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Research Paper

Street view environments are associated with the walking duration of pedestrians: The case of Amsterdam, the Netherlands

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HIGHLIGHTS

- Pedestrians' walking duration related to multiple street view (SV) characteristics.
- Environment-walking associations differed between weekdays and weekends.
- SV environments were primarily associated with weekend walking.
- SV-derived people within a threshold may be more optimal in promoting walking.
- Walking policy and urban planning need to account for specific street environments.

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ABSTRACT

Different aspects of the built and natural environment appear related to people's walking behavior. State-of-the-art transport studies typically incorporate built environmental measures (e.g., density, diversity, design). However, street view (SV) environments capturing how pedestrians perceived their surroundings on site are understudied. Therefore, this study examined possibly non-linear associations between multiple SV-derived environmental features and pedestrians' walking duration in Amsterdam, the Netherlands. We used travel survey data ($N = 1,886$) between 2014 and 2017. SV-derived environmental measures (e.g., cars and people) were extracted from SV images through a fully convolutional neural network. Covariate-adjusted generalized additive mixed models were fitted to the data. Our results showed that walking-SV features associations differed between weekdays and weekends. On weekdays, pedestrians walked more in neighborhoods with fewer individual standing walls and lower address density. On weekends, pedestrians' walking duration increased with more street greenery, fewer cars, higher address density, pronounced land-use diversity, and further distances to train stations. Non-linear associations were found only in the case of weekday SV-derived people, even after adjusting for other neighborhood characteristics (e.g., address density, land-use mix, and street connectivity). Our findings suggest that SV environmental features complement the typically used built environmental measures to explain pedestrians' mobility. Policy-makers and urban planners are advised to incorporate characteristics of the street environments, also should not only rely on the conventional thinking "the more, the merrier".

1. Introduction

Walking is a healthy, environment-friendly, and cost-free travel mode with numerous health benefits (Hanson & Jones, 2015; Marques et al., 2020). Social-ecological models suggest that individual-level characteristics shape people's walking behavior (e.g., demographics and socioeconomics) (Barnett et al., 2017; Stokols, 1992). Furthermore, growing evidence supports links between the built and natural environments and people's walking behavior (Cervero & Kockelman, 1997; Ewing & Cervero, 2001; Peters et al., 2020; Saelen & Handy, 2008; Wang et al., 2016).

Studies, relying primarily on cross-sectional designs, show that higher residential density (Frank et al., 2005), more connected streets (Wang et al., 2016), better access to destinations (Ewing & Cervero, 2010), pronounced land-use diversity (Grasser et al., 2013), and more greenery (Mäki-Opas et al., 2016) are positively associated with people's walking. Most of these studies assess travel on weekdays (Handy, 2005; Raux et al., 2016). However, some suggest that walking behaviors differ

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between weekdays and weekends (Cerin et al., 2017; Gim, 2018; Wang et al., 2021). These findings appear reasonable because the weekday walking, including travel purposes, trip lengths, and destinations, is more structured (e.g., commuting). In contrast, weekend travel (e.g., leisure trips) is more flexible (Bhat & Gossen, 2004). For instance, a Dutch study indicated that train accessibility is only significantly negatively associated with transit-related transport walking on weekdays, while more bus stops are positively associated with weekend walking (Gao et al., 2020).

However, these traditional measures of the built environment (e.g., land-use mix) are deficient in characterizing pedestrian environmental conditions. First, while they capture the broader physical environment on a neighborhood level, small-scale streetscape features, such as pedestrian facilities and street trees, remain unrecognized (Helbich et al., 2021; Ibrahim et al., 2020; Peters et al., 2020). Second, such measures are usually determined based on geographic information system-based measures, remote sensing-based measures, or both, which while providing bird's eye views of the earth's surface, fail to capture pedestrians' perspectives of the environment on the ground (Badland et al., 2010; Helbich et al., 2021; Ibrahim et al., 2020; Kang et al., 2020). Third, field observations and in-person audits, which have previously been used to assess streetscapes (e.g., Ewing et al., 2006; Nagata et al., 2020; Steinmetz-Wood et al., 2019), are only practicable for a few neighborhoods rather than entire cities because they are time-consuming, costly, and labor-intensive.

