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Spaces of Integration – Living Together

Revitalising Streets Through Pandemic-Induced Street Experiments: A Longitudinal Assessment of Outdoor Dining Programmes' Impact on Vitality in Toronto

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Abstract: The COVID-19 pandemic disrupted street vitality, challenging governments to sustain local economies and public well-being. Nevertheless, the effects of pandemic-induced street experiments on vitality remain underexplored, and the relationships between built environment qualities and urban vitality are less understood for the period during and after the pandemic given their changing dynamics. This study investigates the street vitality in Toronto by analysing bikeshare data from 2020 and 2021, using trip-volume frequency as a proxy. We employed explainable machine learning models to reveal the nonlinear impact of the CaféTO outdoor dining programme. Design metrics of curbside cafés—such as patio dimensions and planters—were examined. We compared the impacts on weekdays and weekends across both years, assessed built environmental characteristics, and extracted micro-level environmental features from street views using machine learning algorithms. It was found that: (1) Curbside cafés can significantly promote vitality; their impacts increased in 2021 compared to 2020 possibly due to policy relaxations, while metrics including length, width and planters all exhibited non-linear threshold effects. (2) The emphasis on variables like open space and street qualities highlighted a strong demand for recreational spaces during and after the pandemic, with other demands for infrastructures partially recovered.

Keywords: street experiment; pandemic; vitality; machine learning; non-linear relationship

1. Introduction

1.1. Urban vitality and street experiments

Urban vitality emphasises the importance of having "sufficient eyes on the street" (Jacobs, 1961), a definition further elaborated by many later urban scholars who highlight the role of activities and the sense of liveliness in public spaces (Lynch, 1984). Enhancing urban vitality yields numerous benefits, including increased resilience, strengthened social cohesion (Mouratidis & Poortinga, 2020), and stimulated innovation (Chen et al., 2022), rendering it essential for sustainable development towards a liveable city.

The COVID-19 pandemic significantly disrupted urban life, exacerbating long-standing challenges such as unequal access to public space, weakened local economies, and limited social interaction (Bissell, 2021; Florida et al., 2021). It renewed attention to the role of vibrant public spaces and highlighted promoting urban vitality as a critical pathway for recovery. To address these challenges—particularly those resulting from restrictions on physical contact due to health concerns, many cities implemented various

street experiments to revitalise urban areas, such as outdoor dining programmes, street closures, and pop-up bike lanes, to encourage active travel (Combs & Pardo, 2021). Temporary outdoor dining initiatives in major cities like New York City, Chicago, and Toronto served as lifelines for businesses and were proposed to invigorate the economy (Brody et al., 2024).

However, the extent to which these pandemic-induced street experiments have influenced street vitality remains unexplored empirically. Taking Toronto as an example, the CaféTO programme repurposed curbside parking spaces into outdoor patios to support restaurant operations and maintain socially distanced interactions to facilitate local economic recovery (Mandhan & Gregg, 2023). Unlike many temporary experiment initiatives discontinued post-pandemic (Combs & Pardo, 2021), the success of CaféTO led to its long-term adoption in a tactical urbanism approach, underscoring the need to better understand the potential effects of such street-level experiments on influencing urban vitality.

1.2. The vitality and built environment

Previous studies have established strong connections between urban vitality and macro-scale built environment (BE) attributes–such as morphological characteristics, building density, land-use diversity, and landscape features (Meng & Xing, 2019; Xiao et al., 2021). Notably, research is scarce on the effects of micro-scale street environment (SE) perceived qualities, particularly urban design qualities such as complexity (Song, Fang, et al., 2024). The advancement in computer vision and street view imagery (SVI) has enabled researchers to effectively quantify and measure street-level, micro-scale features compared to the conventional virtual or on-site audit. These place-specific qualities reflect the nuances of daily life experiences and are crucial in promoting vitality through human–environment interactions (Jiang et al., 2022; Wu et al., 2023). Given the long-lasting impacts of the pandemic, such as the persistence of hybrid work modes in many North American cities, it is imperative to re-evaluate how SE and BE attributes have collectively influenced urban vitality during and after the pandemic.

