THE EFFECTS OF CURBSIDE CAFÉS ON BIKE TRAVEL BEHAVIOURS: SPATIOTEMPORAL EVIDENCE FROM TORONTO

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Abstract. North American cities embraced a range of tactical strategies to proactively reinvigorate urban street life during the pandemic. However, it is still largely unknown whether such programs contributed to changed mobility choices, including increased use of cycling and walking. This study uses Toronto's CaféTO program as an example to examine how the design metrics of tactical curbside cafés can attract people commuting through bikeshare systems and increase street vitality. Employing linear regression analysis and spatially varying coefficient regression models, it reveals the impact of curbside café programs on spatiotemporal bikeshare travel patterns. The results indicate that both the dimension of the patios and the number of cafés can significantly influence ridership, but the impact on weekends is generally higher than on weekdays. The effectiveness of such tactical programs demonstrates their potential to solicit active travel and health-improving behaviours. This research is the first empirical study that offers insights into the spatially varying effects of café design properties and calls for tailored and site-specific policies to enhance bikeshare use and develop more sustainable urban environments.

Keywords. Curbside Dining Program, Bikeshare Ridership, Pandemic, Spatial Heterogeneity, Spatiotemporal Variation.

1. Introduction

In response to the global pandemic, North American cities have embraced a range of tactical strategies to proactively reinvigorate urban street life, support local businesses and promote sustainable transportation while ensuring public health. Notably, the experimental repurposing of empty parking spaces into parklets for leisure and recreation transformed urban spaces reserved for vehicles into amenities that served a broad public interest (Mandhan & Gregg, 2023). Toronto's CaféTO initiative is an exceptional example, demonstrating collaborative efforts between government authorities, local Business Improvement Areas (BIAs) associations, and urban design and transportation practitioners. Together, in 2020, they ingeniously converted nearly 10,000 linear meters of underutilised curb lanes into animated places for social

ACCELERATED DESIGN, Proceedings of the 29th International Conference of the Association for Computer-Aided Architectural Design Research in Asia (CAADRIA) 2024, Volume 2, 475-484.

gatherings and dining experiences, enhancing the character of main streets.

Existing literature has investigated the effects of temporary dining programs in North America, mainly from sales, policy and public opinion perspectives. Meanwhile, we witnessed the expansion of the bikeshare system due to health concerns on public transit. Such increased bikeshare ridership is critical in shifting towards sustainable transportation modes and a healthier environment. Using public surveys, a recent study found that temporary dining programs can lead to more active use of cycling (Noland et al., 2023). The assumption is that curbside cafés as destinations attract people to commute through bikeshare systems, providing a cycling friendly environment, increasing street vitality. However, survey data may not reflect the on-the-ground travelling behaviour. Given the persisting hybrid work mode trend post-pandemic in North America and associated behavioural changes (Song, Dou, et al., 2023), several under-researched questions remains yet to be answered. How have the design metrics (e.g., length, width of patios, number of planters) of the curbside café program affected the bikeshare ridership during the pandemic? And how do the impacts of curbside cafés on bikeshare ridership vary across space and time? Such questions shed lights on how to incite active transportation behaviours and guide future sustainable development.

2. Data & Method

2.1. STUDY AREA & ANALYTICAL FRAMEWORK

The study area for this research is Toronto, the largest metropolitan city in Canada. In 2020, Toronto was home to approximately seven million people. During the global pandemic, the city government developed the CaféTO dining program, which reallocated public right-of-way on streets and created temporary outdoor dining patios. It is an ideal site to investigate the effectiveness of such initiatives in influencing people's travel behaviour and promoting Sustainable Development Goals (SDGs).

The analytical framework of this study (Figure 1) consists of multiple statistical models, employing various CaféTO curbside café design metrics and built environment variables to perform Ordinary Least Squares (OLS) regression analysis on public bikeshare data. Furthermore, a more advanced spatial statistical model, the Geographic Gaussian Process - Generalised Additive Model (GGP-GAM), was applied to assess their spatiotemporally varying impacts on bikeshare travel behaviour in Toronto in 2020.