Street view (SV) images have emerged as an alternative data source to extract person-centric streetscape environmental features of urban spaces and achieved good agreement with in-person audits (Gullón et al., 2015; Ibrahim et al., 2020; Kang et al. 2020; Rundle et al., 2011). However, scant evidence to date scrutinizes associations between SV-derived environments and walking (Hankey et al., 2021; Sallis et al., 2015); of these, even fewer used SV images (Goel et al., 2018; Christman et al., 2020). Most of these studies (Christman et al., 2020; Goel et al., 2018; Vanwolleghem et al., 2016) audited streetscapes by trained observers based on predefined checklists, which are costly, labor-intensive, and time-consuming to collect, rather than using automated machine learning-based procedures. Among those few studies incorporating deep learning approaches, virtually all focused on street-level greenery (Li et al., 2018; Lu, 2019; Tsai et al., 2019; Zang et al., 2020; Ki & Lee, 2021). Evidence about how other automatically extracted SV features (e.g., people and cars) related to pedestrians' walking behavior is largely absent.

Finally, most studies have pre-assumed linear relationships between the built environment and walking behavior. However, such relationships may be more complex (van Wee & Handy, 2016). Possible mechanisms to explain non-linearities include that people may have an intrinsic walking desire considering the utilitarian nature of travel while disregarding the immediate built environment (Mokhtarian & Salomon, 2001). Additionally, it could be that the built environmental effects on walking become saturated beyond a specific threshold value (Cheng et al., 2020; Frank & Pivo, 1994; Yang et al., 2022). While several Anglophone (Cerin et al., 2018; Kerr et al., 2016) and Asian studies (Cheng et al., 2020; Ding et al., 2019; Liu et al., 2021; Yang et al., 2022) have explored non-linear walking-built environment relationships, European studies focusing on SV-derived built environmental characteristics are lacking. Due to differences in travel behaviors and variations in urban forms, neither Anglophone nor Asian findings can be translated into the European context.

To address these research gaps, we aimed to examine possible non-linear associations between SV-derived built environmental characteristics and the walking duration of pedestrians in Amsterdam, the Netherlands. Our research questions were: (1) What SV environmental features are associated with pedestrians' walking duration? (2) Do the associations between SV environmental features and walking duration differ across weekdays and weekends? (3) Are the SV environmental characteristics non-linearly related to the walking duration of pedestrians?

2. Materials and methods

2.1. Study design and study population

Walking data were obtained from the Dutch National Travel Survey (CBS, 2015). The travel survey is conducted annually by Statistics Netherlands based on a random sample of approximately 40,000 people from the Dutch population. These participants recorded their daily travel in a travel diary on a specific day of the week. For each trip, respondents provided socio-demographic and travel-related information (e.g., travel mode, trip date, trip origin and destination, time of departure and arrival).

The residential location of each respondent was geocoded with a 4-digit postal code (PC4) level (Gao et al., 2020), which permitted linkage to environmental data. Within the constraints of the availability of SV data, we extracted pedestrians living in Amsterdam. On average, a PC4 in Amsterdam was 2.46 km^2 (standard deviation [SD] $\pm$ 2.32). The sample size was maximized by pooling data from 2014 through 2017, resulting in a preliminary 1,979 respondents.

2.2. Outcome variable

Our dependent variable was walking duration. It was defined as the total duration of all walking trips (in minutes) per person per day. We excluded respondents ($N = 7$) with an unusually high walking duration of >300 min, which corresponded to 12 times the standard deviation (SD $\pm$ 30.42). We log-transformed the outcome to stabilize the variance (Park et al., 2020). Because walking behavior was found to vary between weekdays and weekends (Gim, 2018; Wang et al., 2021), we a priori stratified the data.

2.3. Deep learning for extracting SV characteristics

SV services provide panoramic images allowing virtual navigation through urban streetscapes (Ibrahim et al., 2020). While most earlier studies extracted SV features (e.g., trees, vehicles) manually (Ewing et al., 2016; Sallis et al., 2015; Steinmetz-Wood et al., 2019), recent deep learning-based advances in computer vision allow accurate, objective volume processing of SV images (Helbich et al., 2021; Kang et al., 2020). Such approach has been employed to assess greenery (Lu, 2019), walkability (Koo et al., 2021), and visual enclosure (Yin & Wang, 2016).

We obtained geo-tagged SV images from Amsterdam's data portal (Gemeente Amsterdam, 2022). The panoramic images were collected by the municipality of Amsterdam and captured with a special camera mounted on a car. The Global Navigation Satellite System (e.g., Global Positioning System [GPS]) was used to determine the camera position accurately. The accuracy of the locational measurements was increased through reference data provided through base stations and atmospheric corrections.

We sampled the images at 16 m intervals throughout the street network obtained from OpenStreetMap. We queried cubic 360-degree panoramas for each location, including metadata describing the urban scenery. Each panorama comprised four cubic images of 512 $\times$ 512 pixels, as we excluded the additional top and bottom images due to nonrelevant content (Helbich et al., 2021).