2. Research gaps & objectives

2.1. Gaps

Several gaps exist in the current urban studies literature concerning street experiments and urban vitality. First, existing studies have primarily focused on policies, sales, and public views of the programmes (Noland et al., 2023), neglecting their potential effects on promoting active travel that influences street vitality for the economy. Second, how the street experiments have continually influenced the "after-pandemic" condition (such as in 2021) is unknown, and the longitudinal effects of street-level experiments on urban vitality are barely discussed. Prior limited research primarily relied on the year 2020 data (during the pandemic), which may overlook its long-term effects on vitality (Song, Li, & van Ameijde, 2024). Third, while connections between urban vitality and macro-scale BE attributes are established, there is a lack of knowledge regarding the effects of micro-scale SE attributes during and after the pandemic (Wu et al., 2023). Moreover, the pandemic's transformation of social engagement dynamics necessitates testing new relationships between urban vibrancy and BE. Lastly, conventional regression models may miss valuable insights, such as thresholds at which variables become effective, highlighting the need for nonlinear machine learning (ML) models to capture such nuances.

2.2. Objectives

By analysing and comparing data during (2020) and after (2021) the pandemic, this research provides one of the earliest attempts at a longitudinal perspective on revealing the impact of street experiments and BE characteristics on urban vitality. This paper contributes a novel analytical framework for jointly investigating street experiment features, micro-level SE, and macro-level BE features to reveal their non-linear effects on influencing urban vitality and identify threshold points for further interpretation. It assesses the threshold effects of the CaféTO curbside café programme on vitality in both years, their associated design metrics (e.g., patio length, planter boxes), and how their nuanced effects vary between weekdays and weekends. Furthermore, the research enriches our understanding of how macro-level BE and micro-level SE perceived qualities influence the dynamics of street vitality by year and within the week. These insights help city planners understand how to optimise tactical interventions without overinvesting, thus improving resource-allocation efficiency and effectiveness in urban design to mitigate ongoing challenges.

3. Data and methods

3.1. Analytical framework

The proposed analytical framework is shown in Figure 1. It mainly consists of three steps, including data collection and processing, ML model training and testing using eXtreme Gradient Boosting (XGBoost) for four instances (weekday/weekend in 2020 and 2021), and model interpretations from the dimensions of feature importance and nonlinear associations using SHAP local dependence plot for further comparison across years.