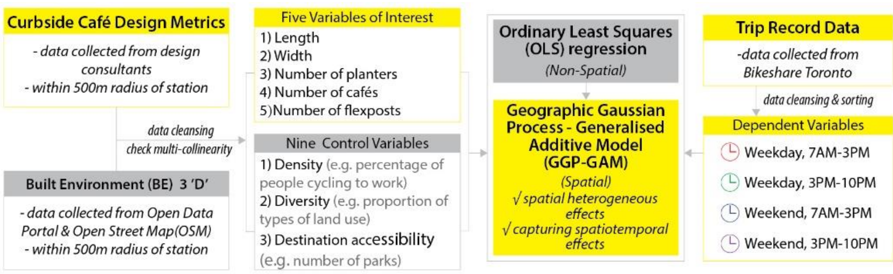


Figure 1. Analytical framework of the study

2.2. SELECTION OF VARIABLES

2.2.1. Bikeshare Ridership

The bikeshare ridership is provided by Bikeshare Toronto, the only bikeshare system provider in Toronto. Adopting a docked bike operation system, each trip record includes information on the trip origin and destination (OD) station, start and end time, and trip duration. To ensure the reliability of the data, only regular trips (1min < duration <30mins) were kept in our analysis. The thresholds were set to filter out test rides and redistribution activities conducted by the system operators. And because the curbside dining program was incrementally implemented between July and August in 2020, we chose the ridership data in the time frame from Sep. 1st to 30th to make sure the curbside cafés were in full operation. After processing, over 410,000 trips were left for the analysis. Figure 2 shows the hourly intensities and histogram of trip durations, with most rides ranging from 3 to 15 minutes.

Prior research demonstrated that bikeshare rides exhibit temporal differences during the day and week and this temporal characteristic should be examined to reflect the travelling behaviour dynamics (Faghih-Imani & Eluru, 2015). Depending on the trip purposes during different time windows, the effects of built environment factors inevitably vary. Therefore, we first aggregated the trip to the bikeshare stations based on the destination station, and we used daily arrival trip frequency of weekends and weekdays to account for their potential travel behaviour disparity. We divided the daily trip frequency into two periods, 7AM-3PM (Morning-Afternoon) and 3PM-10PM (Evening-Night), for further analysis. As Figure 1 demonstrates, the peak of the bikeshare trips concentrates in afternoon and evening hours.

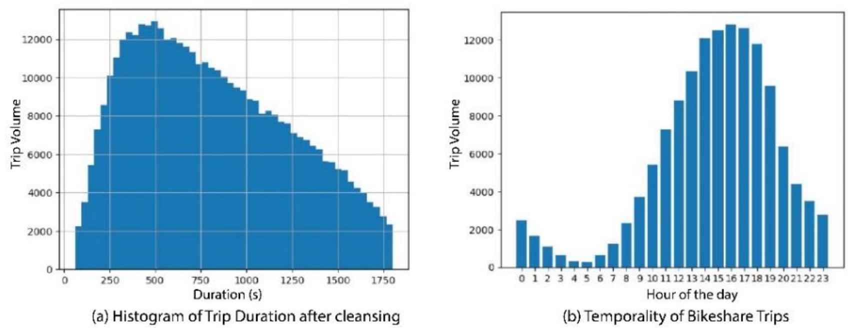


Figure 2. Bikeshare trip duration and temporality

2.2.2. Curbside dining program design metrics

Figure 3 depicts the geographical distribution of the curbside cafés that participated in the initiative through local BIAs, with most of these dining patios installed in downtown Toronto, particularly along prominent main streets such as Bloor and Yonge Street. To understand how the design of curbside café could potentially influence and solicit bikeshare riding behaviour, detailed design metrics of each café were collected from urban planning and transportation consultants, then mapped spatially to their corresponding locations. The metrics were aggregated at the station level within a

500m walking buffer, including average width, length of café patios, number of planters, number of concrete jersey walls, flexposts (elements to separate bike lanes from patios for safety purpose), and number of cafés.

Figure 3. Curbside café locations in Toronto

2.2.3. Other Built Environment Covariates

Besides curbside café metrics, we followed the widely used '3D' (i.e., density, diversity, destination accessibility) framework to select environmental variables as covariates to control their effects. The density dimension included the percentage of people cycling to work, and the diversity dimension considered the proportion of different types of land use within buffers around each station, covering employment, open space, residential neighbourhood, apartment neighbourhood, institutional, and regeneration land. Lastly, destination accessibility is proxied by the length of the dedicated bike lane, the number of nearby subway stations, the number of parks, and the area size of parks. These variables were reported to significantly influence active cycling behaviour in previous research (Griffin & Sener, 2016).

