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Urban Trees and Perceived Neighborhood Safety: Neighborhood Upkeep Matters

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Abstract

The perception of safety significantly influences choices in outdoor activities, profoundly impacting overall well-being. While previous studies have highlighted urban trees' potential to reduce crime rates, the link between urban trees and perceived safety remains uncertain. This study investigates the relationship between urban trees and safety perception in Austin, Texas, USA, with a specific focus on the moderating role of neighborhood cleanliness and environmental justice considerations. Using multinomial logistic regression models, our analysis reveals a positive association between urban tree canopy coverage and safety perception, with a significant interaction between tree canopies and neighborhood cleanliness, further enhancing the sense of safety. Furthermore, we identified an optimal threshold of tree canopy that maximizes this effect. This highlights the crucial role of well-maintained urban green spaces, particularly tree canopies, in bolstering perceived safety. Such insights hold significance for evidence-based urban planning and community development, fostering well-being and safety for all residents.

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Introduction

Perceptions of safety significantly impact the well-being and livability of urban residential areas (Sarriera et al., 2021), particularly densely populated environments (Cabrera-Barona et al., 2019). Feeling safe in one's neighborhood is essential for encouraging outdoor activities (Gómez et al., 2004; Zougheibe et al. 2021), supporting social interactions (De Jesus et al., 2010), improving sleep quality (Hill et al., 2016), and even reducing functional decline in older adults (Sun et al., 2012). The safety concerns can pose a pervasive and distressing challenge, which may result in mental illness (Wang et al., 2019), limit their movements, avoid public spaces altogether (Tandogan & Ilhan, 2016), and decline in overall quality of life (Stafford et al., 2007). Creating safe and secure urban residential environments, therefore, is a key for creating thriving and cohesive living environments and should be a top priority for urban planners, policy makers, and community leaders (Austin City Council, 2018).

It is widely acknowledged that urban vegetation plays an important role in reducing crime, considering its significant role in enhancing visual appeal, creating shaded spaces for relaxation, and building social interactions. Several studies have found inverse associations between urban tree canopy and crime, particularly when the tree canopy is composed of taller trees that do not obstruct visibility and serve as hiding spots for criminals (Kuo & Sullivan, 2001). For instance, Donovan and Prestemon (2012) conducted a study in Portland, Oregon, where they analyzed aerial photographs to measure tree size and quantity along public rights of way. They found that street trees located in front of houses were associated with lower property crime rates. Similarly, Wolfe and Mennis (2012) examined green vegetation using the normalized difference vegetation index (NDVI) in Philadelphia, Pennsylvania, and discovered a negative relationship between vegetation and crime. Troy et al. (2012) investigated tree canopy data in Baltimore, Maryland, and demonstrated that an increase in tree canopy was linked to a decrease in crime in the city and surrounding county. A study in Bogota, Colombia, revealed an inverse relationship between homicides and public areas with taller trees and higher tree density (Escobedo et al., 2018). Recent studies also found that tree canopy and tree images derived from Google Street View imagery were associated with crime (S. Lee, Koo, & Kim, 2023; Lin et al., 2021).

There is an important distinction between "feeling" safe and actually "being" safe. The perception of safety is not exclusively determined by actual crime rates, but rather by how individuals assess the risk of victimization. Studies have found that the perceptions do not always correspond closely with objective crime data (Zhang et al., 2021), and factors influencing safety perceptions encompass personal experiences (James et al., 2020), media portrayals of crime (Hollis et al., 2017), and neighborhood conditions (Austin & Furr, 2002). For example, a neighborhood might have a relatively low crime rate, but if it is poorly lit, has graffiti or other signs of neglect, and lacks a sense of community presence, residents may still feel unsafe and have a heightened fear of crime. On the other hand, a community with higher crime rates but well-maintained public spaces, active community engagement, and visible law enforcement might have residents who feel safer despite the statistics (Camacho Doyle et al., 2022; H. D. Lee et al., 2020; Zhang et al., 2021). Past studies have identified various neighborhood characteristics as influencing how safe individuals feel in their surroundings, including lighting, street design, and the presence of security measures. Well-lit streets often create a sense of comfort and security, while poorly lighted areas can foster feelings of vulnerability and fear (Haans & De Kort, 2012). Good neighborhood maintenance, such as regular upkeep and the absence of litter, is also known to increase perceived safety from crime and overall neighborhood satisfaction (Hur & Nasar, 2014). Moreover, the design and layout of buildings and streets can impact natural surveillance, affecting the visibility and oversight of public spaces, which, in turn, influences safety perceptions. Residents who are embedded in local social networks are more likely to become familiar with their neighbors, and this familiarity is associated with greater perceptions of safety (Drakulich, 2015).

Although several studies have demonstrated the overall benefits of tree canopy in reducing actual crime rates (Gilstad-Hayden et al., 2015; Schusler et al., 2018; Troy et al., 2012), the association between tree canopy and perceived safety is unclear and inconsistent. One study by Mouratidis (2019) found that increased tree cover can contribute to a higher sense of safety among residents. However, a study by Coleman et al. (2021) did not find empirical evidence that street trees play a significant role in shaping people's perceptions of safety in urban environments, indicating that street trees may not directly lead to improved perceptions of safety for pedestrians. Therefore, further research is needed to better understand and clarify the complex relationship between tree canopy and perceived safety in urban environments. Investigating this gap is essential for comprehensively understanding how urban greenery, such as tree canopy, can impact actual crime rates and perceptions of safety in neighborhoods.

This study aims to investigate the intricate relationship between tree canopy and perceived safety in neighborhoods. We explore the following four specific questions:

1. How does the presence of urban trees directly relate to residents' perceptions of safety in their neighborhood?
2. Does neighborhood quality, particularly cleanliness, moderate the association between tree canopy and perceived safety?
3. To what extent do neighborhoods benefit from the quantity of urban trees in enhancing perceived safety, considering differences in neighborhood socioeconomic status?
4. How can the quantity of trees be optimized to maximize their benefits?

Ultimately, the findings derived from this research will serve as a foundation for evidence-based urban planning and community development strategies aimed at enhancing safety and well-being for all residents.

Theoretical Background—Mechanisms of Urban Trees in Perceived Safety

The role of urban trees in enhancing perceived safety is a multifaceted concept that can be understood through three interconnected aspects: social, physical, and psychological settings. Urban trees aid in fostering the development of collective efficacy, enhancing the quality of the physical environment, and contributing to the psychological well-being of residents.

Social Setting: Collective Efficacy. A key mechanism through which urban trees can enhance perceived safety is the cultivation of collective efficacy within communities. This involves the intricate social dynamics surrounding individuals' connections and closeness to their neighbors, encompassing elements like social cohesion and trust (Mihaylov & Perkins, 2014). Tree canopy coverage plays a significant role in building collective efficacy by providing gathering places for neighbors and locals to interact (Holtan et al., 2015). These green spaces foster stronger and denser neighborhood networks, as they serve as venues for community events and activities (Vargas-Hernández et al., 2017). The sense of community and togetherness that arises from these interactions contributes to increased levels of informal social control and neighborhood attachment, ultimately enhancing perceived safety within these areas (Brown et al., 2003; Proshansky, 1983). An example of a successful community effort in this regard is the Austin Community Trees program (ACT; City of Austin, 2006), which not only distributed free trees to residents but also organized community events for tree planting. Through these activities, ACT not only increased tree canopy coverage but also brought neighbors closer together, promoting a sense of collective efficacy and enhancing safety perceptions within the community (Pike et al., 2020).

Physical Setting: The Environmental Design and Broken Window Theory. Urban trees also influence perceived safety through their impact on the physical environment. They play a role in reducing noise levels (Margaritis & Kang, 2017) and mitigating local air pollution (Nowak et al., 2006). Additionally, trees can hide visually unattractive items, such as factories or unsightly structures, improving the aesthetics of the neighborhood (Schwab, 2009). These endeavors closely align with the principles of the Broken Windows Theory, which underscores the enhancement of safety by addressing disorder and incivility through interventions that elevate the visual impression and physical appearance of a place, reinforcing the idea that the design of urban environments can significantly impact safety (Welsh et al., 2015). In daily urban management practices, environmental clean-up and tree planting are emblematic of these types of interventions. Moreover, urban trees integrate seamlessly with the principles of Crime Prevention Through Environmental Design (CPTED), supporting strategies such as maintenance, activity support, natural surveillance, natural access control, and natural territorial reinforcement (S. Lee, Lee, et al., 2023).

The presence of trees are known to enhance public surveillance, facilitate natural access control, and create inviting spaces that encourage community engagement, collectively contributing to a safer urban environment (Wolfe & Mennis, 2012). However, it is essential to acknowledge that trees, especially smaller ones or shrubs, may also function as a screen or a hiding place, providing potential hiding spots for both criminals and victims (Coupe & Blake, 2006; S. Lee, Koo, & Kim, 2023). According to Fisher & Nasar, 1992, these areas serve dual roles by offering escape routes for potential victims and refuge for potential offenders, presenting a nuanced perspective on their role in safety promotion. Their prospect-refuge model explains that environments offering clear views (prospect) and places to hide (refuge) affect people's perceptions of safety. Open, visible spaces are generally perceived as safer due to easy monitoring, while areas with hiding spots can provide comfort to those seeking refuge but also to potential offenders. Balancing these elements is crucial in urban design to enhance both actual and perceived safety.

Psychological Setting: The Stress Reduction Theory. Urban trees have a profound impact on the psychological well-being of residents, influencing their perceived safety. The Stress Reduction Theory (Ulrich et al., 1991) posits that nature, including urban green spaces, has a stress-reducing and restorative influence. This positive impact extends to emotional states and physiological recovery. Empirical studies have consistently supported the restorative and stress-reducing benefits of urban nature (Nordh et al., 2009; Roe et al., 2013). Denser urban tree cover has been linked to stronger stress-reducing benefits. The presence of trees in urban environments offers residents opportunities for relaxation, connection with nature, and a respite from the stresses of urban life (Jiang et al., 2016). These psychological benefits contribute to an overall sense of safety and well-being. Nevertheless, it is important to note that a certain degree of disorganized or overgrown tree growth can be associated with adverse effects on mental health, underscoring the complex interplay between urban tree canopy and psychological well-being (Everett et al., 2018).

Material and Methods

Study Area

Austin, TX, a rapidly growing city in the United States, has experienced a significant population surge, with the Austin metropolitan area's population increasing from 1.7 million to 2.3 million between 2010 and 2020. This increase is attributed predominantly to domestic migration, accounting for 59.4%, and international migration, contributing 11.7% (Ramser, 2022). However, as urban areas like Austin continue to expand, there is a growing concern about the potential increase in crime rates and safety concerns associated with such demographic shifts (Stansfield et al., 2013). Research has indicated that in growing cities, crime rates are more likely to rise at an accelerated pace, especially for certain types of crimes like automobile theft and robbery, which tend to outpace population growth (Yang et al., 2019).