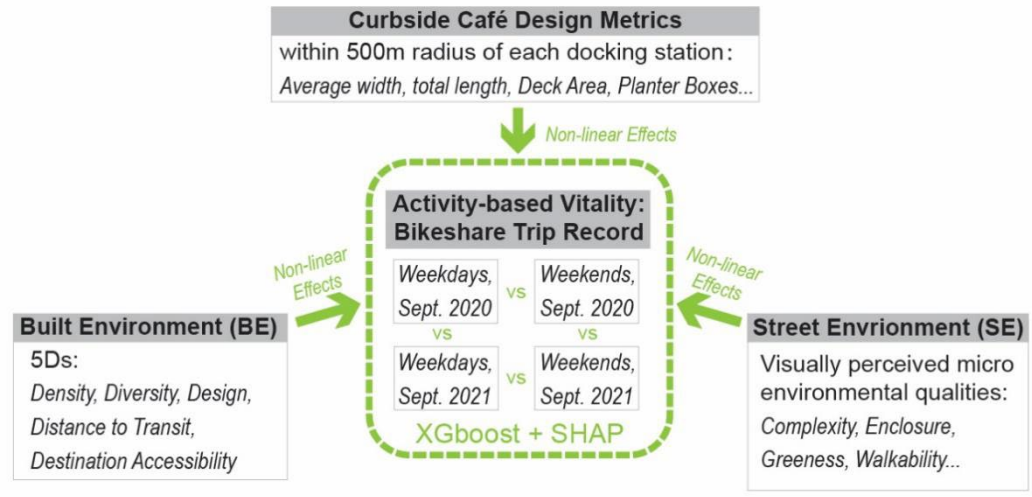

Figure 1 Analytical framework

3.2. Study area

Toronto was chosen as the study area because it uniquely exemplifies the impact of pandemic-induced street experiments on urban vitality (Figure 2). The city's successful programme repurposed curbside parking spaces into outdoor patios, supporting restaurants and enabling socially distanced interactions; unlike similar initiatives elsewhere, it continued beyond the pandemic, allowing for longitudinal analysis to assess its impact over time (Mandhan & Gregg, 2023). Additionally, Toronto has a well-developed bike-sharing system that promotes active travel behaviour, which is crucial for determining how outdoor dining programmes influence street vitality. The city's rich cultural scene, diverse built environment, and varied street perception features enable a comprehensive examination of macro- and micro-scale factors affecting urban vitality in post-pandemic conditions.

3.3. Variables

3.3.1. Dependent variable: Activity-based vitality

To obtain street vitality, inspired by a study using mobility data to proxy the flow of people (Sulis et al., 2018), we use the frequency of bikeshare users presented at each docked bikeshare station to reflect foot traffic during the pandemic. The daily frequency at each station is calculated as the sum of all trips originating from and destined for that station. Considering that the effects of the built environment may vary during different periods, we grouped the data into weekdays and weekend vitality to account for potential disparities in travel behaviour.

The bikeshare ridership data was obtained from Bikeshare Toronto, the sole public bikeshare provider in the city, which operates a docked bike system. For our longitudinal analysis, we collected data from 2020 and 2021. And since the curbside dining programme was incrementally implemented between July and August each year, we selected the entire September to ensure that the curbside cafés were actively used. We filtered the dataset to include only "normal trips" lasting between 1 and 45 minutes. After pre-processing, over 428,000 trips in September 2020 and over 444,000 in September 2021 remained for further analysis; rainy days (daily precipitation > 5 mm) were further excluded due to their disruptive impact on vitality. Results revealed that, for instance, during the weekends in September 2021, vitality hotspots primarily concentrated along the waterfront area.

3.3.2. Dependent variable: Curbside dining patio metrics

Figure 2 depicts the geographical distribution of the close to 1,000 curbside cafés in 2021 that participated in the initiative through local BIAs, with most of these dining patios installed in downtown Toronto, particularly along main streets such as Bloor and Yonge Streets. To understand how the design of curbside cafés could potentially solicit urban vitality, which can benefit the local economy, detailed design metrics for each café were collected from urban planning and transportation consultants and then mapped spatially to their corresponding locations. The metrics were aggregated at the station level within a reasonable 500-m walking buffer, including average width, length of café patios, number of planters, number of concrete jersey walls; for the year 2021, we also included the total area of the wooden decks, which were introduced as a new feature after 2020.