Street environmental features were semantically segmented with a fully convolutional neural network (CNN). Specifically, we applied the Xception-71 CNN (Chollet, 2017), which was pre-trained based on annotated images from the Cityscapes dataset (Cordts et al., 2016). Cityscape is a benchmark image collection including pixel-level annotated street scenes from 50 different cities. Compared to alternative CNN architectures, the Xception-71 CNN performed favorably in a benchmark (Kamann & Rother, 2020).

Previous studies on walking only focused on street greenery (Ki &

Lee, 2021; Lu, 2018; Yang et al., 2021). Our study also included other built environmental characteristics when they were (1) potentially related to walkability (Ewing & Handy, 2009; Nagata et al., 2020; Saelens & Handy, 2008; Yin, 2017) and (2) occurred sufficiently often with enough variation across Amsterdam. We used the following object classes: people (e.g., persons who were walking, standing, or sitting), cars (e.g., passenger cars, trucks); street greenery (i.e., horizontal and vertical greenery), and individual standing walls (i.e., walls that are not part of a building, fence, or guard rail).

We determined the average number of pixels per class per panorama for each sampling point for each object class. To assign the SV variables to each survey respondent, we computed the average proportion of all sampling points per PC4.

2.4. Covariates

We adjusted for several covariates (Peters et al., 2020; Wang et al., 2021). We included gender (male, female), nationality (Dutch/Non-Dutch), possession of a driving license (yes/no), and bicycle ownership (yes/no). Age was divided into four categories: 18–24, 25–44, 45–64, and ≥ 65 (Gao et al., 2020; Liao et al., 2020). Education level was classified as low (i.e., primary education and lower vocational education), medium (i.e., secondary education), and high (i.e., college and university). On the household-level, monthly household income was categorized as low (<€2,000), medium (€2,000-€4,000), or high (>€4,000). Household composition could be single, couple without a child, couple with ≥ 1 child, and single parent with ≥ 1 child. We also controlled for household car ownership (yes/no).

Guided by previous studies (Barnett et al., 2017; Ewing & Cervero, 2010; Gao et al., 2020; Helbich, 2017; Wang et al., 2021) and data availability, five neighborhood environmental variables per PC4 area were included. Address density was captured as the total number of addresses (e.g., residential, shopping) per km^2 (CBS, 2017). Land-use mix was measured through the Shannon entropy index based on residential, recreational, commercial, industrial, and other land-uses (Gao et al., 2020). Land-use data were obtained from the Basic Registers Addresses and Buildings for the year 2017. Street connectivity was calculated as the number of 4-way crossings per PC4 derived from the Dutch topographical base map for 2017. Distance to the nearest train station represented the average distance of all residents in a PC4 area to the nearest train station (CBS, 2017). The number of bus stops per PC4 was obtained through OpenStreetMap. We normalized both covariates by PC4 area because the number of 4-way crossings and bus stops depended on the PC4 size.

2.5. Statistical analyses

Data were summarized using descriptive statistics (i.e., means, SD, and percentages). Bivariate associations were examined using multilevel correlations (Makowski et al., 2020). Specifically, we used Tetrachoric correlations for the nominal variables, and continuous variables were examined using Pearson's correlations. We applied Holm's procedure to account for multiple hypotheses testing (Holm, 1979).

Multicollinearity between the covariates was measured using generalized variance inflation factors (GVIFs). Constrained by our sample size and the covariates applied, we initially identified the best person- and household-level covariate subsets separately for weekdays and weekends (Model 1) via complete subset regression (CSR) (Elliott et al., 2013). As model selection criteria, CSR maximizes the adjusted R^2.

Rather than pre-assuming linear associations as is normal practice (Christman et al., 2020; Goel et al., 2018), we fitted generalized additive mixed models (GAMM) (Wood, 2017) to examine possible non-linear relationships between walking duration and the SV-derived environment. GAMMs can incorporate smooth functions to build non-linear modeling relationships. The smoothing parameters of the thin plate regression splines were automatically determined in the model calibration (Wood, 2017). Non-linearities were evaluated based on the effective degrees of freedom (EDF). The larger the EDFs (>1), the more complex the shape of associations. We also included a random effect to capture arising correlations to account for the hierarchical data structure where respondents were nested in PC4 areas (Leyland & Groenewegen, 2020). Model fits were compared using the Akaike Information Criterion (AIC). A lower AIC score indicated a better model fit. Restricted Maximum Likelihood was used for model estimation. A p-value < 0.10 was considered statistically significant. Analyses were performed using R, version 4.1.0 (R Core Team, 2021) with the "leaps" (Thomas, 2020) and the "mgcv" (Wood, 2017) packages.

