 10.1016/j.jtrangeo.2018.07.013.

[17] P. Zhao, B. Lü, and G. de Roo, "Impact of the jobs-housing balance on urban commuting in Beijing in the transformation era," J. Transp. Geogr., vol. 19, no. 1, pp. 59–69, Jan. 2011, doi: 10.1016/j.jtrangeo.2009.09.008.

[18] D. Wang and M. Zhou, "The built environment and travel behavior in urban China: A literature review," Transp. Res. D Transp. Environ., vol. 52, pp. 574–585, May 2017, doi: 10.1016/j.trd.2016.10.031.

[19] E. Bardaka and J. Hersey, "Comparing the travel behavior of affordable and market-rate housing residents in the transit-rich neighborhoods of Denver, CO," Travel Behav. Soc., vol. 15, pp. 74–87, Apr. 2019, doi: 10.1016/j.tbs.2019.01.001.

[20] D. Salon and S. Gulyani, "Mobility, poverty, and gender: Travel 'choices' of slum residents in Nairobi, Kenya," Transp. Rev., vol. 30, no. 5, pp. 641–657, Sep. 2010, doi: 10.1080/01441640903298998.

ISSN: 3007-9640 DOI: https://doi.org/10.70114/acmsr.2026.9.1.P112
[21] M. Zhang, T. Zhang, Z. Xiao, and Y. Chai, "Property rights redistribution and the spatial evolution of the Chinese danwei compound: a case study in Beijing," Journal of Housing and the Built Environment, vol. 36, no. 4, pp. 1585–1602, Dec. 2021, doi: 10.1007/s10901-020-09810-z.

[22] L. Hu, Y. Liu, M. Sun, and Q. Lu, "To leave or stay? Out-migration of skilled migrants in Beijing, China," Popul. Space Place, vol. 28, no. 8, Nov. 2022, doi: 10.1002/psp.2579.

[23] P. Zhao, "The Impact of the Built Environment on Individual Workers' Commuting Behavior in Beijing," Int. J. Sustain. Transp., vol. 7, no. 5, pp. 389–415, Sep. 2013, doi: 10.1080/15568318.2012.692173.

[24] A. Bezirgani and U. Lachapelle, "Online grocery shopping for the elderly in Quebec, Canada: The role of mobility impediments and past online shopping experience," Travel Behav. Soc., vol. 25, pp. 133–143, Oct. 2021, doi: 10.1016/j.tbs.2021.07.001.

[25] L. Böcker, P. van Amen, and M. Helbich, "Elderly travel frequencies and transport mode choices in Greater Rotterdam, the Netherlands," Transportation (Amst)., vol. 44, no. 4, pp. 831–852, Jul. 2017, doi: 10.1007/s11116-016-9680-z.

[26] T. Shen, Y. Hong, M. M. Thompson, J. Liu, X. Huo, and L. Wu, "How does parking availability interplay with the land use and affect traffic congestion in urban areas? The case study of Xi'an, China," Sustain. Cities Soc., vol. 57, Jun. 2020, doi: 10.1016/j.scs.2020.102126.

[27] B. Sun and C. Yin, "Impacts of a multi-scale built environment and its corresponding moderating effects on commute duration in China," Urban Studies, vol. 57, no. 10, pp. 2115–2130, Aug. 2020, doi: 10.1177/0042098019871145.

[28] M. Zhang, "The role of land use in travel mode choice: Evidence from boston and hong kong," Journal of the American Planning Association, vol. 70, no. 3, pp. 344–360, 2004, doi: 10.1080/01944360408976383.

[29] J. Yang, P. Su, and J. Cao, "On the importance of Shenzhen metro transit to land development and threshold effect," Transp. Policy (Oxf)., vol. 99, pp. 1–11, Dec. 2020, doi: 10.1016/j.tranpol.2020.08.014.

[30] L. Hu, J. Yang, T. Yang, Y. Tu, and J. Zhu, "Urban Spatial Structure and Travel in China," J. Plan. Lit., vol. 35, no. 1, pp. 6–24, Feb. 2020, doi: 10.1177/0885412219853259.

[31] L. Hu and R. J. Schneider, "Different ways to get to the same workplace: How does workplace location relate to commuting by different income groups?," Transp. Policy (Oxf)., vol. 59, pp. 106–115, Oct. 2017, doi: 10.1016/j.tranpol.2017.07.009.

[32] B. Liu, Y. Xu, S. Guo, M. Yu, Z. Lin, and H. Yang, "Examining the Nonlinear Impacts of Origin-Destination Built Environment on Metro Ridership at Station-to-Station Level," ISPRS Int. J. Geoinf., vol. 12, no. 2, Feb. 2023, doi: 10.3390/ijgi12020059.