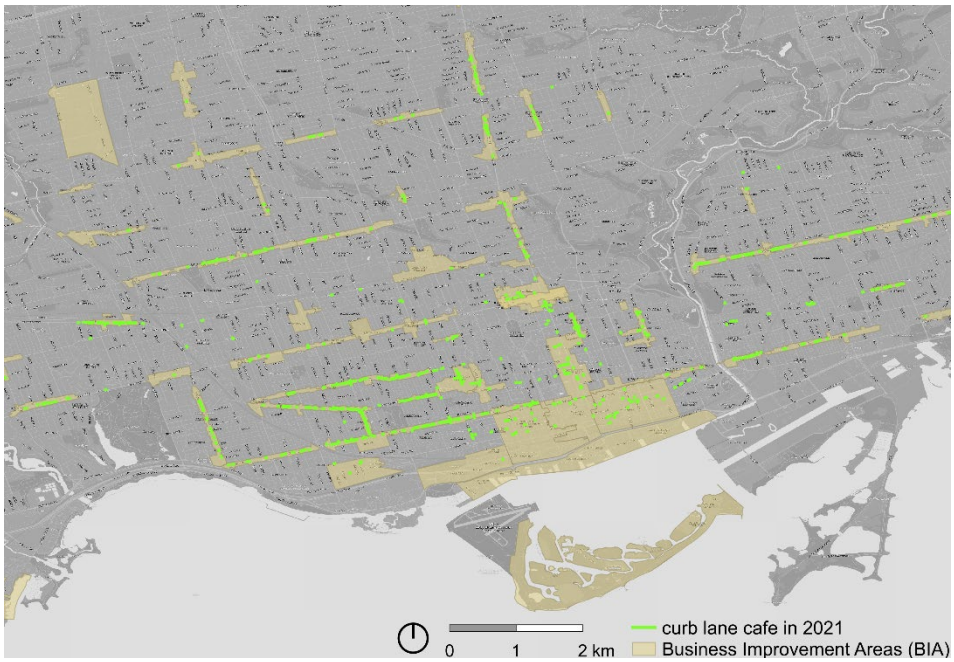

Figure 2 Curbside café locations (2021) as an example

3.3.3. SE-perceived design qualities

Regarding SE's perceptual qualities, we included six design qualities (i.e., complexity, enclosure, greenness, safety, imageability, and walkability) based on classic urban design theory (Ewing & Handy, 2009). These qualities are quantifiable based on an established measurement framework by recombining view indices of SVI (Ma et al., 2021; Song, Fang, et al., 2024). We applied the PSPNet algorithm and quantified the perceived qualities. The qualities around each station are calculated using the mean value within each buffer.

3.3.4. Other BE variables

Besides curbside café metrics, we followed the widely used "5D" framework in walkability studies to select BE variables as covariates to control their effects (Chen et al., 2023). The density dimension included the percentage of people cycling to work and population density collected from census data. The diversity dimension considered the proportion of land uses around each station, encompassing employment, open space, residential neighbourhoods, apartment neighbourhoods, institutional areas, and regeneration (mixed-use) land. The design dimension incorporated the station capacity. Furthermore, the number of subway stations reflected the distance to the transit dimension. Additionally, the destination accessibility dimension was assessed by the length of the collector road, dedicated bike lane, and number of parks/open spaces, which encourage cycling activities and vitality (Faghih-Imani & Eluru, 2015).

3.4. Model architecture and interpretations

3.4.1. ML model

The study applied an explainable ML model, XGBoost, a robust algorithm for handling complex, non-linear relationships in urban studies. It can iteratively build decision trees to capture non-linear interactions without requiring predefined relationships between variables, such as in linear regression models (Chen & Guestrin,

2016). Additionally, XGBoost handles missing values and outliers better, maintaining predictive accuracy even with imperfect data.

We first calculated the variance inflation factors (VIF) of independent variables and removed those variables with VIF > 10 to avoid multicollinearity. Subsequently, we built the XGBoost model for each period separately (4 models) to predict its impact on urban vitality. Following established ML standards, we split our data into 80% for training and 20% for testing. We utilized the 5-fold cross-validation technique to search for the optimal hyperparameters and chose the best-fitted model for further interpretations. We adopted standard metrics such as R-squared (R2) and mean square errors (MSE) to compare the model's performances.

3.4.2 Feature importance and SHapley Additive exPlanations (SHAP)

We further reported the feature importance to assess the general impact of each feature in predicting the urban vitality to rank features based on their overall influence in different years and times (Dong et al., 2023). However, to understand the local impact, SHAP values were used in this analysis to interpret the results of the XGBoost model because they provide a consistent and transparent way to understand the contribution of each feature to the model's predictions, allowing us to see how specific values contribute positively or negatively.