Austin is particularly well-suited as a research location for several key reasons. First and foremost, Austin offers robust data availability, making it conducive to comprehensive research in this area. The city possesses extensive datasets, including community survey data, crime statistics, and detailed information on tree canopy coverage. These data sources provide a rich foundation for conducting empirical research on the relationship between urban trees and perceived safety. Second, Austin's unique demographic dynamics make it a compelling case study. The city's rapid population growth, coupled with concerns about safety and quality of life, underscores the timeliness and relevance of this research. Investigating the role of urban trees in enhancing perceived safety becomes particularly pertinent in the context of a city undergoing such significant demographic changes. Understanding how urban trees influence safety perceptions in this rapidly evolving urban environment is of paramount importance for both policymakers and residents. Furthermore, Austin's commitment to environmental sustainability adds an additional layer of significance to this research. The city's Climate Equity Plan has set an ambitious target of increasing tree canopy coverage from 36% in 2020 to 50% by 2050 (City of Austin, 2021). This commitment reflects a growing awareness of the multiple benefits that trees can bring to urban areas, including enhanced safety and well-being. Therefore, conducting research in Austin provides an opportunity to assess the progress toward this tree canopy target and add valuable evidence supporting the benefits of trees in urban settings.

Community Survey Participants

Annually, the municipality of Austin conducts a community survey aimed at gauging satisfaction levels pertaining to the provision of primary municipal services. This survey serves as a crucial component of the city's ongoing strategic planning process, aiding in the identification of community priorities (ETC Institute, 2019). In this study, the 2019 City of Austin Community Survey, with a sample size of 2,049 respondents, was employed as the primary data source. This survey was exclusively available to individuals aged 18 years and older. It systematically collected demographic information from respondents, evaluated levels of neighborhood satisfaction, and gauged perceptions of safety. These assessments were conducted utilizing a 5-point Likert-type scale, ranging from "strongly disagree" to "strongly agree," employing a combination of both online and paper-based survey methodologies.

Measures

Dependent Variables. We selected perceived safety as our dependent variable, which we assessed through a single questionnaire item from the 2019 Community Survey: "Please rate your level of agreement with the following: I feel safe in my neighborhood at night." In previous studies, perceived safety has been subjectively measured in various ways, including considerations of walking behavior (e.g., "My neighborhood is safe for walking" in Ball et al., 2007), time (e.g., "Feeling safe returning to your home when it is dark" in Shenassa et al., 2006), and a combination of both (e.g., "Would you feel safe walking alone in your neighborhood in the evening?" in Piro et al., 2006; "Perception of walkability and safety during day and night" in Rišová & Madajová, 2020; "Feeling safe walking on specific streets, both during the day and at night" in Park & Garcia, 2020).

While we also had data on perceived safety during the day, it exhibited a high degree of skewness, with a substantial proportion of respondents (89%) reporting satisfaction with their neighborhood during daytime. This lack of variation makes it less suitable as a dependent variable. Additionally, since our participants were adults aged 18 years and older, it is likely that they may not spend a significant amount of their time in their neighborhood during the day. Therefore, we assumed that nighttime safety is a more sensitive indicator for residents when it comes to their neighborhood.

Regarding response categories, the original questionnaire employed a 5-point Likert-type scale based on “Please rate your level of agreement with the following: I feel safe in my neighborhood at night”: 1 (*strongly disagree*), 2 (*disagree*), 3 (*neutral*), 4 (*agree*), and 5 (*strongly agree*). However, as there were very few cases of dissatisfaction for most of the questions (less than 13%), we merged those responses into an “others” category. Consequently, the response categories for the questions were then scaled as follows: 1 (*others-strongly disagree, disagree, and neutral*), 2 (*agree*), and 3 (*strongly agree*).

Independent Variables of Interest. To examine the relationships between urban trees and perceived safety, we employed three distinct measures of tree canopy: overall tree canopy coverage, street tree canopy coverage (i.e., tree canopy coverage within 25 m buffer of a street network), and Tree View Factor (TVF). For the overall and street tree canopy coverage measures, we sourced information from Austin’s Open Data portal for the year 2018. For the overall tree canopy coverage, we captured 2018 tree canopy aerial image within the network service area, as shown in Figure 1. As a way to measure street tree canopy coverage, we established a 25-m buffer around the selected street segments to capture the quantity of trees within walking distance. Using ArcGIS 10.7, we generated 25-m buffers around street segments within each network service area, intersected them with the tree canopy data, and computed the proportion of tree canopy coverage at the service area level. The TVF was measured by applying Masked-attention Mask Transformer (Mask2Former), one of the latest semantic segmentation models, to Google Street View Images and calculating tree canopy coverage as shown in street view images from eye level perspective (Cheng et al., 2022; see Figure 1). We examined overall and street tree canopy separately because the measure of perceived safety in this study does not differentiate whether safety concerns pertain specifically to pedestrian activities or encompass broader neighborhood-related concerns. The unit of analysis is street segments that fall within a ¼ mile (400 m) network area from the midpoint of each coordinate block that the participant lived.

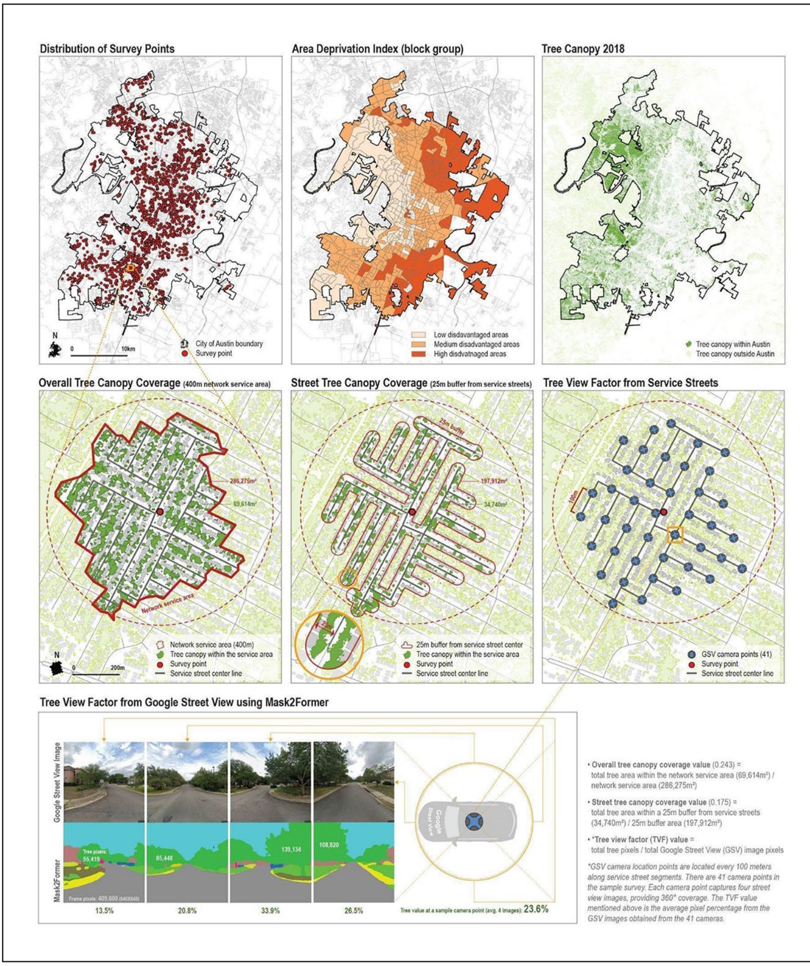

Figure 1. Study area and three types of tree variables, including overall tree canopy coverage, street tree canopy coverage, and Tree View Factor, within a service network area.

Control Variables. To account for potential confounding factors associated with area deprivation and perceived safety, we incorporated both individual and neighborhood-related variables that were likely to exhibit correlations (Braga-Neto et al., 2013). The individual sociodemographic factors, sourced from the 2019 Survey, included age groups (18–24 years, 25–34 years, 35–44 years, 45–54 years, 55–64 years, 65–74 years, and 75+ years), gender (female or male), race (non-Hispanic White or other), income brackets (<$20,000, $20,000–$39,999, $40,000–$59,999, $60,000–$79,999, $80,000–$149,999, $150,000+), and home ownership status (own or rent). Additionally, perceptions of the neighborhood environment were gauged through self-reported assessments of satisfaction with cleanliness, the condition of streets, frequency of social interactions with friends and neighbors outside the home, and adequacy of street lighting in the community. These assessments were drawn from Austin's Community Survey in 2019 and utilized a 3-point Likert-type scale (i.e., others, satisfied, and very satisfied) to account for the skewed distribution of responses and to ensure consistency with the outcome variable.

We also accounted for neighborhood-level variables, which were assessed within a ¼ mile (400 m) network service area centered at the midpoint of each coordinate block where the participant resided. These variables included crime rates, park area ratio, and population density. The crime rate, covering offenses such as robbery, theft, auto theft, burglary, aggravated assault, rape, murder, and assault, was measured through dividing the total number of these crimes in 2019 by the area (per square meter) and population (per 1,000 individuals). The park area ratio was calculated by dividing park land uses, derived from the 2018 land use data provided by the City of Austin, by the area of the network area. Population density, calculated as the number of individuals per square kilometer, was derived the 2020 American Community Survey 5-year estimates at the block group level. When the network service area extended across multiple block groups, we assumed an even distribution of the population within each block group. We initially calculated the overlapping population in each block group, combined these figures, and divided the total by the network area. In cases where a network service area spanned multiple block groups, we also computed the corresponding ratios. Additionally, we employed the Area Deprivation Index (ADI) (Kind et al., 2014; University of Wisconsin School of Medicine and Public Health, 2023) as a measure of neighborhood socioeconomic status. The ADI offers national percentile rankings at the block group level, ranging from 1 (*least disadvantaged*) to 100 (*most disadvantaged*).

Analytical Approach

The descriptive statistics are presented for the entire survey participants, as well as separately for less, moderate, and more disadvantaged neighborhoods, to understand the disparities in sociodemographic, health, behavioral, and environmental characteristics by neighborhood deprivation. Chi-square tests and ANOVA were performed for categorical variables and continuous variables, respectively, to examine whether these variables vary systematically depending on the level of disadvantage.

We used adjusted multinomial logistic regression models to estimate the Relative Risk Ratios (RRRs) and 95% Confidence Intervals (CIs) for each predictor (Table 2). All models used cluster-robust standard errors to address intrastate correlation. We conducted an examination for multicollinearity using the variance inflation factor (VIF) and identified no significant multicollinearity concerns (all VIFs were less than 4). The first series of models examines the association between urban tree measures and perceived safety while controlling for individual-level covariates only (Model 1.1–1.3 in Table 2). In the second series of models (Model 2.1–2.3 in Table 2), we included both individual and objectively measured neighborhood factors to test our research question on the association between urban trees and perceived safety.

Given our second research question, we tested the potential moderating role of neighborhood cleanliness on the association between urban trees and perceived safety. Models 3.1–3.3 in Table 3 present subgroup analyses that examine the relationships between urban trees and perceived safety, stratified by different levels of neighborhood cleanliness. These analyses adjust for the same covariates as those used in Model series 2. We then added interaction terms between a measure of urban trees and neighborhood cleanliness (Model 4.1–4.3 in Table 4), to Model series 2. We also explored potential interaction effects between urban trees and other aspects of neighborhood quality, such as the condition of streets, frequency of social interactions with friends and neighbors outside the home, and adequacy of street lighting in the community. However, no statistically significant effects were found (results not presented in Table A4 in Appendix).

In the fifth series of models (Model 5.1–5.3 in Table 5), we conducted subgroup analyses to investigate the relationships between urban trees and perceived safety across different levels of areal deprivation, adjusting for the same covariates utilized in Model series 2. Specifically, we conducted separate analyses for areas characterized as less, moderate, and more deprived.