[33] H. Yang, J. Peng, Y. Lu, J. Wang, and X. Yan, "Nonlinear impact of built environment on people with disabilities' metro use behavior," Applied Geography, vol. 169, p. 103323, Aug. 2024, doi: 10.1016/j.apgeog.2024.103323.

[34] C. Ding, X. (Jason) Cao, and P. Næss, "Applying gradient boosting decision trees to examine non-linear effects of the built environment on driving distance in Oslo," Transp. Res. Part A Policy Pract., vol. 110, pp. 107–117, Apr. 2018, doi: 10.1016/j.tra.2018.02.009.

[35] Q. Shao, W. Zhang, X. Cao, J. Yang, and J. Yin, "Threshold and moderating effects of land use on metro ridership in Shenzhen: Implications for TOD planning," J. Transp. Geogr., vol. 89, Dec. 2020, doi: 10.1016/j.jtrangeo.2020.102878.

[36] T. Tao and P. Næss, "Exploring nonlinear built environment effects on driving with a mixed-methods approach," Transp. Res. D Transp. Environ., vol. 111, Oct. 2022, doi: 10.1016/j.trd.2022.103443.

[37] B. Yang, Y. Tian, J. Wang, X. Hu, and S. An, "How to improve urban transportation planning in big data era? A practice in the study of traffic analysis zone delineation," Transp. Policy (Oxf)., vol. 127, pp. 1–14, Oct. 2022, doi: 10.1016/j.tranpol.2022.08.002.

[38] B. He et al., "Spatial and temporal characteristics of urban tourism travel by taxi—a case study of shenzhen," ISPRS Int. J. Geoinf., vol. 10, no. 7, Jul. 2021, doi: 10.3390/ijgi10070445.

[39] K. Park et al., "Impacts of disability on daily travel behaviour: A systematic review," Transp. Rev., 2022, doi: 10.1080/01441647.2022.2060371.

ISSN: 3007-9640 DOI: https://doi.org/10.70114/acmsr.2026.9.1.P112
[40] A. Blitz and M. Lanzendorf, “Mobility design as a means of promoting non-motorised travel behaviour? A literature review of concepts and findings on design functions,” J. Transp. Geogr., vol. 87, Jul. 2020, doi: 10.1016/j.jtrangeo.2020.102778.

[41] J. H. Friedman, “Greedy Function Approximation: A Gradient Boosting Machine,” 2001.

[42] C. Ding and X. Cao, “How does the built environment at residential and work locations affect car ownership? An application of cross-classified multilevel model,” J. Transp. Geogr., vol. 75, pp. 37–45, Feb. 2019, doi: 10.1016/j.jtrangeo.2019.01.012.

[43] C. Ding, X. Cao, and Y. Wang, “Synergistic effects of the built environment and commuting programs on commute mode choice,” Transp. Res. Part A Policy Pract., vol. 118, pp. 104–118, Dec. 2018, doi: 10.1016/j.tra.2018.08.041.

[44] C. Yin, J. Cao, and B. Sun, “Examining non-linear associations between population density and waist-hip ratio: An application of gradient boosting decision trees,” Cities, vol. 107, Dec. 2020, doi: 10.1016/j.cities.2020.102899.

[45] C. Ding, T. Liu, X. Cao, and L. Tian, “Illustrating nonlinear effects of built environment attributes on housing renters’ transit commuting,” Transp. Res. D Transp. Environ., vol. 112, Nov. 2022, doi: 10.1016/j.trd.2022.103503.

[46] A. Ibraeva, B. Van Wee, G. H. de A. Correia, and A. Pais Antunes, “Longitudinal macro-analysis of car-use changes resulting from a TOD-type project: The case of Metro do Porto (Portugal),” J. Transp. Geogr., vol. 92, Apr. 2021, doi: 10.1016/j.jtrangeo.2021.103036.

[47] G. Lyu, L. Bertolini, and K. Pfeffer, “Developing a TOD typology for Beijing metro station areas,” J. Transp. Geogr., vol. 55, pp. 40–50, Jul. 2016, doi: 10.1016/j.jtrangeo.2016.07.002.

[48] X. Guan and D. Wang, “Residential self-selection in the built environment-travel behavior connection: Whose self-selection?,” Transp. Res. D Transp. Environ., vol. 67, pp. 16–32, Feb. 2019, doi: 10.1016/j.trd.2018.10.015.

[49] D. Wang and T. Lin, “Built environment, travel behavior, and residential self-selection: a study based on panel data from Beijing, China,” Transportation (Amst)., vol. 46, no. 1, pp. 51–74, Feb. 2019, doi: 10.1007/s11116-017-9783-1.