4. Results

4.1. Predictive performance of the XGBoost models

All four models exhibit a reasonable fit on the test set. The model's performance implies that the models perform better on weekdays and shows improved accuracy in 2021 compared to 2020. The R-squared values range from 0.42 to 0.53, indicating that the models explain between 42% and 53% of the variance in the data. MSE values are notably lower for weekdays than weekends, decreasing from 2020 to 2021.

It can be inferred that models perform better on weekdays and show improved accuracy in 2021 compared to 2020, implying that the city has slowly bounced back from the pandemic and returned to a "new normal" state, in which the variables are more predictable after the pandemic compared to during pandemic times. Over the years, weekdays might have experienced similar mobility patterns that could be better explained by BE and SE variables, which is consistent with prior literature (Chen et al., 2023).

Table 1. Performance metrics of the XGBoost models

1. Model	Weekday 2020	Weekend 2020	Weekday 2021	Weekend 2021
6. R2	7. 0.44	8. 0.42	9. 0.53	10. 0.53
11. MSE	12. 596.21	13. 2504.39	14. 1133.10	15. 1768.61

4.2. Feature importance—Contributions of BE and SE variables

For weekdays during the pandemic in 2020, the most influential features were typically related to population density, station capacity, and institutional land use (Figure 3). In 2021, population density maintains its position as the top determinant of vitality but with reduced dominance, likely due to more balanced mobility patterns. Features like perceived greenness and café design metrics (e.g., deck area and patio length) gain importance in 2021. The importance of bike-docking capacity (capacityca) declines in 2021, as other features related to leisure and aesthetics become more influential.

For weekends, population density remains consistently critical for vitality in both pandemic and post-pandemic contexts. In 2021, institutional land and connectivity features (e.g., collection roads, subway stations) highlight the evolving role of accessibility and mixed-use areas for weekend vitality. Also, experiential and aesthetic features like perceived greenness gained importance as leisure activities resumed. Deck area emerges as a new, highly important feature, indicating the role of well-designed café spaces.