Finally, we employed Gradient Boosted Decision Trees (GBDT) to explore the potential nonlinear relationship between urban trees and perceived safety. GBDT has been extensively used to study nonlinear relationships between the built environment and human behavior, owing to its high performance and capacity to model complex relationships among dependent and independent variables (Friedman, 2001). To avoid overfitting, a grid search was performed using 10-fold cross validation on the training dataset (randomly selected 70% of the total sample). Based on the grid search, a final model was generated using the training dataset. This final model was evaluated against the test dataset (the rest of the sample), showing prediction accuracy of 0.835, 0.812, and 0.843 for tree canopy, street tree canopy, and tree view factor, respectively. Variable importance plots were generated to present the contribution of each independent variable to perceived safety (Figure 3). We also present Individual Conditional Expectation (ICE) to visualize the relationship between each independent variable and perceived safety while accounting for other covariates (Figure 4).

Results

Summary Statistics

The descriptive statistics of key variables are shown in Table 1. The descriptive statistics of other covariates, not shown in Table 1, are presented in Table A1 in the Appendix. Of the selected sample, 27.7% were very satisfied with their perceived safety in their neighborhoods. The average tree canopy coverage was 31.17% for overall tree canopy, 23.89% for street tree canopy, and 18.65% for TVF. About 50% were female, 50.1% were non-Hispanic White, 24.19% were respondents reporting an annual household income below $40,000, and 31.51% were renters. This demographic composition generally aligns well with the city-level demographic characteristics. According to the 2016 to 2020 American Community Survey 5-year estimates, 49.2% were female, 48.2% were non-Hispanic White, 25% were households having household income less than $40,000, and 54.5% were renters in the Austin city.

The three subgroups by the level of disadvantage were defined at the block group level using the following definitions: less disadvantaged block groups are those that fall below the 25th percentile of Area Deprivation Index ($ADI < 13$). Moderately disadvantaged block groups are between the 25th and 75th percentile of ADI ($ADI \geq 13$ and $ADI < 37$). More disadvantaged block groups include those with ADI above the 75th percentile ($ADI \geq 37$). As shown in Table 1, participants living in less disadvantaged neighborhoods were over twice as likely to report very satisfied safety perceptions of their neighborhoods (39.06%) compared to those residing in more disadvantaged neighborhoods (16.9%). Additionally, we observed that less disadvantaged areas exhibited higher overall tree canopy coverage, street tree canopy, TVF, and park area ratio, while also experiencing lower crime rates and population density, compared to more disadvantaged areas.

Table 1. Characteristics of Key Variables Among the Participants Across the Neighborhood Disadvantage (Area Deprivation Index).

Variables		Total sample	By area deprivation index: Less disadvantaged	Moderate disadvantaged	More disadvantaged	χ^2 or ANOVA
Perceived safety	Others	541 (27.49%)	96 (18.11%)	245 (25.87%)	200 (40.73%)	$p<.01$
	Agree	882 (44.82%)	227 (42.83%)	447 (47.2%)	208 (42.36%)	
	Strongly agree	545 (27.69%)	207 (39.06%)	255 (26.93%)	83 (16.9%)	
% Tree canopy (*M*/*SD*)		31.17 (15.41)	42.97 (14.87)	29.92 (13.24)	20.8 (10.65)	$p<.01$
% Street tree canopy (*M*/*SD*)		23.89 (12.75)	34.5 (12.06)	22.82 (10.83)	14.45 (7.42)	$p<.01$
Tree view factor (*M*/*SD*)		18.65 (5.78)	22.35 (6.35)	18.05 (4.91)	15.77 (4.5)	$p<.01$
Perceived neighborhood environments						
Neighborhood cleanliness	Others	606 (31.37%)	106 (20.23%)	282 (30.32%)	218 (45.61%)	$p<.01$
	Satisfied	902 (46.69%)	241 (45.99%)	460 (49.46%)	201 (42.05%)	
	Very satisfied	424 (21.95%)	177 (33.78%)	188 (20.22%)	59 (12.34%)	
Conditions of streets	Others	798 (41.35%)	183 (34.99%)	385 (41.35%)	230 (48.32%)	$p<.01$
	Satisfied	890 (46.11%)	257 (49.14%)	428 (45.97%)	205 (43.07%)	
	Very satisfied	242 (12.54%)	83 (15.87%)	118 (12.67%)	41 (8.61%)	
Frequency of social interactions	Others	426 (22.32%)	76 (14.73%)	219 (23.7%)	131 (27.93%)	$p<.01$
	Satisfied	847 (44.37%)	231 (44.77%)	407 (44.05%)	209 (44.56%)	
	Very satisfied	636 (33.32%)	209 (40.5%)	298 (32.25%)	129 (27.51%)	
Adequacy of street lighting	Others	716 (37.8%)	173 (34.33%)	356 (38.61%)	187 (39.96%)	$p<.01$
	Satisfied	909 (47.99%)	248 (49.21%)	439 (47.61%)	222 (47.44%)	
	Very satisfied	269 (14.2%)	83 (16.47%)	127 (13.77%)	59 (12.61%)	
Objective neighborhood environments						
Crime rate		0.047 (0.06)	0.03 (0.06)	0.04 (0.05)	0.069 (0.06)	$p<.001$
Park area ratio		0.75 (0.1)	0.09 (0.12)	0.07 (0.09)	0.06 (0.08)	$p<.001$
Population density		1.813 (1.125)	1.359 (0.718)	1.784 (0.973)	2.362 (1.474)	$p<.001$

Note. Less Disadvantaged: Participants residing in areas with an Area Deprivation Index (ADI) below the 25th percentile (ADI < 13). Moderately Disadvantaged: Participants living in areas with ADI values falling between the 25th and 75th percentiles (ADI ≥ 13 and ADI < 37). More Disadvantaged: Participants located in areas with ADI values above the 75th percentile (ADI ≥ 37). Individual-level sociodemographic variables are included in Table A1 in the Appendix.

Full Analysis: Adjusted for Socio-Demographic and Built Environment

Effects of Trees on "Satisfied" Perception of Safety Compared to the Reference Category. Table 2 presents the results of multinomial logistic regression analysis from the first and second series of models. The findings from the first series of models illustrated that, after adjusting for individual-level sociodemographic and subjective neighborhood factors, tree canopy (RRR = 1.015, 95% CI [1.005, 1.025]) and street tree canopy (RRR = 1.017, 95% CI [1.004, 1.029]) were positively associated with the "agree" response to the questionnaire "I feel safe in my neighborhood at night" compared to the reference categories (i.e., "others" categories), as shown in Models 1–1 and 1–2. However, when accounting for objective neighborhood factors in Models 2–1 and 2–2, both tree canopy and street tree canopy lost their significance. Across all models, "agree" response on safety perception was significantly associated with neighborhood cleanliness, street conditions, frequency of social interactions, adequacy of street lighting, being female, and population density.

Effects of Trees on "Strongly Agree" Response on Perceived Safety Compared to the Reference Category. For the perception of safety categorized as "strongly agree" relative to the reference category, all three measures of urban trees showed stronger associations with perceived safety. Tree canopy (RRR = 1.029, 95% CI [1.016, 1.041]), street tree canopy (RRR = 1.036, 95% CI [1.021, 1.052]), and TVF (RRR = 1.032, 95% CI [1.001, 1.064]) were positively associated with a "strongly agree" response on safety perception in Models 1–1 to 1–3 after adjusting for individual-level factors. However, adding objective neighborhood-level factors renders TVF to lose its significance, while tree canopy (RRR = 1.017, 95% CI [1.002, 1.033]) and street tree canopy (RRR = 1.022, 95% CI [1.003, 1.041]) continued to be significant in Models 2–1 to 2–2.

Among the control variables, neighborhood cleanliness, street conditions, frequency of social interactions (with the exception of the "satisfied" perception), adequacy of street lighting, being female, population density, and ADI showed statistically significant associations with both "agree" and "strongly agree" responses on safety perception. Additionally, the low-income ($20,000–$39,999) and high-income ($150,000 or more) ranges displayed significant associations with "strongly agree" response on safety perception, but not with "agree," as illustrated in Tables A2 and A3 in the Appendix.

Table 2. Multinomial Logistic Regression Analysis, Comparing Perceived Safety: Agree and Strongly Agree Versus Others.

Variables		Adjusted for individual-level socio-demographic			Adjusted for all covariates		
		M 1–1 RRR [95% CI]	M 1–2 RRR [95% CI]	M 1–3 RRR [95% CI]	M 2–1 RRR [95% CI]	M 2–2 RRR [95% CI]	M 2–3 RRR [95% CI]
Dependent variable levels: perception on safety (others vs. agree)							
Tree canopy		**1.015**** [1.005, 1.025]	—	—	1.005 [0.992, 1.018]	—	—
Street tree canopy		—	**1.017*** [1.004, 1.029]	—	—	1.003[0.988, 1.019]	—
TVF		—	—	1.005 [0.980, 1.030]	—	—	0.987 [0.957, 1.018]
Neighborhood cleanliness	Satisfied	**3.256***** [2.431, 4.363]	**3.247***** [2.424, 4.350]	**3.328***** [2.484, 4.457]	**3.143***** [2.324, 4.250]	**3.142***** [2.324, 4.249]	**3.153***** [2.331, 4.264]
	Very satisfied	**4.388***** [2.542, 7.573]	**4.357***** [2.522, 7.528]	**4.623***** [2.680, 7.973]	**4.029***** [2.305, 7.043]	**4.028***** [2.303, 7.047]	**4.105***** [2.345, 7.186]
Condition of streets	Satisfied	**1.733***** [1.294, 2.322]	**1.741***** [1.300, 2.330]	**1.770***** [1.324, 2.368]	**1.800***** [1.332, 2.432]	**1.804***** [1.335, 2.437]	**1.810***** [1.340, 2.444]
	Very satisfied	**2.250*** [1.128, 4.489]	**2.258*** [1.133, 4.498]	**2.195*** [1.104, 4.364]	**2.236*** [1.115, 4.480]	**2.226*** [1.111, 4.460]	**2.204*** [1.100, 4.417]
Frequency of social interactions	Satisfied	**1.480**** [1.061, 2.065]	**1.487*** [1.066, 2.073]	**1.535*** [1.102, 2.138]	**1.577**** [1.121, 2.220]	**1.585**** [1.127, 2.231]	**1.606**** [1.141, 2.259]
	Very satisfied	1.380 [0.952, 2.000]	1.378 [.951, 1.997]	1.428 [.987, 2.067]	**1.495*** [1.023, 2.184]	**1.499*** [1.026, 2.190]	**1.504*** [1.030, 2.196]
Adequacy of streetlight	Satisfied	**1.645**** [1.238, 2.186]	**1.653***** [1.244, 2.196]	**1.649***** [1.243, 2.189]	**1.647**** [1.229, 2.207]	**1.651***** [1.232, 2.212]	**1.652***** [1.233, 2.214]
	Very satisfied	1.098 [0.592, 2.037]	1.107 [0.597, 2.052]	1.068 [0.578, 1.976]	1.034 [0.550, 1.942]	1.031 [0.549, 1.936]	1.024 [0.545, 1.922]
Park ratio					2.637 [0.453, 15.337]	2.822 [0.492, 16.193]	2.639 [0.454, 15.356]

(continued)

Table 2. (continued)