2.3. MODEL ARCHITECTURE

Variance Inflation Factors (VIFs) were calculated to examine the potential collinearity issue between all the independent variables, and those that exhibited high VIFs (>10) were eliminated. Due to the linear nature of the café patios, the number of jersey walls was deleted to avoid the collinearity in the model. In this study, four curbside café design metrics and nine built environment covariates were kept for the final regression analyses. We first applied the OLS regression, which can provide interpretable implications on urban planning and design policies. Nevertheless, its unbiasedness and efficiency largely rely on satisfying several underlying assumptions, among which one major concern is the existence of spatial autocorrelation in the spatial dataset that would violate such assumptions. This prompted us to check Moran's I statistics on the residuals of the OLS model results. If the spatial autocorrelation effect is confirmed significant, then the spatial model should be adopted for further analysis. Additionally, OLS regression only provides an interpretation of the global effects without considering the spatial heterogeneous effects of the independent variables. In this regard, adopting a local regression model to model spatially varying coefficients could provide an alternative solution and more insights.

In this study, we employed a state-of-the-art local regression model recently developed by Comber et al. (2023), who proposed the GGP-GAM. It can be viewed as a counterpart to the most popular local regression model, the Multiscale Geographic Weighted Regression (MGWR) model (Fotheringham et al., 2017). The GGP-GAM was reported to outperform the MGWR model regarding prediction accuracy in a simulation case study. It applies Gaussian Process (GP) splines to the GAM and calibrates via observation location in a multiscale varying coefficient model to account for the spatial heterogeneous effects of independent variables instead of assuming fixed coefficient processes by OLS regression. In the meantime, the GAM model can capture the non-linear relationship by smooth non-linear functions in contrast to the default linear terms used in OLS. The interpretable GGP-GAM provides a middle ground between OLS and complex 'black box' Deep Learning algorithms, and it outperforms most of Machine Learning models. The basic model could be written as follows:

$$y = \alpha(z) + x_1 f_1(z) + \cdots + x_m f_m(z) + \epsilon$$

where y is the dependent variable, $f_i(z)$ is an unspecified form linear regression coefficient of an independent variable x_i , z represents a vector specifying spatial locations and models the variable's spatially varying effects, ϵ indicates the error term for those unexplained variables. And to control the smoothness of the function by jointly considering the covariance function:

$$y = f(x) + \epsilon = \sum_{i=1}^{d} \kappa_i(x)\gamma_i + \epsilon$$

Where the $\kappa_i$is a basis function of the transformed x and the γ are corresponding regression coefficient estimates. The GGP-GAM uses a GP basis, and with a variance-covariance matrix R of the spatial, the covariance function kappa allows the variance-covariance function of the values of β_i in each location to be found. It could be translated into a set of n basis vector $\kappa_i(x)$, and the GAM is calibrated this way to model the potential non-linear relationship and construct splines that represent the GP parameterised by location and attribute space. Each covariate i has a spatially varying coefficient $\beta_i(z)$, where the $z_i = (u_i, v_i)$.

The model architecture is straightforward in this research. We ran an OLS regression model separately on each dependent variable, i.e., Model 1 (Weekday 7AM-3PM ridership); Model 2 (Weekday 3PM-10PM ridership); Model 3 (Weekend 7AM-3PM ridership) and Model 4 (Weekend 3PM-10PM ridership). And if spatial effects were detected, a set of GGP-GAM models (i.e., Model 5, 6, 7, 8) was applied respectively to model the spatial non-stationarity and to reveal the spatially varying effects of the curbside café metrics and other built environment factors.