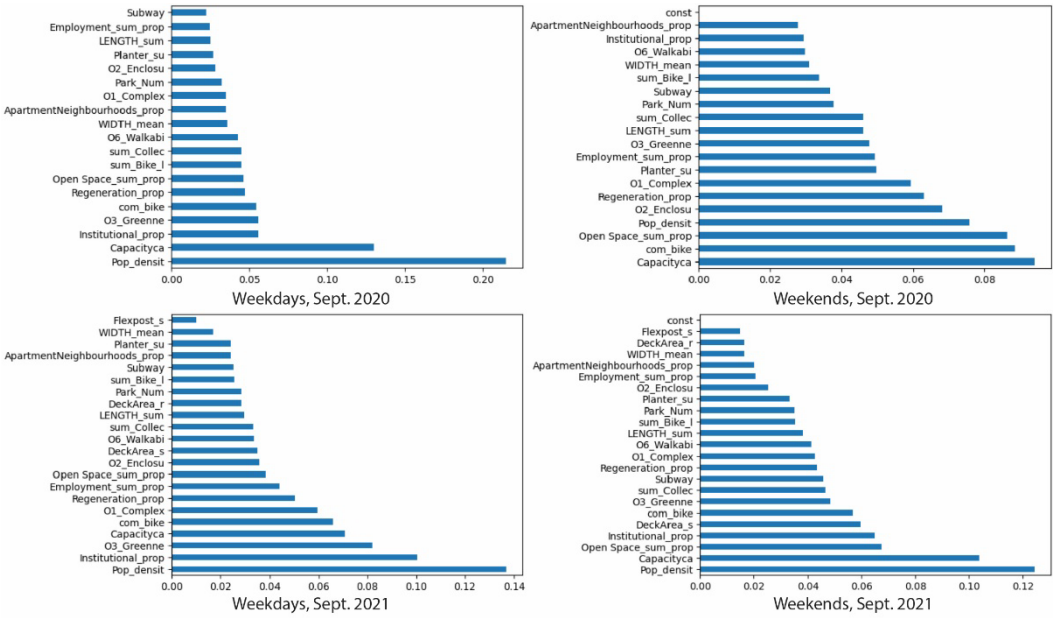

Figure 3. Feature importance comparison between 2020 and 2021

4.3. Nonlinear and threshold effects

The SHAP local dependence plots (Figure 4) reveal distinct, non-linear effects of several features on vitality in 2020 and 2021, with essential shifts in response as conditions moved from highly restrictive to more relaxed (Zhao et al., 2024). For brevity, we do not present all the plots in our manuscript. Specific café design features—such as planter boxes, average café width, and total café length—and BE and SE features like population density, the ratio of people commuting by bike, perceived street greenness, and bike-docking capacity all demonstrate non-linear impacts.

Notably, as shown in Figure 4, the total length of cafés in both years shows an initial increase in biking activity as the length of the café area expanded, reflecting a preference for extended café zones. The change from a 100-m threshold in 2020 to 400 m in 2021 indicates a shift in public space utilization. In 2020, the compact use of outdoor cafés adapted to constrained social interaction and was a preliminary attempt to promote urban vitality. In 2021, the public's willingness to use more café spaces for extended periods or larger groups increased as the restrictions relaxed, and residents became more aware of the programme. Furthermore, the average café width exhibits a distinct non-linear effect in 2020 and 2021, especially on weekends. Specifically, the SHAP value initially increases with width, indicating that more spacious café areas drew more attention from users, likely due to their comfort and suitability for social distancing. However, the effect plateaus beyond a threshold, implying diminishing marginal returns beyond specific points for space in encouraging café visitation.

Moreover, several BE factors demonstrate explicit non-linear impacts, such as the ratio of people commuting to work by bike. The associated SHAP values were generally higher in 2021 compared to 2020, reflecting a more substantial role of cycling in driving street vitality post-pandemic. In 2021, moderate cycling activity continues to contribute positively, but the plateau effect is less prominent. The impact remains strong up to 15%, reflecting a broader reliance on cycling for both leisure and mobility.

Regarding SE qualities, moderate levels of perceived greenness contribute positively to street vitality, enhancing the aesthetic and environmental quality of urban spaces. However, a negative relationship emerges at higher levels of greenness, likely because overly green areas are often located in less dense, suburban settings with fewer activity-generating uses.