Variables		Adjusted for individual-level socio-demographic			Adjusted for all covariates		
		M 1–1 RRR [95% CI]	M 1–2 RRR [95% CI]	M 1–3 RRR [95% CI]	M 2–1 RRR [95% CI]	M 2–2 RRR [95% CI]	M 2–3 RRR [95% CI]
Population density					**0.822**** [0.708, 0.954]	**0.824*** [0.71, 0.956]	**0.834*** [0.718, 0.97]
ADI					0.991 [0.981, 1.001]	0.991 [0.980, 1.001]	**0.989*** [0.979, 0.999]
Crime rate					0.594 [.0244, 14.502]	0.470 [0.020, 11.079]	0.245 [0.010, 5.936]
Dependent variable levels: Perception on safety (others vs. strongly agree)							
Tree canopy		**1.029***** [1.016, 1.041]	—	—	**1.017*** [1.002, 1.033]	—	—
Street tree canopy		—	**1.036***** [1.021, 1.052]	—	—	**1.022*** [1.003, 1.041]	—
TVF		—	—	**1.032*** [1.001, 1.064]	—	—	1.007 [0.971, 1.045]
Neighborhood cleanliness	Satisfied	**4.552***** [2.953, 7.017]	**4.414***** [2.863, 6.807]	**4.546***** [2.956, 6.992]	**4.081***** [2.626, 6.343]	**4.004***** [2.577, 6.221]	**4.001***** [2.578, 6.211]
	Very satisfied	**22.068***** [11.984, 40.634]	**20.916***** [11.346, 38.560]	**22.905***** [12.468, 42.077]	**19.127***** [10.250, 35.691]	**18.450***** [9.885, 34.434]	**18.988***** [10.177, 35.428]
Condition of streets	Satisfied	**1.980***** [1.351, 2.902]	**2.003***** [1.366, 2.935]	**2.097***** [1.435, 3.064]	**2.032***** [1.371, 3.010]	**2.046***** [1.381, 3.031]	**2.105***** [1.422, 3.114]
	Very satisfied	**4.703***** [2.287, 9.670]	**4.865***** [2.369, 9.992]	**4.594***** [2.244, 9.403]	**4.548***** [2.198, 9.411]	**4.645***** [2.245, 9.613]	**4.487***** [2.170, 9.277]
Frequency of social interactions	Satisfied	1.324 [0.845, 2.076]	1.326 [0.846, 2.079]	1.378 [0.881, 2.154]	1.499 [0.945, 2.378]	1.506 [.949, 2.390]	1.527 [.963, 2.420]
	Very satisfied	**2.107**** [1.310, 3.389]	**2.082**** [1.293, 3.351]	**2.188***** [1.364, 3.511]	**2.272***** [1.394, 3.702]	**2.272***** [1.394, 3.704]	**2.305***** [1.416, 3.754]

(continued)

Table 2. (continued)

Variables		Adjusted for individual-level socio-demographic			Adjusted for all covariates		
		M 1–1 RRR [95% CI]	M 1–2 RRR [95% CI]	M 1–3 RRR [95% CI]	M 2–1 RRR [95% CI]	M 2–2 RRR [95% CI]	M 2–3 RRR [95% CI]
Adequacy of streetlight	Satisfied	**1.978***** [1.359, 2.877]	**2.017***** [1.385, 2.937]	**1.995***** [1.373, 2.897]	**2.099***** [1.425, 3.091]	**2.139***** [1.451, 3.151]	**2.127***** [1.444, 3.131]
	Very satisfied	**6.054***** [3.236, 11.327]	**6.321***** [3.376, 11.834]	**5.957***** [3.201, 11.087]	**5.972***** [3.148, 11.330]	**6.135***** [3.233, 11.642]	**5.999***** [3.167, 11.364]
Park ratio					3.923 [0.509, 30.248]	4.904 [0.646, 37.224]	5.562 [0.716, 43.229]
Population density					**0.778*** [0.637, 0.95]	**0.773*** [0.633, 0.944]	**0.777*** [0.635, 0.952]
ADI					**0.985*** [0.971, 0.998]	**0.986*** [0.973, 1.000]	**0.980**** [0.967, 0.993]
Crime rate					12.580 [0.010, 0.152]	12.499 [0.252, 620.502]	3.359 [0.064, 177.645]

Note. 95% confidence interval. Significant coefficients are printed in bold. RRR = relative risk ratio.
*$p < .05$. **$p < .01$. ***$p < .001$.

Sub-Group and Full Analyses: Moderating Factor of Neighborhood Cleanliness

The sub-group analysis in Table 3 explores the relationship between urban trees and perceived safety, segmented by levels of neighborhood cleanliness. In neighborhoods with non-satisfied cleanliness (M3–1), there is a negative association with safety perception for urban tree measurements, particularly TVF (RRR = 0.946, 95% CI [0.902, 0.993]). Conversely, for neighborhoods with satisfied cleanliness (M3–2), tree canopy and street tree canopy show a slight positive but not significant relationship with perceived safety. The impact becomes more pronounced in very satisfied neighborhoods (M3–3), where tree canopy (RRR = 1.087, 95% CI [1.022, 1.157]) and street tree canopy (RRR = 1.134, 95% CI [1.044, 1.232]) exhibit a significant positive association with safety perception. This trend is consistent when considering those who strongly agree on safety perception, with tree canopy and street tree canopy in very satisfied neighborhoods showing RRR values of 1.117 and 1.168, respectively. Overall, the findings highlight that higher levels of neighborhood cleanliness enhance the positive impact of urban trees on perceived safety.

Table 4 presents the interaction terms between the three urban tree measures and neighborhood cleanliness, illustrating their combined influence on perceived safety. These relationships underscore how urban trees can interact with the maintenance or overall quality of the neighborhood environment in influencing the perceived safety. To examine this, we incorporated interaction terms composed of neighborhood cleanliness and overall tree canopy (M 4–1), street tree canopy (M 4–2), and TVF (M 4–3). The interactions between overall tree canopy and street tree canopy with neighborhood safety emerged as significant factors influencing both "agree" and "strongly agree" responses on safety perception, while no significant interaction was found between TVF and neighborhood cleanliness.

Figure 2 illustrates the marginal effects of tree measures on the probability of perceived safety from Models 4–1 to 4–3. As the tree canopy coverage increases in Models 4–1 and 4–2, there is a gradual rise in the likelihood of achieving a "strongly agree" response on safety perception. This rise is particularly more pronounced when the respondents were "very satisfied" with the cleanliness. Put differently, when comparing areas with different levels of neighborhood cleanliness, particularly in the case of areas with "very satisfied" cleanliness versus those with suboptimal cleanliness, the gap in perceived safety becomes more pronounced as the tree canopy level increases. In areas with poor cleanliness, the probability of attaining a "satisfied" safety perception can even decline as the tree canopy increases. In contrast, in well-maintained and clean areas, the probability of achieving an "agree" response safety perception increases with the increase in tree canopy.

Table 3. Sub-Group Analysis: The Relationship Between Urban Trees and Perceived Safety Based on the Levels of Neighborhood Cleanliness.

Variables	Non-satisfied neighborhood cleanliness (M3–1) RRR [95% CI]	Satisfied neighborhood cleanliness (M3–2) RRR [95% CI]	Very satisfied neighborhood cleanliness (M3–3) RRR [95% CI]
Perception on safety (others vs. agree)			
Tree canopy	0.985 [0.966, 1.005]	1.017 [0.999, 1.034]	**1.087**** [1.022, 1.157]
Street tree canopy	0.979 [0.954, 1.004]	1.016 [0.995, 1.038]	**1.134*** [1.044, 1.232]
TVF	**0.946*** [0.902, 0.993]	1.016 [0.975, 1.058]	1.051 [0.937, 1.180]
Perception on safety (others vs. strongly agree)			
Tree canopy	0.998 [0.966, 1.030]	1.017 [0.996, 1.038]	**1.117**** [1.049, 1.188]
Street tree Canopy	0.986 [0.945, 1.028]	1.024 [0.999, 1.050]	**1.168**** [1.076, 1.268]
TVF	1.017 [0.929, 1.113]	1.036 [0.987, 1.087]	1.063 [0.949, 1.192]

Note. 95% confidence interval. Significant coefficients are printed in bold. RRR = relative risk ratio. Each model is controlled for confounding variables.

*$p < .05$. **$p < .01$. ***$p < .001$.

Table 4. The Moderating Effects of Neighborhood Cleanliness on the Association Between Tree Characteristics and Perceived Safety.

Variables		M 4–1 RRR [95% CI]	M 4–2 RRR [95% CI]	M 4–3 RRR [95% CI]
Perception on safety (others vs. agree)				
Tree Canopy × Cleanliness	Satisfied	1.016 [0.994, 1.038]		
	Very satisfied	**1.047*** [1.004, 1.091]		
Street Tree Canopy × Cleanliness	Satisfied		1.016 [0.990, 1.044]	
	Very satisfied		**1.058*** [1.005, 1.115]	
TVF × Cleanliness	Satisfied			1.046 [0.989, 1.106]
	Very satisfied			1.047 [0.951, 1.153]
Perception on safety (others vs. strongly agree)				
Tree Canopy × Cleanliness	Satisfied	1.010 [0.981, 1.041]		
	Very satisfied	**1.055*** [1.008, 1.104]		
Street Tree Canopy × Cleanliness	Satisfied		1.020 [0.982, 1.06]	
	Very satisfied		**1.073*** [1.014, 1.137]	
TVF × Cleanliness	Satisfied			1.037 [0.956, 1.126]
	Very satisfied			1.021 [0.916, 1.14]

Note. 95% confidence interval. Significant coefficients are printed in bold. RRR = relative risk ratio. Each model is controlled for confounding variables.
*$p < .05$. **$p < .01$. ***$p < .001$.

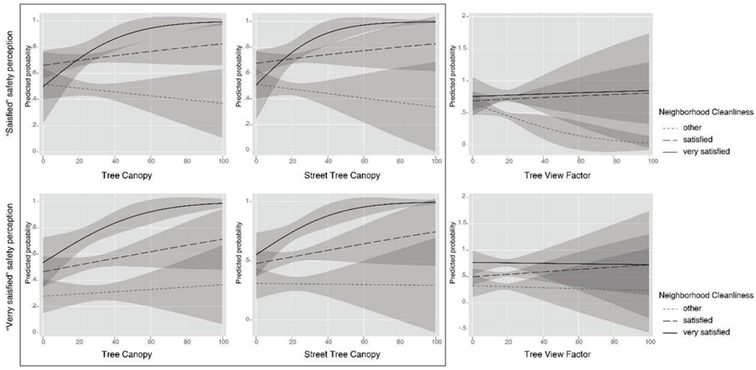

Figure 2. Predictive margins with 95% CIs: Tree characteristics and perceived safety contingent upon the neighborhood cleanliness level.

Subgroup-Analysis: Logistic Regression by Neighborhood Disadvantage Level

Table 5 displays the relationship between urban trees and perceived safety analyzed separately in less, moderately, and more disadvantaged neighborhood using sub-group analysis based on the areal deprivation index. We found varying relationships between urban trees and perceived safety depending on the socioeconomic status of the neighborhoods. In areas characterized as relatively less disadvantaged, we identified robust and statistically significant associations between tree canopy coverage and street tree canopy coverage with both "agree" and "strongly agree" responses on perceived safety. Specifically, for each additional unit of overall tree canopy coverage and street tree canopy coverage, holding all other variables constant, we observed a significant increase in RRR of residents being "strongly agree" response on safety perception in comparison to others. The RRRs indicated for an increment of 1-percentage point in overall tree canopy coverage, the probability of being very satisfied of the perceived safety in their neighborhoods increased by a factor of 1.069, and for street tree canopy coverage, the probability of being " strongly agree" response on safety perception in their neighborhoods increased by a factor of 1.075. In contrast, our analysis found no significant associations between tree canopy and perceived safety in areas with medium or high levels of socioeconomic disadvantage. These results suggest that the relationship between urban trees and perceived safety is contingent on the neighborhood's socioeconomic context.