Four models of progressively increasing complexity were built to analyze the weekday and weekend datasets, respectively. In Model 2 we extended Model 1 by additionally adding neighborhood environmental covariates. Model 3 added SV covariates instead of neighborhood-level covariates to Model 1. Model 4 simultaneously adjusted for both SV and neighborhood covariates. In Model 5, significant linearly associated neighborhood and SV covariates were replaced with non-linear smoothers.

3. Results

3.1. SV image segmentation

A total of 269,550 panoramas were collected between March 2016 and July 2019. Most images (65%) were taken between April and

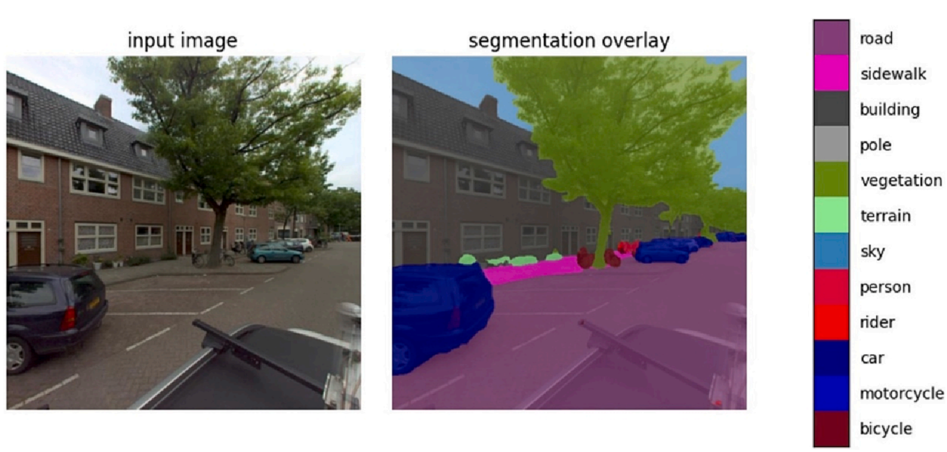

Fig. 1. Input SV image (left) and labelled image after segmentation (right).

October, during which most trees in the Netherlands maintained leaves (Fig. S1). The CNN showed good accuracy across all the object segmentations (Fig. 1). For example, the Jaccard index reached 94% accuracy for greenery (Kamann & Rother, 2020).

3.2. Descriptive statistics

In total, 1,886 respondents were included in our analysis after removing those who provided incomplete data ($N = 86$). Of the retained respondents, 58% were female, 20% were older than 65 years, 59% were married, and 61% were Dutch. Most of the respondents (77%) owned a bike, more than half (54%) had at least one car within their households.

The overall walking duration was 24.96 min/day (SD ± 30.42), and 70% of the trips took place on weekdays. The average walking duration of pedestrians was longer on weekends (26.22 min/day, SD ± 33.79) compared to weekdays (24.43 min/day, SD ± 28.87). Weekend walkers resided, on average, in areas with higher address densities and better train and bus stop accessibility compared to those walking on weekdays (Table 1). The neighborhoods of pedestrians walking on weekdays were characterized by better street connections and were further away from train stations.

3.3. Correlation analysis

Fig. 2 summarizes the pair-wise correlations between the environmental variables. The strongest correlations were observed for address density and cars both for weekdays and weekends. Street greenery and people had a strong negative correlation.

3.4. Regression results for weekdays

Based on the variable pre-screening through the CSR (Model 1), sex, age, nationality, bicycle ownership, and household composition were selected for weekdays (Fig. S2). There was no multicollinearity among covariates. The highest GVIF was 7.47 (Table S1), well below the critical value of 10 (Alin, 2010).

Table 2 shows the GAMM results for weekdays. Results of the intermediate Models 2 and 3 are provided in Table S2. The fully adjusted Models 4 and 5 explained approximately 9% of the total deviance. Model 4 indicated that only SV-derived people were significantly and positively associated with walking duration among the four SV features. Concerning the traditional built environmental characteristics, address density was negatively associated with the pedestrian walking duration

Table 1
Descriptive statistics of the sample.