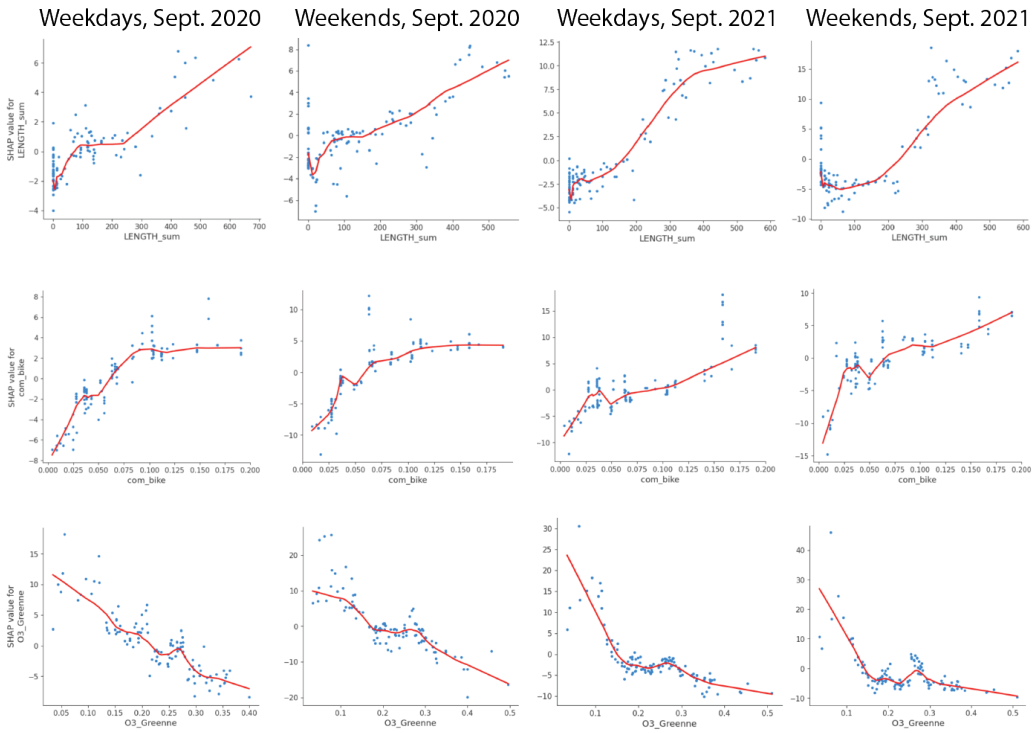

Figure 4. Main effects of selected variables as an example

5. Discussion

The comparative SHAP analysis between 2020 and 2021 highlights significant shifts in urban space utilisation, likely driven by evolving mobility patterns and changing needs. Across both years, the preference for parks, open spaces and a high-quality street environment remained consistent on both weekdays and weekends, underscoring the enduring value of accessible public spaces in urban environments.

In 2021, compared to 2020, there was a notable increase in the influence of leisure-focused factors on urban vitality. The emergence of the "wood deck" as a new and highly significant design feature in 2021 emphasises the role of well-designed patio spaces. Features related to patio capacity, such as patio length and width, maintained their significance in promoting street vitality and enhancing the urban experience, contributing to the creation of walkable streets (Lovasi et al., 2012).

Our findings also reveal that during the pandemic, urban behaviour concentrated heavily on local amenities, such as institutional property and bike-docking capacity. This trend reflects a reliance on localized activity and essential infrastructure to support restricted urban mobility. By 2021, connectivity features such as subway access and the length of collector roads gained increased importance, indicating a partial reversion to pre-pandemic commuting behaviour.

Future research could expand upon our framework in several ways. For instance, scholars could incorporate other data types, such as mobility heatmaps, to quantify urban vitality more comprehensively, using multi-source urban data to better depict human flow on streets (Huang et al., 2020). While our research examines 2020 (pre-pandemic) and 2021 (post-pandemic), extending the analysis to later years would enable a long-term investigation into whether the observed impact on urban vitality persists over time. Additionally, future studies could explore how micro-level characteristics, including street features and perceived qualities, could jointly impact activity-based urban vitality more comprehensively (Song, Huang, et al., 2024).

6. Conclusion

In summary, leveraging two years of data, this study uncovers the critical role of street experiments and various BE and SE factors in fostering urban vitality, with a particular emphasis on curbside café design metrics during and after the pandemic in Toronto. Longitudinally, urban vitality in 2020 was primarily shaped by essential infrastructure and functional needs, whereas 2021 revealed a marked shift toward leisure, aesthetics, and quality-of-life factors. This evolution reflects a return to pre-pandemic travel behaviours and urban functions as societal conditions began to normalise.

By carefully analysing the nuanced non-linear effects of environmental features on vitality, policymakers and urban planners can develop sustainable measures that enhance urban resilience during periods of uncertainty and adapt to shifting community needs. This underscores the necessity of urban design strategies that promote street vitality to stimulate local economic activity while ensuring sufficient and efficient traffic infrastructure.

Data Availability Statement

The design metrics and locations of CaféTO analysed in this study were provided by the consultant and further processed by the authors; the authors do not have permission to share the data. Raw datasets of other variables used in this study are accessible through the Toronto Open Data Portal.

Contributor Statement

M.L: Illustration, Data Curation, Formal Analysis, Manuscript Writing; Q.S: Conceptualisation, Methodology, Supervision, Resources, Data Curation, Formal Analysis, Manuscript Review & Writing; J.v.A: Supervision, Review & Writing

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