Table 5. Sub-Group Analysis: The Relationship Between Urban Trees and Perceived Safety Based on Median Household Income Level.

Variables	Less disadvantaged (M5–1) RRR [95% CI]	Moderate disadvantaged (M5–2) RRR [95% CI]	More disadvantaged (M5–3) RRR [95% CI]
Perception on safety (others vs. agree)			
Tree Canopy	**1.048**** [1.011, 1.085]	0.994 [0.976, 1.012]	1.019 [0.991, 1.048]
Street Tree Canopy	**1.053*** [1.01, 1.098]	0.993 [0.971, 1.015]	1.016 [0.978, 1.056]
TVF	1.008 [0.933, 1.09]	0.985 [0.941, 1.032]	0.998 [0.935, 1.065]
Perception on safety (others vs. strongly agree)			
Tree Canopy	**1.069***** [1.027, 1.113]	1.006 [0.985, 1.028]	1.006 [0.962, 1.051]
Street Tree Canopy	**1.075**** [1.026, 1.126]	1.007 [0.982, 1.034]	1.006 [0.945, 1.071]
TVF	1.054 [0.966, 1.15]	0.986 [0.934, 1.041]	0.954 [0.861, 1.057]

Note. 95% confidence interval. Significant coefficients are printed in bold. RRR = relative risk ratio. Each model is controlled for confounding variables.

*$p < .05$. **$p < 0.01$. ***$p < .001$.

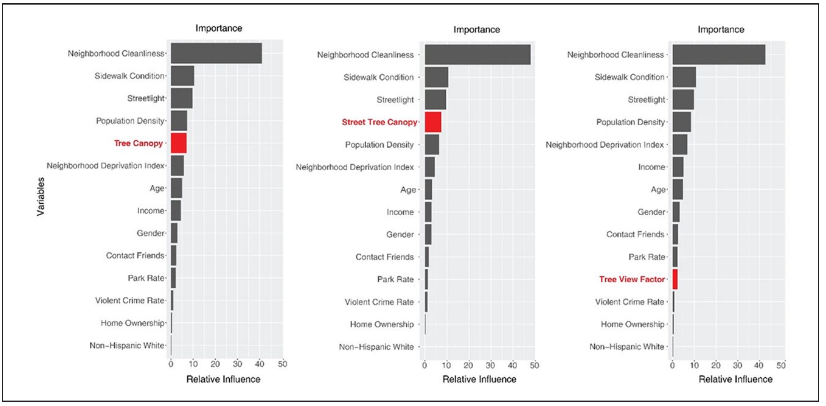

Figure 3. Variable importance plots of three GBDT models.
Note. Each fitted with tree canopy, street tree canopy, and TVF, respectively. The longer the bar, the greater importance the variable has on improving the model performance.

Examining Nonlinear Relationship Using Gradient Boosted Decision Trees

Figure 3 shows the variable importance plot for three GBDT models predicting perceived safety using the same set of independent variables used in Model series 2. Note that GBDT models were fitted with a binary dependent variable containing only “others” and “strongly agree” levels of safety perception. The “agree” level of safety perception was excluded because Model 2.1–2.3 in Table 2 showed the insignificance of all three tree canopy measures as predictors of “agree” response on safety perception.

Neighborhood cleanliness shows dominance in improving the model fit across the three models, followed by sidewalk condition and streetlight. Tree canopy and street tree canopy ranked as the 5th and 4th most important variables, respectively, while TVF showed a considerably lower contribution to the model fit, holding the 11th position. Individual-level sociodemographic factors consistently showed lower contributions than environmental factors, with age, income, and gender being the top three individual-level factors.

Figure 4 presents ICE plots for the three tree canopy measures. The red lines are partial dependence plots, representing the average predicted probability of survey respondents choosing “strongly agree” response on safety perception. Overall, while the predicted probability tends to increase as urban trees increase, the two urban tree measures—tree canopy and street tree canopy—from satellite images showed similar effects, but TVF demonstrated distinctively weaker associations with perceived safety. For tree canopy and

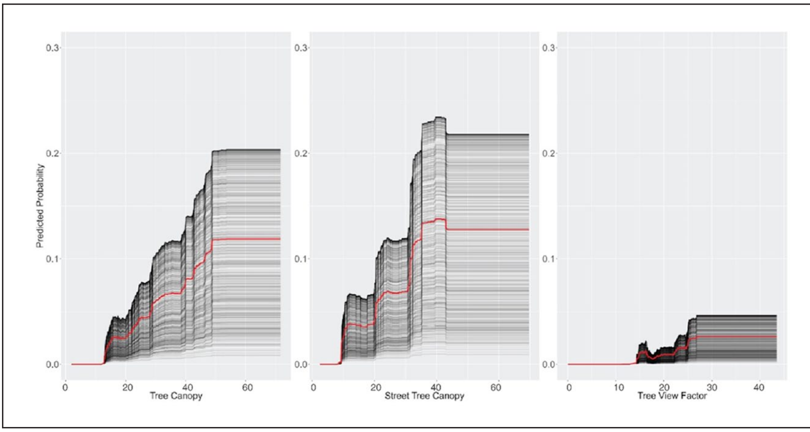

Figure 4. Individual conditional expectation plot from the three GBDT models.
Note. Each fitted with tree canopy, street tree canopy, and TVF, respectively. The red lines demonstrate the average predicted probability of being "very satisfied" with safety perception.

street tree canopy, having trees less than 10% does not appear to be associated with perceived safety. They both showed associations with increased probability of being "strongly agree" with perceived safety in their neighborhoods, ranging from approximately 10 to 40% for street tree canopy and 10 to 45% for tree canopy. Within this range, the predicted probability tends to gradually increase with tree canopy. For street tree canopy, there are sharp increases in predicted probability when street tree canopy reaches around 10, 20, and 30%. They both plateau after tree canopy coverage reaches above 40 to 50% range. TVF showed a distinctly weaker association compared to tree canopy and street tree canopy. The range of average predicted probability associated with changes in TVF is narrower, indicating a weaker impact. The increase in predicted probability associated with TVF is also confined to a narrower band, approximately between 15 and 25%.

Discussions

In the wake of the increasing urbanization of our world, the well-being and livability of urban residential areas have become subjects of paramount importance. Among the multifaceted determinants of residents' quality of life, safety from crime, and perceptions of safety stand out as critical factors shaping the urban experience (Alfonzo et al., 2008). This study delves into the intricate relationship between safety perceptions and one specific element of the urban environment—urban trees. While urban trees have been extensively studied for their potential to reduce crime rates (Gilstad-Hayden et al., 2015; Schusler et al., 2018; Troy et al., 2012), less attention has been given to their impact on residents' perceptions of safety. To assess the impact of urban trees from diverse perspectives, we utilized three different measures of urban trees including overall tree canopy, street tree canopy, and tree view factor. This study explored this relatively underexplored domain and addressed gaps in the existing literature in multiple ways. First, we found positive associations between urban trees and residents' perceptions of safety when tree canopy was measured using satellite images but not when it was measured using street images. Second, we found the significant moderating effects of neighborhood cleanliness on the relationship between urban trees and perceived safety. Third, subgroup-analysis found that the relationship between tree canopy and perceived safety was stronger in less disadvantaged areas, compared to more disadvantaged areas. Finally, our research indicates that although urban trees positively contribute to perceived safety, there exists an optimal threshold of tree canopy that maximizes this effect.

From Socio-Ecological Viewpoint: Urban Trees and Perceived Safety

Our research has identified a notable role of tree canopy cover in improving perceptions of safety. This finding is consistent with existing literature that highlights the benefits of urban green spaces (Jansson et al., 2013; Mouratidis, 2019). Trees are an integral component of urban green spaces that offer not only aesthetic and ecological benefits but also discernible influences on the psychological and social aspects of urban living (Haq, 2011). In addition, our study has revealed that the significance of tree canopy concerning perceived crime weakens when we factor in the influence of the objective neighborhood environment. This finding suggests that certain components of the built environment, such as neighborhood cleanliness, condition of streets, adequacy of streetlight, population density and ADI, may be functioning as significant predictors of perceived safety, potentially overshadowing the impact of tree canopy. Notably, among the various urban tree characteristics we examined, overall tree canopy and street tree canopy demonstrated a more substantial association with perceived safety than TVF, as indicated in Table 2. There are multiple potential explanations for the TVF's insignificance: some street view images may be unavailable in gated communities (Smith et al., 2021) or may be outdated, particularly in socioeconomically disadvantaged areas (Fry et al., 2020). Another possibility could be that street view images primarily capture what is visually perceptible from an eye-level perspective on the street (Anguelov et al., 2010), which may not capture backyard trees or trees behind the buildings. However, further investigation is required to unravel the intricacies of these relationships.

Furthermore, our study has unveiled an interesting pattern: the impact of tree canopy on perceived safety varies depending on the cleanliness of one's neighborhood. Specifically, we observed that individuals who report themselves as "very satisfied" with their neighborhoods are notably more influenced by tree canopy, while those who are "satisfied" display a weaker or statistically insignificant association with the extent of tree canopy. This divergence can be attributed to a multitude of factors. When individuals are "very satisfied" with the cleanliness of their neighborhoods, it often signifies their contentment with a range of aspects in their local environment. This heightened contentment can lead to the establishment of a sense of ownership and connection to their surroundings. Consequently, they become more attuned to environmental enhancements, including an increase in tree canopy, and attribute their heightened sense of safety to these improvements. Additionally, neighborhood characteristics, including cleanliness and quietness, tend to nurture a stronger sense of community and social cohesion (Mouratidis, 2020). In such communal settings, residents collectively appreciate and maintain green spaces, including trees, further reinforcing the link between tree canopy and perceived safety.

From the Environmental Justice Viewpoint: Neighborhood Cleanliness

The findings related to neighborhood cleanliness shed light on an important dimension of urban environmental justice. Our result showed that neighborhood cleanliness is acting as a moderator, strengthening the relationship between urban tree canopy and perception of safety. This finding underscores the profound implications of environmental disparities within urban settings. Clean and well-maintained neighborhoods have long been associated with improved quality of life, fostering a sense of pride and community among residents (Dempsey, 2008). However, neglected areas tend to have more physical disorders which can inhibit collective efficacy and social interaction (Browning & Cagney, 2002). This study extends our understanding by demonstrating how the benefits of urban tree canopy coverage can vary depending on the neighborhood environmental conditions, particularly cleanliness of neighborhoods, in the context of perceived safety.

Trees, in the absence of appropriate maintenance, may increase the perception of mess through fallen fruit, leaves, dead trees, or dropping of ticks, while this problem may vary depending on the tree species (Tomalak et al, 2011). Particularly in neglected spaces, byproducts of trees can reduce safety by increasing the impression of disorder due to uncollected debris (Roman et al, 2021). Thus, the findings may reflect a combination of these impacts, particularly in neglected areas. In well-maintained areas, on the other hands, the positive effects of greenery are more pronounced because the trees can be cared and rubbish could be promptly removed, leading to discrepancies in the impact of greenery on perceived safety across different areas.