	Weekdays		Weekends	
	% per category	Mean (SD)	% per category	Mean (SD)
Sample size (N)	1,328		558	
Gender				
Male	40.21		47.49	
Female	59.79		52.51	
Age (years)				
18–24	6.55		8.06	
25–44	40.59		43.73	
45–64	32.00		28.85	
65+	20.86		19.35	
Nationality				
Dutch	59.11		64.87	
Non-Dutch	40.89		35.13	
Income				
Low	22.81		26.78	
Medium	37.68		37.52	
Hight	39.51		35.70	
Education				
Low	18.17		16.82	
Medium	25.64		23.03	
High	56.20		60.15	
Bicycle ownership				
No	22.82		22.38	
Yes	77.18		77.62	
Household car ownership				
No	45.41		47.67	
Yes	53.59		52.53	
Drive license				
No	25.90		27.42	
Yes	74.10		72.58	
Household composition				
Single	35.99		36.74	
Couple without child(ren)	30.72		33.33	
Couple with child(ren)	28.09		24.55	
Single parent with child(ren))	5.20		5.38	
Neighbourhood environment (per PC4)				
Address density (1,000 addresses/km^2)		6,535.85 (3,133.84)		6,716.84 (3,049.19)
Land-use mix		0.28 (0.14)		0.28 (0.15)
Street connectivity (4-way crossings/km^2)		57.95 (23.47)		56.88 (23.34)
Distance nearest train station (km)		2.21 (1.30)		2.19 (1.16)
Number of bus stops (number/km^2)		14.7 (37.19)		15.49 (38.64)
SV-derived environment (%) (per PC4)				
Cars		4.49 (1.62)		4.40 (1.61)
People		0.30 (0.21)		0.32 (0.23)
Street greenery		19.57 (6.62)		18.72 (6.77)
Individual standing walls		0.33 (0.16)		0.35 (0.17)

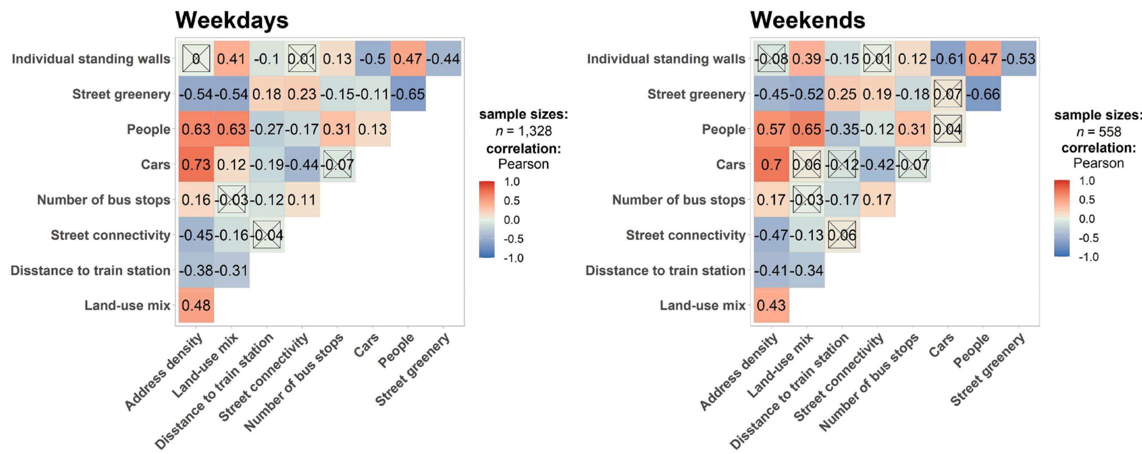

Fig. 2. Results of Pearson's correlation analyses between neighborhood and SV-derived environmental covariates on weekdays (left) and weekends (right). Those correlations crossed out were insignificant ($p > 0.05$) after adjusting for multiple hypotheses testing (Holm, 1979).

Table 2
GAMM regression results for the walking duration of pedestrians on weekdays.

	Weekdays N = 1,328			
Parameters	Model 1 Coefficient (**S.E.**)	Model 4 Coefficient (**S.E.**)	Model 5 Coefficient (**S.E.**)	
Intercept	2.595 (0.137)***	2.942 (0.311)***	2.872 (0.323)***	
Gender				
Male (ref.)				
Female	0.083 (0.056)	0.095 (0.056)†	0.095 (0.056)†	
Age (in years)				
18–24 (ref.)				
25–44	0.065 (0.115)	0.067 (0.115)	0.066 (0.115)	
45–64	0.245 (0.117)*	0.222 (0.117)†	0.218(0.117)†	
65+	0.538 (0.126)***	0.505 (0.125)***	0.500 (0.125)***	
Nationality				
Dutch (ref.)				
Non-Dutch	0.104 (0.060)†	0.113 (0.060)†	0.113 (0.060)†	
Bicycle ownership				
No (ref.)				
Yes	−0.219 (0.069)**	−0.226 (0.069)**	−0.229 (0.069)**	
Household composition				
couple with children (ref.)				
single	−0.197 (0.074)**	−0.136 (0.075)†	−0.140 (0.075)†	
couple without children	0.079 (0.075)	0.114 (0.075)	0.108 (0.075)	
single parent with children	0.119 (0.131)	0.131 (0.131)	0.131 (0.131)	
Address density		−0.00005 (0.00003)*		
Land-use mix		0.230 (0.307)	0.303 (0.291)	
Street connectivity		−0.0005 (0.002)	−0.002 (0.002)	
Distance to train station		0.045 (0.025)†		
Number of bus stops		0.0008 (0.0009)	0.0007 (0.0009)	
Cars		−0.007 (0.041)	−0.014 (0.040)	
People		0.479 (0.262)†		
Street greenery		−0.006 (0.006)	−0.004 (0.006)	
Individual standing walls		−0.473 (0.300)	−0.521 (0.289)†	
Smoothing functions			**EDF**	**p-value**
Address density			1.003	0.018**
People			2.088	0.069†
Distance to train station			1.798	0.105
Deviance explained	**5.93%**	**8.60%**	**8.46%**	
AIC	**3752.38**	**3750.79**	**3741.84**	