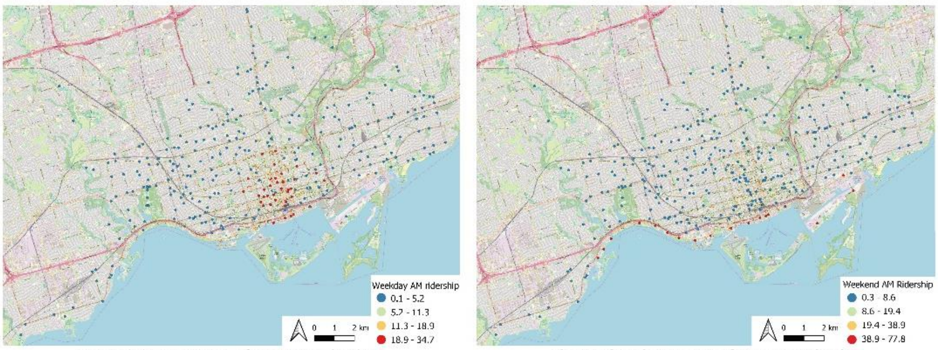
3. Results & Discussions

3.1. SPATIOTEMPORAL VARIATIONS OF BIKESHARE RIDERSHIP

Our analysis reveals distinct temporal patterns in bike-share usage. On average, the period from 3 PM to 10 PM experiences a higher volume of trips, consistent across weekdays and weekends. Notably, certain stations exhibit a pronounced increase in weekend ridership, with the highest recorded weekend station activity surpassing weekday figures by approximately 2.5 times (see Table 1). Apart from the temporal differences, the bikeshare ridership also varies spatially, with the downtown area consistently receiving more rides throughout the day. Furthermore, similarities and differences are identified between ridership patterns on weekdays and weekends. For instance, Figure 4 depicts the 7AM-3PM trips. However, on weekdays, predominant destination spots concentrate along main commercial corridors such as Yonge Street and around Queen's Park. Conversely, weekend usage shifts predominantly towards waterfront areas and major open spaces in downtown Toronto, areas recognised for contributing to resident wellbeing, especially during the pandemic. In the later hours of the day (3 PM to 10 PM), we observe a more dispersed spatial distribution pattern of trips. Both the western and eastern parts of downtown experience an uptick in bikeshare usage, surpassing levels seen earlier in the day.

Table 1. Descriptive statistics of bikeshare ridership

Bikeshare Ridership	Count	Mix	Mean	Max
Weekday 7AM-3PM	539	0.13	7.46	34.72
Weekday 3PM-10PM	539	0.18	12.56	66.09
Weekend 7AM-3PM	539	0.25	10.39	77.75
Weekend 3PM-10PM	539	0.25	16.22	163.62



(a) Weekday Morning-Afternoon Ridership (b) Weekend Morning-Afternoon Ridership

Figure 4. Bikeshare ridership patterns (e.g., 7AM-3PM trips)

3.2. OLS REGRESSION RESULTS

Table 2 presents the outcomes of the OLS regression analysis. Model 1 exhibits the strongest goodness-of-fit, accounting for 45.1% of the variance in bikeshare ridership during weekdays from 7 AM to 3 PM. This suggests that factors like curbside café design and built environment characteristics are significant predictors of this timeslot's ridership. The results indicate that these variables more effectively explain ridership patterns during the 7 AM to 3 PM window, both on weekdays and weekends, compared to the 3 PM to 10 PM timeframe. It implies that bikeshare usage is more associated with lunchtime activities than dinner, particularly on weekdays. Among the café design metrics, the number of cafés reports a positive influence on bike-share ridership across all times, with its most pronounced impact observed during weekdays, 7AM-3PM. The average patio width also significantly affects ridership during these hours on both weekdays and weekends. Specifically, increasing the patio width could be associated with more weekend ridership than weekdays. However, this influence diminishes in the evening to night hours. The number of planters and flexposts does not report a statistically significant effect, suggesting their limited influences on active travel behaviour across the study area.

It's important to note that all linear models demonstrate strong positive spatial autocorrelation effects, as indicated by Moran's I on residuals. This suggests that the OLS regression may yield biased coefficient estimates. Therefore, employing the GGP-GAM model could better explain the spatial heterogeneity of the data.