When examined from an environmental justice perspective, these results highlight the imperative for fair resource allocation and thoughtful urban planning. Historically marginalized communities have frequently endured a lack of access to green spaces and clean environments, further widening existing disparities in well-being (Kim et al., 2022). Recognizing the moderating role of neighborhood cleanliness means that investments in green infrastructure should go beyond simply increasing the number of trees. Instead, it should prioritize the overall quality or maintenance of neighborhoods, particularly in underserved areas. This holistic approach can not only advance environmental justice but also fosters a heightened sense of security and well-being among residents. Additionally, it indicates the need to appropriately select tree species whose impact on impressions of disorder is minimized in the absence of land maintenance.

From the Environmental Justice Viewpoint: Neighborhood Disadvantage

The subgroup-analysis of our data has revealed insightful findings, elucidating the intricate dynamics that govern the interplay between tree canopy and perceived safety in neighborhoods with differing levels of disadvantage and cleanliness, as shown in Tables 3 and 4 and Figure 2. This investigation has unveiled a pronounced positive relationship between tree canopy and perceived safety, with its strength notably more pronounced in less disadvantaged areas than in more marginalized counterparts. This finding compels us to reconsider the one-size-fits-all approach to urban greening initiatives (Dennis et al. 2020). While the significance of planting trees in urban areas cannot be overstated, a mere increase in tree canopy should not be the exclusive focus in marginalized neighborhoods when the goal is to bolster perceived safety. This aligns with the broader advantages of increased tree canopy cover for marginalized populations and communities, showing that tree canopy serves not only to enhance the environment overall but also to offer cooling effects specifically beneficial in socially vulnerable areas (Zhou et al., 2021). These results underscore the need for a holistic approach, combining tree planting initiatives with strategies that tackle the social and economic inequalities (Koo, Boyd, et al., 2023). This approach aims to create a safer and more equitable urban environment that benefits all residents, regardless of their level of disadvantage.

From a Dose-Response Perspective on Urban Tree Intervention and Perceived Safety

Through the ICE plots from GBDT models, we identified specific thresholds of tree canopy cover that significantly impact perceived safety. When tree cover extends to a maximum threshold, its influence on people's sense of safety stabilizes. Specifically, the pivotal range spans roughly from 10 to 45% for tree canopy and street tree canopy while the impactful range is more constrained for TVF, falling between 15 and 25%. When measured using tree canopy, approximately 70% of the survey respondents in this study falls within 10 and 45% range. Only about 20% of the observations in this study surpass 45% of tree canopy coverage. This result aligns with a study by Suppakittpaisarn et al. (2019), which found that an increase in the amount of greenery did not result in a corresponding increase in preference after a certain value was exceeded. This unveils an opportunity for effective interventions: public policies and plans for tree planting can enhance perceived safety until the tree canopy reaches its upper limit of 45%. Given that planting trees in private lots often falls beyond public jurisdiction, the finding also suggests that street tree canopies can be effective intervention targets. To strategically enhance perceived safety, policymakers may identify target communities by comparing available planting spaces on streets, existing tree canopy coverage, and the associated costs within each community.

Furthermore, this insight suggests that combining tree planting with neighborhood upkeep efforts could significantly benefit disadvantaged neighborhoods, echoing findings from the earlier subgroup-analysis based on ADI levels. These areas tend to have lower tree canopy coverage, with the street tree canopy in more disadvantaged neighborhoods averaging 14.5%, as shown in Table 1. This surprisingly aligns closely with the starting point of the upward slopes, illustrated in Figure 4. Notably, below this threshold, there were no discernible benefits observed in enhancing perceived safety. This underscores the importance of policy options tailored to these neighborhoods, emphasizing a balance between planting new trees and maintaining surrounding neighborhoods.

Urban Planning, Urban Forestry, and Policy Implications

The intersection of urban planning and urban forestry implications represents a critical nexus in the pursuit of creating sustainable, livable, and safe urban environments. Urban planning serves as the foundation for shaping the physical and social fabric of cities, while urban forestry contributes to the ecological and aesthetic aspects of urban areas (Jim et al., 2018). A comprehensive approach to policy development encompasses green infrastructure policies, revisions to zoning and building regulations, environmental justice initiatives, and community engagement. These policies collectively contribute to creating safer, more livable, and more equitable urban residential areas.

The research findings present the compelling need for robust green infrastructure policies aimed at enhancing the safety and well-being of urban residential areas. These policies should prioritize the seamless integration of urban trees, with a particular emphasis on street trees, into the urban landscape. Essential components of such policies should include the establishment of clear canopy cover targets and the implementation of incentives to encourage the planting of street trees in residential neighborhoods. Notably, the city has set a goal to increase tree canopy coverage to 50% by 2050 as part of its Climate Equity Plan (City of Austin, 2021). The NeighborWoods initiative, a collaborative effort between the City of Austin and a local non-profit organization, TreeFolks, exemplifies a commendable free tree program aimed at providing trees to residents in Austin (Tree Folks, 2023). This initiative aligns seamlessly with the study's findings, which shed light on the significant correlation between street trees and residents' perceptions of safety, particularly at nighttime.

Furthermore, these green infrastructure policies necessitate a comprehensive review of zoning regulations and urban design guidelines. By mandating the inclusion of trees and green spaces in development plans, cities can ensure that tree canopy becomes an integral component of their growth (Ong, 2003). This proactive approach harmonizes with the study's insights, which emphasize the strategic integration of tree canopy into urban design guidelines to foster safer and more aesthetically pleasing urban environments.

Addressing environmental justice concerns takes on heightened importance in light of the study's findings, which illuminate the intricate relationship between the quantity of urban trees and safety perceptions, especially in more disadvantaged areas. A report in 2021 from the conservation non-profit organization American Forests has revealed a striking 20% disparity in canopy coverage between high-income and low-income neighborhoods in Austin, marking the widest gap observed nationwide (Henrikson, 2021). The findings also underscore the importance of the quality and maintenance of urban trees in conjunction with neighborhood socioeconomic status, which serves as a key social determinant of health.

The neglected areas may offset the benefits of trees in increasing perceived safety by increasing the impression of disorder through fallen fruit, leaves, branches, or debris. Policymakers should proactively allocate resources and initiatives towards historically marginalized communities to address these issues. Ensuring regular maintenance and selecting appropriate tree species can help ameliorate existing disparities in well-being and safety in these areas. Policies that prioritize equitable access to green infrastructure can also play a pivotal role in mitigating these disparities (Dunn, 2010). By implementing concrete measures to prioritize underserved areas, both in terms of quantity and quality of urban trees, policymakers can make substantial strides in advancing environmental justice.

Limitations

We recognize several limitations inherent in our study. Our primary tool for assessing perceived safety was a single item, which may be inherently limited in fully capturing the multifaceted nature of this construct. Specifically, this global measure of safety is not an actual fear of crime or an emotional reaction to crime itself. Thus, this measurement can only capture the simple awareness of the relative risk of neighborhood safety (Hale, 1996). Additionally, framing the statement "I feel safe in my neighborhood at night" in this affirmative way could introduce a response bias. Dillman et al. (2014) highlighted that framing questions in such an affirmative way posits a positive scenario. Future research should aim to employ more neutral questions to minimize potential bias. An example of a more neutral question would be, "how would you describe your feeling of safety in relation to crime while you are walking in your neighborhood at night?" This approach helps to ensure that the data collected reflects a more accurate range of perceptions rather than being skewed toward the affirmative. In addition to that, there might be a potential bias in the survey responses. The survey used in this study was conducted by the city to assess agreement and satisfaction with the delivery of major city services and to determine community priorities as part of the city's ongoing planning process. There is a possibility that participants may have felt compelled to give favorable responses, influenced by concerns about potential repercussions or social judgment for expressing negative views about their community. These concerns could include worries about alienation from their neighbors, potential impacts on property values, or negative perceptions from local authorities (Tourangeau & Yan, 2007). Groves et al. (2012) further suggested that government-sponsored surveys tend to achieve higher response rates and more positive responses compared to surveys sponsored by commercial businesses. Another limitation is that while the conventional practice in research often designates a 400-meter distance from one's residence as the perceived neighborhood boundary (e.g., Ewing et al., 2013; Koo, Guhathakurta, et al., 2023), there is a notable variability in participants' conceptualization of neighborhood size. This aspect warrants further investigation and explication. Additionally, it is important to acknowledge that our study's scope was confined to just one city, which may restrict the generalizability of our findings to a broader context. Moreover, our study focused on assessing perceived safety but did not delve into exploring the downstream consequences of varying levels of perceived safety. While perceived safety is undoubtedly crucial for enhancing livability, it is worth considering that a certain level of fear may be necessary. Many individuals respond to fear of victimization by taking precautionary actions to mitigate risks or reduce their exposure through risk management strategies. Lastly, we must acknowledge that our measurement of urban trees has limitations. To address this, we complemented the TVF data with other satellite images for a more comprehensive assessment.

Conclusion

In conclusion, this study provides valuable insights into the intricate relationship between urban trees and residents' perceptions of safety, carrying implications for urban forestry and human behaviors. It underscores the multifaceted impact of tree canopy on residents' safety perceptions within their neighborhoods. This study also offers significant insights for urban planning and environmental justice considerations. The research highlights the moderating role of neighborhood cleanliness, underscoring the importance of addressing environmental disparities. Moreover, the study uncovers an inverse relationship between tree canopy and perceived safety in disadvantaged areas, accentuating the necessity of a comprehensive strategy that combines tree planting with social and economic disparity mitigation. These findings call for the formulation of green infrastructure policies that prioritize urban tree integration, equitable resource allocation, and community engagement to ultimately foster safer, more livable, and more equitable urban environments.

Acknowledgments

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Appendix

Table A1. Characteristics of Key Variables Among the Participants Across the Neighborhood Disadvantage (Area Deprivation Index).