Note: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, †$p < 0.1$.

on weekdays, and distance to the train station was positively associated. However, in Model 5, after applying smooth terms, variables that initially possessed significant values continued to maintain statistical significance except for the distance to the train station (Table 2). Model 5 improved on Model 4 by demonstrating a lower AIC score. In addition, individual standing walls became inversely associated with the walking duration on weekdays.

The smooth functions in Fig. 3 indicate more complex relationships between people and distance to train stations and walking duration on weekdays. With an EDF of 2.088, SV-derived people demonstrated a curvilinear relationship with walking duration. Within the range of 0.10% and 0.50%, SV-derived people were positively and monotonically associated with walking duration. However, the association became saturated and flattened after the percentage exceeded 0.60 (Fig. 3a).

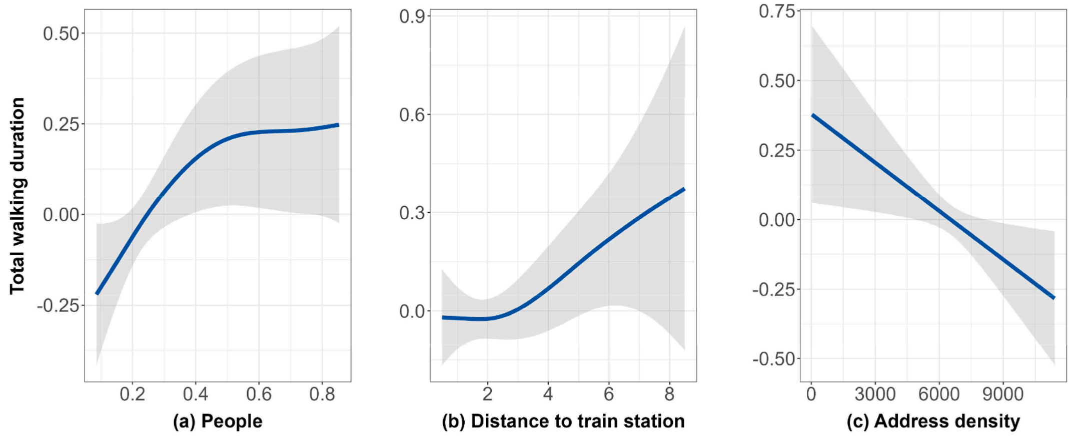

Fig. 3. Associations and 95% confidence intervals (shaded regions) between environmental features and walking duration on weekdays based on Model 5. A *p*-value < 0.10 was considered statistically significant.

Notably, the confidence intervals became larger beyond 0.60% due to a limited number of observations. Distance to the train station was unrelated to walking duration up to 2 km, but thereafter we observed a positive association (Fig. 3b). However, this non-linear association only reached borderline significance. With an EDF close to 1, there was no evidence that address density was non-linearly related (Fig. 3c).

3.5. Regression results for weekends

CSR analysis indicated that the best subset of the individual- and household-level variables during weekends included age, nationality, household car ownership, and household composition (Fig. S2). The highest GVIF was 6.63 (Table S1), indicating no multicollinearity.

Table 3 depicts the GAMM results for weekends. Model 4 had the lowest AIC score and explained 12.30% of the total deviance. Because

Table 3
GAMM regression results for the walking duration of pedestrians on weekends.