Table 2. The diagnostic results of OLS linear regression models (n=539)

OLS	Model 1	Model 2	Model 3	Model 4
Dependent Variable	Ln (Weekday 7AM-3PM Ridership)	Ln (Weekday 3PM-10PM Ridership)	Ln (Weekend 7AM-3PM Ridership)	Ln (Weekend 3PM-10PM Ridership)
Adjusted R^2	0.451	0.324	0.369	0.336
F-statistic (sig.)	35.0***	20.9***	14.6***	21.9***
Moran's I	0.640***	0.683***	0.622***	0.695***

Note: *** $p < 0.01$

3.3. GGP-GAM RESULTS

Table 3. The diagnostic results of GGP-GAM models (n=539)

GGP-GAM	Model 5	Model 6	Model 7	Model 8
Dependent Variable	Ln (Weekday 7AM-3PM Ridership)	Ln (Weekday 3PM-10PM Ridership)	Ln (Weekend 7AM-3PM Ridership)	Ln (Weekend 3PM-10PM Ridership)
Adjusted R^2	0.594	0.534	0.514	0.540
Approximate significance of smooth terms of the selected curbside café and built environment variables				
s (Planter_sum)	0.093	0.010**	0.888	0.020*
s (Flexpost)	0.250	0.004**	0.241	0.029*
s (Number_Cafe)	0.003**	1.93e-05***	2e-16***	1.2e-05***
s (Width_mean)	0.0007***	5.16e-05***	6.3e-05***	1.28e-05***
s (Subway)	0.476	0.539	0.468	0.353
s (open space ratio)	0.001***	1.52e-05***	6.4e-07***	3.01e-06***

Note: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Table 3 reports the results of GGP-GAM models from Model 5 to 8, respectively. Each model demonstrates a notable improvement in adjusted R2 value over their respective OLS counterparts. Particularly, Model 8, when utilising the GGP-GAM approach, explains an additional 20.4% of the variance in weekend evening-night ridership compared to Model 4. These findings substantiate our hypothesis that the global associations obtained through OLS are inadequate for capturing the complex spatiotemporal effects posed by curbside café designs on bikeshare usage at different times. The outcomes indicate that these effects exhibit spatial variability, necessitating more detailed interpretations.

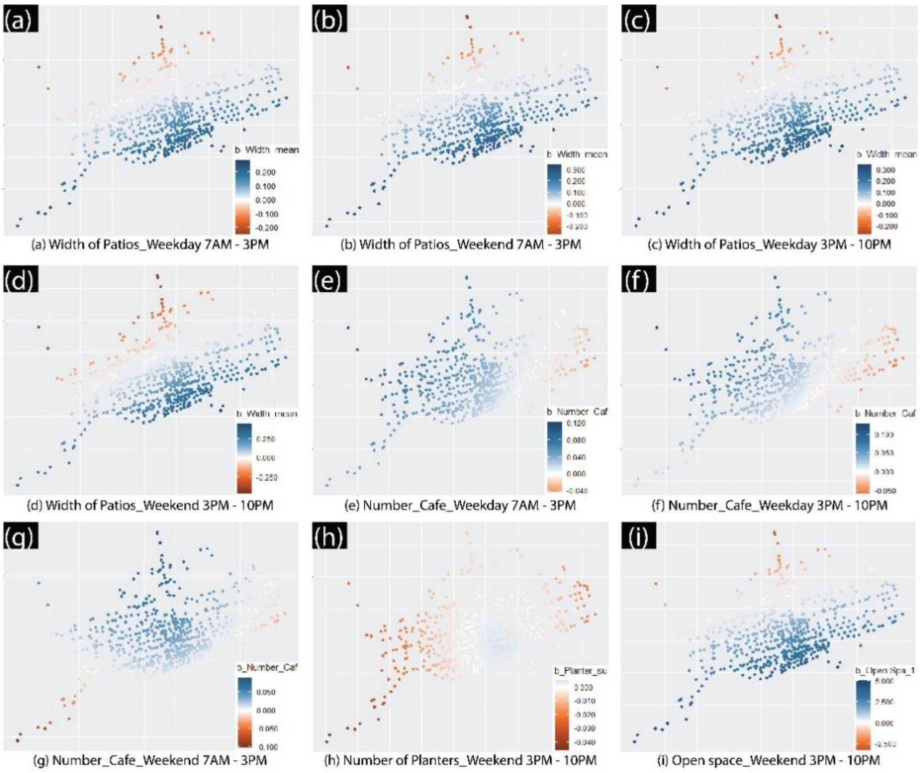


Figure 5. Spatial Distribution of coefficients of selected variables in different GGP-GAM models

The p-value of smooth terms implies the local significant impact. Within the curbside café design metrics, both the number of cafés and patio width consistently show significant impacts across all reported periods. And in line with the OLS results, the number of flexposts shows no significant effect. Conversely, the presence of planters significantly influences bikeshare usage during both weekend and weekday periods only from 3 PM to 10 PM. This suggests that planters may have a more pronounced effect during specific times of the day.