Variables		Total sample	By area deprivation index: Less disadvantaged	Moderate disadvantaged	More disadvantaged	χ^2 or ANOVA
Perceived safety	Others	541 (27.49%)	96 (18.11%)	245 (25.87%)	200 (40.73%)	$p < .01$
	Agree	882 (44.82%)	227 (42.83%)	447 (47.2%)	208 (42.36%)	
	Strongly agree	545 (27.69%)	207 (39.06%)	255 (26.93%)	83 (16.9%)	
Tree canopy (*M*/*SD*)		31.17 (15.41)	42.97 (14.87)	29.92 (13.24)	20.8 (10.65)	$p < .01$
Street tree canopy (*M*/*SD*)		23.89 (12.75)	34.5 (12.06)	22.82 (10.83)	14.45 (7.42)	$p < .01$
Tree view factor (*M*/*SD*)		18.65 (5.78)	22.35 (6.35)	18.05 (4.91)	15.77 (4.5)	$p < .01$
Perceived neighborhood environments						
Neighborhood cleanliness	Others	606 (31.37%)	106 (20.23%)	282 (30.32%)	218 (45.61%)	$p < .01$
	Satisfied	902 (46.69%)	241 (45.99%)	460 (49.46%)	201 (42.05%)	
	Very satisfied	424 (21.95%)	177 (33.78%)	188 (20.22%)	59 (12.34%)	
Conditions of streets	Others	798 (41.35%)	183 (34.99%)	385 (41.35%)	230 (48.32%)	$p < .01$
	Satisfied	890 (46.11%)	257 (49.14%)	428 (45.97%)	205 (43.07%)	
	Very satisfied	242 (12.54%)	83 (15.87%)	118 (12.67%)	41 (8.61%)	
Frequency of social interactions	Other	426 (22.32%)	76 (14.73%)	219 (23.7%)	131 (27.93%)	$p < .01$
	Satisfied	847 (44.37%)	231 (44.77%)	407 (44.05%)	209 (44.56%)	
	Very satisfied	636 (33.32%)	209 (40.5%)	298 (32.25%)	129 (27.51%)	
Adequacy of street lighting	Others	716 (37.8%)	173 (34.33%)	356 (38.61%)	187 (39.96%)	$p < .01$
	Satisfied	909 (47.99%)	248 (49.21%)	439 (47.61%)	222 (47.44%)	
	Very satisfied	269 (14.2%)	83 (16.47%)	127 (13.77%)	59 (12.61%)	

(continued)

Table A1. (continued)

Variables		Total sample	By area deprivation index			χ^2 or ANOVA
			Less disadvantaged	Moderate disadvantaged	More disadvantaged	
Objective neighborhood environments						
Crime rate		0.047 (0.06)	0.03 (0.06)	0.04 (0.05)	0.069 (0.06)	$p < 0.001$
Park area ratio		0.75 (0.1)	0.09 (0.12)	0.07 (0.09)	0.06 (0.08)	$p < .001$
Population density		1813.97 (1125.82)	1359.73 (718.16)	1784.39 (973.27)	2362.61 (1474.44)	$p < .001$
Individual level sociodemographic						
Age group	18–24 years	100 (5.23%)	12 (2.3%)	57 (6.18%)	31 (6.65%)	$p < .01$
	25–34 years	350 (18.32%)	77 (14.75%)	187 (20.26%)	86 (18.45%)	
	35–44 years	369 (19.31%)	117 (22.41%)	169 (18.31%)	83 (17.81%)	
	45–54 years	342 (17.9%)	108 (20.69%)	155 (16.79%)	79 (16.95%)	
	55–64 years	381 (19.94%)	107 (20.5%)	173 (18.74%)	101 (21.67%)	
	65–74 years	257 (13.45%)	75 (14.37%)	126 (13.65%)	56 (12.02%)	
	75+ years	112 (5.86%)	26 (4.98%)	56 (6.07%)	30 (6.44%)	
Gender	Female	967 (50%)	227 (43.24%)	464 (50.05%)	276 (57.26%)	$p < .01$
	Male	967 (50%)	298 (56.76%)	463 (49.95%)	206 (42.74%)	
Race/ethnicity	Non-Hispanic white	969 (50.1%)	298 (56.87%)	473 (50.75%)	198 (41.42%)	$p < .01$
	Others	965 (49.9%)	226 (43.13%)	459 (49.25%)	280 (58.58%)	
Household income	Less than $20K	158 (9.12%)	23 (4.95%)	69 (8.19%)	66 (15.57%)	$p < .01$
	$20K–39,999	261 (15.07%)	26 (5.59%)	126 (14.95%)	109 (25.71%)	
	$40K–59,999	316 (18.24%)	54 (11.61%)	178 (21.12%)	84 (19.81%)	
	$60K–79,999	286 (16.51%)	59 (12.69%)	148 (17.56%)	79 (18.63%)	
	$80K–149,999	454 (26.21%)	157 (33.76%)	231 (27.4%)	66 (15.57%)	
	$150K or more	257 (14.84%)	146 (31.4%)	91 (10.79%)	20 (4.72%)	
Home ownership	Own	1339 (68.49%)	426 (80.68%)	630 (66.81%)	283 (58.47%)	$p < .01$
	Rent	616 (31.51%)	102 (19.32%)	313 (33.19%)	201 (41.53%)	

Note. Less Disadvantaged: Participants residing in areas with an Area Deprivation Index (ADI) below the 25th percentile (ADI < 13). Moderately Disadvantaged: Participants living in areas with ADI values falling between the 25th and 75th percentiles (ADI ≥ 13 and ADI < 37). More Disadvantaged: Participants located in areas with ADI values above the 75th percentile (ADI ≥ 37).

Table A2. Multinomial Logistic Regression Analysis, Comparing Perceived Safety: Agree Versus Others.

		Adjusted for individual-level socio-demographic			Adjusted for all covariates		
Dependent variable levels: perception on safety (others vs. agree)		M 1–1 RRR [95% CI]	M 1–2 RRR [95% CI]	M 1–3 RRR [95% CI]	M 2–1 RRR [95% CI]	M 2–2 RRR [95% CI]	M 2–3 RRR [95% CI]
Tree canopy		**1.015**** [1.005, 1.025]	—	—	1.005 [0.992, 1.018]	—	—
Street tree canopy		—	**1.017*** [1.004, 1.029]	—	—	1.003 [0.988, 1.019]	—
TVF		—	—	1.005 [0.980, 1.030]	—	—	.987 [0.957, 1.018]
Neighborhood cleanliness	Satisfied	**3.256***** [2.431, 4.363]	**3.247***** [2.424, 4.350]	**3.328***** [2.484, 4.457]	**3.143***** [2.324, 4.250]	**3.142***** [2.324, 4.249]	**3.153***** (2.331, 4.264)
	Very satisfied	**4.388***** [2.542, 7.573]	**4.357***** [2.522, 7.528]	**4.623***** [2.680, 7.973]	**4.029***** [2.305, 7.043]	**4.028***** [2.303, 7.047]	**4.105***** (2.345, 7.186)
Condition of streets	Satisfied	**1.733***** [1.294, 2.322]	**1.741***** [1.300, 2.330]	**1.770***** [1.324, 2.368]	**1.800***** [1.332, 2.432]	**1.804***** [1.335, 2.437]	**1.810***** (1.340, 2.444)
	Very satisfied	**2.250*** [1.128, 4.489]	**2.258*** [1.133, 4.498]	**2.195*** [1.104, 4.364]	**2.236*** [1.115, 4.480]	**2.226*** [1.111, 4.460]	**2.204*** (1.100, 4.417)
Frequency of social interactions	Satisfied	**1.480**** [1.061, 2.065]	**1.487*** [1.066, 2.073]	**1.535*** [1.102, 2.138]	**1.577**** [1.121, 2.220]	**1.585**** [1.127, 2.231]	**1.606**** (1.141, 2.259)
	Very satisfied	1.380 [0.952, 2.000]	1.378 [0.951, 1.997]	1.428 [0.987, 2.067]	**1.495*** [1.023, 2.184]	**1.499*** [1.026, 2.190]	**1.504*** (1.030, 2.196)
Adequacy of streetlight	Satisfied	**1.645**** [1.238, 2.186]	**1.653***** [1.244, 2.196]	**1.649***** [1.243, 2.189]	**1.647**** [1.229, 2.207]	**1.651***** [1.232, 2.212]	**1.652***** (1.233, 2.214)
	Very satisfied	1.098 [0.592, 2.037]	1.107 [0.597, 2.052]	1.068 [0.578, 1.976]	1.034 [0.550, 1.942]	1.031 [0.549, 1.936]	1.024 (0.545, 1.922)
Age	25–34 years	1.113 [0.584, 2.121]	1.129 [0.593, 2.150]	1.121 [0.589, 2.133]	1.095 [0.567, 2.116]	1.099 [0.569, 2.123]	1.098 (0.569, 2.118)
	35–44 years	1.066 [0.555, 2.047]	1.073 [0.559, 2.058]	1.098 [0.573, 2.105]	0.980 [0.503, 1.912]	0.979 [0.502, 1.909]	0.980 (0.503, 1.908)
	45–54 years	1.580 [0.819, 3.046]	1.600 [0.831, 3.083]	1.658 [0.861, 3.191]	1.599 [0.814, 3.141]	1.603 [0.816, 3.148]	1.606 (0.818, 3.152)
	55–64 years	1.320 [0.687, 2.534]	1.332 [0.694, 2.555]	1.375 [0.717, 2.635]	1.282 [0.658, 2.500]	1.288 [0.661, 2.510]	1.293 (0.664, 2.518)

(continued)

Table A2. (continued)

		Adjusted for individual-level socio-demographic			Adjusted for all covariates		
Dependent variable levels: perception on safety (others vs. agree)		M 1–1 RRR [95% CI]	M 1–2 RRR [95% CI]	M 1–3 RRR [95% CI]	M 2–1 RRR [95% CI]	M 2–2 RRR [95% CI]	M 2–3 RRR [95% CI]
	65–74 years	1.428 [0.697, 2.927]	1.454 [0.710, 2.975]	1.482 [0.725, 3.028]	1.414 [0.679, 2.946]	1.423 [0.684, 2.962]	1.423 (0.685, 2.958)
	75+ years	2.317 [.915, 5.866]	2.367 [.934, 5.999]	2.412 [.954, 6.096]	**2.702*** [1.032, 7.077]	**2.739*** [1.046, 7.172]	**2.727*** (1.043, 7.130)
Gender (female = 1)		**0.606***** [0.458, 0.803]	**0.604***** [0.456, 0.799]	**0.590***** [0.446, 0.781]	**0.588***** [0.441, 0.786]	**0.587***** [0.439, .783]	**0.583***** [0.437, 0.778]
Race (non-white = 1)		0.975 [0.744, 1.279]	0.974 [0.744, 1.277]	0.984 [0.752, 1.289]	1.011 [0.765, 1.335]	1.012 [0.766, 1.337]	1.015 [0.768, 1.341]
Home ownership		1.127 [0.830, 1.531]	1.133 [0.835, 1.539]	1.141 [0.840, 1.550]	1.049 [0.766, 1.437]	1.048 [0.765, 1.436]	1.047 [0.765, 1.435]
Income	$20K–39,999	1.370 [0.823, 2.281]	1.364 [0.820, 2.270]	1.361 [0.819, 2.262]	1.271 [0.753, 2.145]	1.267 [0.751, 2.138]	1.265 (0.750, 2.136)
	$40K–59,999	1.359 [0.818, 2.256]	1.361 [0.820, 2.260]	1.452 [0.876, 2.408]	1.229 [0.730, 2.068]	1.233 [0.732, 2.075]	1.249 (0.742, 2.102)
	$60K–79,999	1.479 [.888, 2.460]	1.493 [0.897, 2.482]	1.592 [0.960, 2.641]	1.349 [.798, 2.279]	1.353 [0.800, 2.286]	1.363 (0.807, 2.302)
	$80K–149,999	1.283 [0.772, 2.132]	1.284 [0.772, 2.135]	1.424 [0.861, 2.353]	1.112 [.659, 1.876]	1.114 [0.660, 1.882]	1.136 (0.674, 1.916)
	$150K or more	1.671 [0.912, 3.062]	1.692 [0.924, 3.100]	**1.958*** [1.078, 3.555]	1.367 [.726, 2.575]	1.376 [0.730, 2.591]	1.413 (0.752, 2.656)
Park ratio					2.637 [0.453, 15.337]	2.822 [0.492, 16.193]	2.639 [0.454, 15.356]
Population density					**0.822**** [0.708, 0.954]	**0.824*** [0.71, 0.956]	**0.834*** [0.718, 0.97]
ADI					0.991 [0.981, 1.001]	0.991 [0.980, 1.001]	**0.989*** [0.979, 0.999]
Crime rate					0.594 [0.024, 14.502]	0.470 [0.020, 11.079]	0.245 [0.010, 5.936]

Note. 95% confidence interval. Significant coefficients are printed in bold. RRR = relative risk ratio.
*$p < .05$. **$p < .01$. ***$p < .001$.