	Weekends N = 558			
Parameters	Model 1 Coefficient (**S.E.**)	Model 4 Coefficient (**S.E.**)	Model 5 Coefficient (**S.E.**)	
Intercept	2.425 (0.196)***	2.054 (0.463)***	2.768 (0.320)***	
Age (in years)				
18–24 (ref.)				
25–44	0.050 (0.171)	0.029 (0.169)	0.029 (0.170)	
45–64	0.272 (0.178)	0.232 (0.177)	0.232 (0.177)	
65+	0.710 (0.191)***	0.642 (0.193)***	0.642 (0.193)***	
Nationality				
Dutch (ref.)				
Non-Dutch	0.301 (0.097)**	0.293 (0.096)**	0.293 (0.096)**	
Household car ownership				
No (ref.)				
Yes	0.135 (0.096)	0.112 (0.094)	0.112 (0.094)	
Household composition				
couple with child(ren) (ref.)				
single	−0.176 (0.130)	−0.154 (0.130)	−0.154 (0.130)	
couple without child(ren)	−0.165 (0.125)	−0.146 (0.126)	−0.146 (0.126)	
single parent with child(ren)	−0.422 (0.215)*	−0.440 (0.212)*	−0.439 (0.212)*	
Address density		0.00009 (0.00004)*		
Lan-use mix		0.875 (0.470)†		
Street connectivity		0.002 (0.003)	−0.002 (0.003)	
Distance to the train station		0.164 (0.044)***		
Number of bus stops		0.0001 (0.001)	0.0001 (0.001)	
Cars		−0.213 (0.066)**		
People		0.123 (0.55)	0.123 (0.355)	
Street greenery		0.03 (0.01)*		
Individual standing walls		−0.700 (0.456)	−0.699 (0.456)	
Smoothing functions			**EDF**	**p-value**
Address density			1.001	0.020*
Land-use mix			1.000	0.063†
Distance to the train station			1.000	0.000***
Cars			1.000	0.001**
Street greenery			1.000	0.012*
Deviance explained	**7.32%**	**12.30%**	**12.30%**	
AIC	**1641.37**	**1628.29**	**1628.29**	

Note: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, †$p < 0.1$.

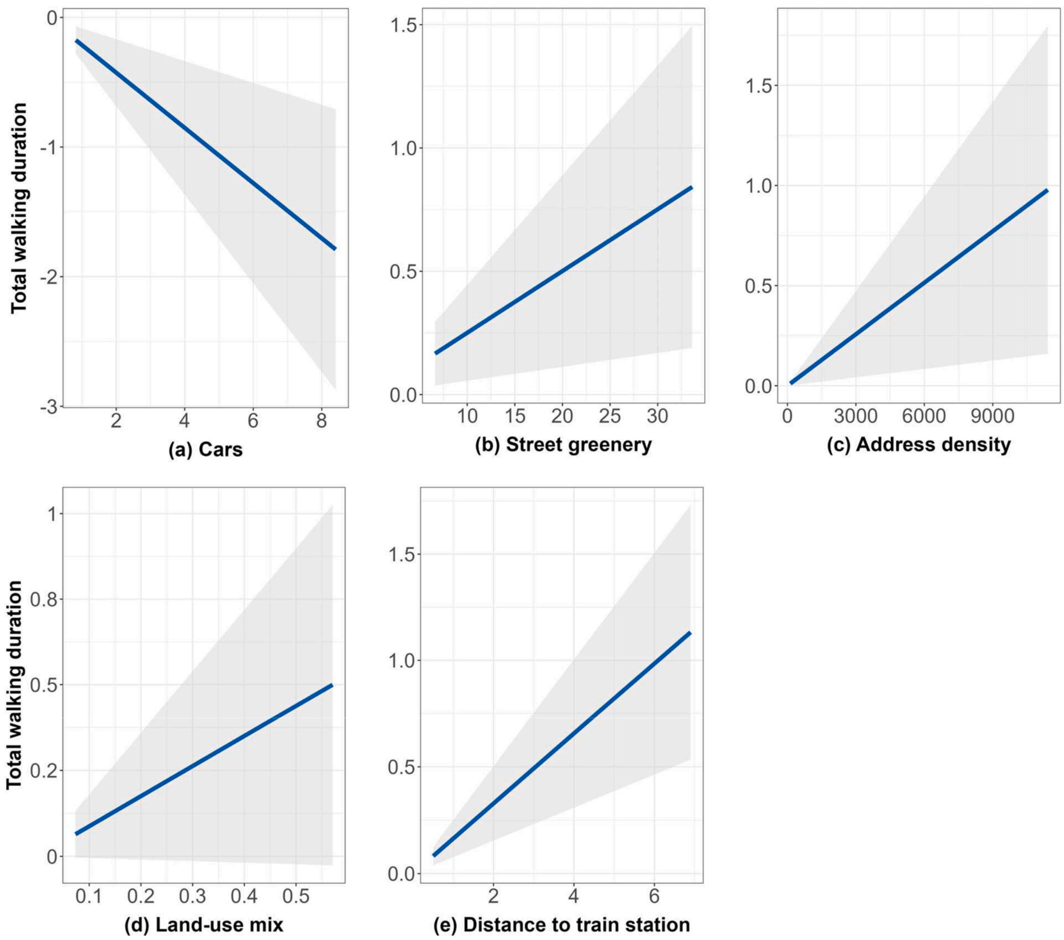

Fig. 4. Associations and 95% confidence intervals (shaded regions) between environmental features and walking duration on weekends based on Model 4. A *p*-value < 0.10 was considered statistically significant.

we observed no improvements in the goodness-of-fit after replacing significant covariates with smoothers (EDFs were close to 1) (Table 3), we focused on Model 4 rather than Model 5.