The spatially varying coefficients of selected variables are mapped out in Figure 5 to present their impacts across different regions visually. Generally, the effect of patio width is positive and more pronounced near waterfront areas in the south compared to the northern downtown regions (Fig.5a, 5b, 5c, 5d), diminishing gradually northward. Notably, such impact patterns on bikeshare ridership are similar across different periods. Additionally, the patio width's impact is more significant during weekends than weekdays, with a slightly greater effect observed from 3 PM to 10 PM (Fig.5d) compared to 7 AM to 3 PM (Fig.5a). For example, a one-meter increase in patio width near some bikeshare stations could result in over a 30% increase in ridership frequency. The allowed patio width is presumably largely determined by the street hierarchy and indicates the potential carrying capacity of customers in the outdoor spaces. Therefore, strategically implementing road widening in par with curbside dining may be suitable for certain urban areas in the downtown core.

Furthermore, the number of cafés positively impacts ridership in the western and downtown areas during weekdays (Fig.5e, 5f). Conversely, positive impacts are identified on weekends (Fig.5g) in the north and downtown regions, suggesting a spatiotemporally varied influence. Notably, this trend does not extend to the eastern region, indicating that an increase in café numbers here does not necessarily promote cycling behaviour.

Moreover, the presence of planters (Fig. 5h) shows a predominantly positive impact on ridership in downtown areas, particularly along commercial roads, with this effect diminishing outwardly. Consistent with prior literature, the study further supports the importance of other conventional built environment variables, such as the proportion of open space (Fig.5i), which influences bikeshare rides but decreases in impact as we move northward. Additionally, the negligible impact of subway stations during the period implies a shift in public transit behaviours.

3.4. LIMITATIONS

However, this research is not without limitations. First, due to the constraint of resources, we only examined the dataset of 2020. Though our analysis is useful in understanding bikeshare behaviour, we plan to conduct multi-year analysis to evaluate this effect over time. This can consider the tension between bikeshare and other slowly recovering transit mode like subway. Second, previous studies have utilised Street View Imagery to proxy the perceived built environment at the eye level (Song, Li, et al., 2023). We posit that combining street features into our future analysis could better reflect the ground truth when curbside cafés were operational to better explain active travelling behaviours. Third, this research solely relies on the OD data. Modelling the routes based on the calibration of travel speed might provide some nuanced insights into how the curbside café design could attract cyclists to deviate from the shortest routes at the street segment level. Lastly, the causal mechanism cannot be inferred from cross-sectional data, while quasi-experimental analysis can provide a more confident interpretation of policies when longitudinal data is available.

4. Conclusion

This empirical research offers the first study that evaluates the effectiveness of curbside café program on encouraging bikeshare use. It reveals the nuanced spatiotemporally relationship across different time periods during the pandemic. This study utilises both linear global regression and spatially varying coefficient local regression models to untangle the intricate spatially heterogeneous connections between ridership and the curbside café design metrics. First, our results indicate that both the patio width and number of cafés could significantly influence ridership, but the impact on weekends is generally higher than on weekdays. Second, the effectiveness of such tactical programs justifies the immense potential in soliciting active travel behaviour. Compared with planning variables like open space proportion, governments need to wait for a lengthy consultation process to redevelop public open spaces to achieve comparable impacts. In contrast, the cost-effectiveness of the program renders it advantageous to be quickly implemented to increase active behaviour in the short term. Through such programs, urban planners and designers can potentially induce more active traveling behaviours by encouraging business owners located in those less involved BIAs. Lastly, the spatially varying coefficients offer unique interpretations on effectively increasing the bikeshare ridership in different locations. For example, increasing the number of cafés might be more appropriate in suburban and north downtown areas, while for downtown areas, increasing both number and patio width may jointly pose more impacts on bikeshare. When adequately considered with other socioeconomic factors, such a nuanced understanding of varying effects of the variables can offer site-specific policy for different geographical areas. In summary, the curbside café dining program enables modern cities to acknowledge the built environment's unique role in shaping a sustainable future. It advocates for street environments prioritizing people over vehicles and raises cultural awareness of low carbon transportation and underscores the necessity of integrating cost-efficient actions into design disciplines to enhance people 's quality of life.

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