Table A3. Multinomial Logistic Regression Analysis, Comparing Perceived Safety: Strongly Agree Versus Others.

Dependent variable levels: perception on safety (others vs. strongly agree)		Adjusted for individual-level socio-demographic			Adjusted for all covariates		
		M 1–1 RRR [95% CI]	M 1–2 RRR [95% CI]	M 1–3 RRR [95% CI]	M 2–1 RRR [95% CI]	M 2–2 RRR [95% CI]	M 2–3 RRR [95% CI]
Tree canopy		**1.029***** [1.016, 1.041]	—	—	**1.017*** [1.002, 1.033]	—	—
Street tree canopy		—	**1.036***** [1.021, 1.052]	—	—	**1.022*** [1.003, 1.041]	—
TVF		—	—	**1.032*** [1.001, 1.064]	—	—	1.007 [0.971, 1.045]
Neighborhood cleanliness	Satisfied	**4.552***** [2.953, 7.017]	**4.414***** [2.863, 6.807]	**4.546***** [2.956, 6.992]	**4.081***** [2.626, 6.343]	**4.004***** [2.577, 6.221]	**4.001***** (2.578, 6.211)
	Very satisfied	**22.068***** [11.984, 40.634]	**20.916***** [11.346, 38.560]	**22.905***** [12.468, 42.077]	**19.127***** [10.250, 35.691]	**18.450***** [9.885, 34.434]	**18.988***** (10.177, 35.428)
Condition of streets	Satisfied	**1.980***** [1.351, 2.902]	**2.003***** [1.366, 2.935]	**2.097***** [1.435, 3.064]	**2.032***** [1.371, 3.010]	**2.046***** [1.381, 3.031]	**2.105***** (1.422, 3.114)
	Very satisfied	**4.703***** [2.287, 9.670]	**4.865***** [2.369, 9.992]	**4.594***** [2.244, 9.403]	**4.548***** [2.198, 9.411]	**4.645***** [2.245, 9.613]	**4.487***** (2.170, 9.277)
Frequency of social interactions	Satisfied	1.324 [0.845, 2.076]	1.326 [0.846, 2.079]	1.378 [0.881, 2.154]	1.499 [0.945, 2.378]	1.506 [0.949, 2.390]	1.527 (0.963, 2.420)
	Very satisfied	**2.107**** [1.310, 3.389]	**2.082**** [1.293, 3.351]	**2.188***** [1.364, 3.511]	**2.272***** [1.394, 3.702]	**2.272***** [1.394, 3.704]	**2.305***** (1.416, 3.754)
Adequacy of streetlight	Satisfied	**1.978***** [1.359, 2.877]	**2.017***** [1.385, 2.937]	**1.995***** [1.373, 2.897]	**2.099***** [1.425, 3.091]	**2.139***** [1.451, 3.151]	**2.127***** (1.444, 3.131)
	Very satisfied	**6.054***** [3.236, 11.327]	**6.321***** [3.376, 11.834]	**5.957***** [3.201, 11.087]	**5.972***** [3.148, 11.330]	**6.135***** [3.233, 11.642]	**5.999***** (3.167, 11.364)
Age	25–34 years	1.253 [0.546, 2.878]	1.259 [0.550, 2.883]	1.268 [0.555, 2.899]	1.220 [0.529, 2.817]	1.222 [0.530, 2.817]	1.212 (0.527, 2.789)
	35–44 years	1.714 [0.749, 3.925]	1.696 [0.743, 3.872]	1.798 [0.789, 4.097]	1.514 [0.655, 3.504]	1.502 [0.651, 3.466]	1.489 (0.646, 3.432)
	45–54 years	1.520 [0.650, 3.554]	1.504 [0.645, 3.506]	1.657 [0.712, 3.854]	1.458 [0.615, 3.460]	1.442 [0.609, 3.413]	1.473 (0.623, 3.483)
	55–64 years	.933 [0.401, 2.168]	.922 [0.398, 2.138]	1.021 [0.442, 2.358]	0.816 [0.347, 1.917]	0.808 [0.344, 1.895]	0.839 (0.358, 1.964)

(continued)

Table A3. (continued)

Dependent variable levels: perception on safety (others vs. strongly agree)		Adjusted for individual-level socio-demographic			Adjusted for all covariates		
		M 1–1 RRR [95% CI]	M 1–2 RRR [95% CI]	M 1–3 RRR [95% CI]	M 2–1 RRR [95% CI]	M 2–2 RRR [95% CI]	M 2–3 RRR [95% CI]
	65–74 years	1.116 [0.449, 2.778]	1.128 [0.455, 2.799]	1.217 [0.493, 3.008]	1.088 [0.433, 2.733]	1.091 [0.435, 2.736]	1.126 (0.450, 2.818)
	75+ years	1.416 [0.455, 4.401]	1.402 [0.450, 4.366]	1.566 [0.507, 4.833]	1.648 [0.518, 5.245]	1.626 [0.511, 5.175]	1.715 (0.541, 5.441)
Gender (female = 1)		**0.406***** [0.287, 0.575]	**0.408***** [0.288, 0.578]	**0.406***** [0.287, 0.575]	**0.395***** [0.277, 0.565]	**0.396***** [0.277, 0.566]	**0.387***** [0.271, 0.552]
Race (non-white = 1)		1.103 [0.787, 1.546]	1.085 [0.774, 1.520]	1.103 [0.787, 1.546]	1.163 [0.822, 1.646]	1.152 [0.814, 1.630]	1.159 [0.820, 1.640]
Home ownership		1.309 [0.877, 1.953]	1.309 [0.877, 1.954]	1.309 [0.877, 1.953]	1.222 [0.811, 1.842]	1.223 [0.811, 1.844]	1.216 [0.807, 1.833]
Income	$20K–39,999	**2.465*** [1.157, 5.252]	**2.433*** [1.141, 5.188]	**2.360*** [1.111, 5.011]	**2.740*** [1.240, 6.056]	**2.714*** [1.228, 5.998]	**2.668*** (1.207, 5.895)
	$40K–59,999	2.069 [0.981, 4.363]	2.049 [0.971, 4.326]	**2.241*** [1.067, 4.709]	2.187 [0.995, 4.805]	2.182 [0.993, 4.796]	**2.248*** (1.024, 4.935)
	$60K–79,999	1.490 [0.699, 3.176]	1.489 [0.699, 3.174]	1.647 [0.777, 3.491]	1.589 [0.715, 3.532]	1.586 [0.714, 3.525]	1.629 (0.734, 3.615)
	$80K–149,999	1.657 [0.788, 3.482]	1.616 [0.768, 3.401]	1.948 [0.935, 4.057]	1.693 [0.774, 3.701]	1.669 [0.763, 3.652]	1.774 (0.813, 3.871)
	$150K or more	**2.413*** [1.058, 5.502]	**2.409*** [1.057, 5.493]	**3.064**** [1.361, 6.895]	2.264 [0.945, 5.420]	2.280 [0.953, 5.458]	2.428* (1.018, 5.794)
Park ratio					3.923 [0.509, 30.248]	4.904 [0.646, 37.224]	5.562 [0.716, 43.229]
Population density					**0.778*** [0.637, 0.95]	**0.773*** [0.633, 0.944]	**0.777*** [0.635, 0.952]
ADI					**0.985*** [0.971, 0.998]	**0.986*** [0.973, 1.000]	**0.980**** [0.967, 0.993]
Crime rate					12.580 [0.010, 0.152]	12.499 [0.252, 620.502]	3.359 [0.064, 177.645]

Note. 95% confidence interval. Significant coefficients are printed in bold. RRR = relative risk ratio.
$^{*}p < .05$. $^{**}p < .01$. $^{***}p < .001$.

Table A4. The Moderating Effects of Neighborhood Conditions on the Association Between Tree Characteristics and Perceived Safety.

Moderating role of condition of streets		M 3–1 RRR [95% CI]	M 3–2 RRR [95% CI]	M 3–3 RRR [95% CI]
Perception on safety (others vs. agree)				
Tree Canopy × Condition of Streets	Satisfied	0.991 [0.971, 1.012]		
	Very satisfied	1.002 [0.955, 1.052]		
Street Tree Canopy × Condition of Sreets	Satisfied		0.992 [0.967, 1.018]	
	Very satisfied		1.002 [0.941, 1.066]	
TVF × Condition of Streets	Satisfied			1.010 [0.957, 1.067]
	Very satisfied			0.931 [0.820, 1.056]
Perception on safety (others vs. strongly agree)				
Tree Canopy × Condition of Streets	Satisfied	0.999 [0.974, 1.026]		
	Very satisfied	0.994 [0.946, 1.045]		
Street Tree Canopy × Condition of Streets	Satisfied		0.998 [0.966, 1.03]	
	Very satisfied		0.980 [0.92, 1.044]	
TVF × Condition of Streets	Satisfied			1.019 [0.952, 1.091]
	Very satisfied			0.886 [0.779, 1.006]

Moderating role of frequency of social interactions		M 3–1 RRR [95% CI]	M 3–2 RRR [95% CI]	M 3–3 RRR [95% CI]
Perception on safety (others vs. agree)				
Tree Canopy × Frequency of Social Interactions	Satisfied	0.999 [0.974, 1.026]		
	Very satisfied	0.986 [0.960, 1.013]		
Street Tree Canopy × Frequency of Social Interactions	Satisfied		0.998 [0.966, 1.030]	
	Very satisfied		0.983 [0.950, 1.016]	
TVF × Frequency of Social Interactions	Satisfied			1.002 [0.938, 1.070]
	Very satisfied			0.982 [0.919, 1.049]

(continued)

Table A4. (continued)

Moderating role of frequency of social interactions		M 3–1 RRR [95% CI]	M 3–2 RRR [95% CI]	M 3–3 RRR [95% CI]
Tree Canopy × Frequency of Social Interactions	Satisfied	0.993 [0.961, 1.026]		
	Very satisfied	0.974 [0.942, 1.007]		
Street Tree Canopy × Frequency of Social Interactions	Satisfied		1.007 [0.967, 1.049]	
	Very satisfied		0.983 [0.943, 1.024]	
TVF × Frequency of Social Interactions	Satisfied			1.054 [0.967, 1.150]
	Very satisfied			0.994 [0.913, 1.082]

Moderating role of street lighting		M 3–1 RRR [95% CI]	M 3–2 RRR [95% CI]	M 3–3 RRR [95% CI]
Perception on safety (others vs. agree)				
Tree Canopy × Street Lighting	Satisfied	0.988 [0.967, 1.009]		
	Very satisfied	1.037 [0.987, 1.090]		
Street Tree Canopy × Street Lighting	Satisfied		0.978 [0.953, 1.003]	
	Very satisfied		1.034 [0.970, 1.103]	
TVF × Street Lighting	Satisfied			0.989 [0.937, 1.043]
	very satisfied			0.983 [0.871, 1.109]
Perception on safety (others vs. strongly agree)				
Tree Canopy × Street Lighting	Satisfied	0.994 [0.968, 1.021]		
	Very satisfied	1.025 [0.975, 1.077]		
Street Tree Canopy × Street Lighting	Satisfied		0.988 [0.957, 1.021]	
	Very satisfied		1.022 [0.958, 1.091]	
TVF × Street Lighting	Satisfied			1.016 [0.949, 1.087]
	Very satisfied			1.027 [0.909, 1.160]

Note. Each model is controlled for confounding variables.
$^*p < .05$. $^{**}p < .01$. $^{***}p < .001$.

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