On weekends, cars were significantly negatively associated with walking duration. Street greenery was significantly positively related to walking duration. The traditional built environmental characteristics, pronounced address density, diverse land-use, and increasing distances to the nearest train stations were positively associated with pedestrians' walking duration (Fig. 4).

4. Discussion

4.1. Main findings

This study is among the first to apply deep learning to SV-images in a European city to examine non-linear associations between multiple SV environmental characteristics and pedestrians' weekday and weekend walking durations. Our results showed that some SV characteristics were associated with the walking duration of pedestrians. However, these associations differed markedly between weekdays and weekends. On weekdays, walking duration was inversely associated with individual standing walls and address density and positively associated with SV-derived people. By contrast, we observed that pedestrians' weekend walking duration was positively associated with street greenery, address density, land-use mix, and distance to the train station. In contrast, cars were inversely associated. Except for the significant non-linear relationship between SV-derived people and walking duration on weekdays, we found little evidence that these associations had complex shapes demonstrating non-linearity.

4.2. Other available evidence

While previous studies primarily focused on SV greenery (Ki & Lee, 2021; Li et al., 2018; Lu, 2019; Yang et al., 2019), our results suggested that multiple other SV features related to the walking duration of pedestrians. We observed that cars and individual standing walls impose some restrictions on walking behavior. Arising safety issues related to cars are a possible explanation for this observation; otherwise, individual standing walls may decrease the attractiveness and aesthetic of the pedestrian environment (Hipp et al., 2021; Mehdizadeh et al., 2017). Street greenery was positively correlated with the walking duration of pedestrians but solely on weekends. To some extent, this could be due to different walking needs. We speculated that, for example, people might walk in public open spaces (e.g., parks) on weekends for recreational purposes (Gao et al., 2020). On weekdays, however, walking would take place to fulfill utilitarian purposes (e.g., commuting to work) where greenery plays a minor role.

Our results also added to slowly mounting evidence that environmental characteristics non-linearly affect walking behaviors (Ding et al., 2019; Liu et al., 2021; Park et al., 2020; Yang et al., 2021; Yang et al., 2022). SV-derived people seemed only to enhance weekday walking up to a threshold beyond which the association became marginal (Lu et al., 2019; Cheng et al., 2020; Yang et al., 2021). The presence of more people may mean a pedestrian-friendly environment (e.g., safe and pleasure) with an increased provision of services and shops, resulting in more walking (Cheng et al., 2020; Hajrasouliha & Yin, 2014). However, the presence of over-dense populations on streets could evoke feelings of crowding and increase the risk of injury (Cheng et al., 2020; Yang et al., 2021). Altogether, population densities up to a threshold may be more effective in promoting walking.

The absence of non-linear associations between street greenery and walking duration conflict with the results of a study on older adults in Hong Kong, China (Yang et al., 2021). A reason for this conflict could lie with the possibility that greenery-walking relationships may vary across different age groups (Maas et al., 2008). The average age in our sample was 47.36 (SD ± 16.94), while in the Hong Kong study, it was 73.82 years (SD ± 6.93) (Yang et al., 2021). Different generations might also exhibit differing travel behaviors, shaping their susceptibility to environmental surroundings (Jamal & Newbold, 2020). In addition, Amsterdam and Hong Kong have striking differences in urban forms and cultural settings, etc., which may further contribute to such unlike findings.

In alignment with previous studies (Gao et al., 2020; Keskinen et al., 2020; Wang et al., 2021), the environment-walking associations differed on weekdays and weekends. For example, address density was negatively associated with walking on weekdays but positively correlated on weekends. To some extent, different walking purposes between weekdays and weekends can explain these inconsistencies (Doescher et al., 2017; Kang et al., 2017; Mirzaei et al., 2018; Perchoux et al., 2019). Most walking on weekdays likely had utilitarian purposes. Thus, function-oriented environments (e.g., transport accessibility) would facilitate weekday walking by supporting people's ability to accomplish daily activities and transfers across modes of public transport. Walking on weekends was more likely to be motivated by the need to maintain social contacts and for recreation (Ho & Mulley, 2013). Therefore, green space and diverse land use encourage people to walk more on the weekends than on weekdays by providing more attractive destinations (Zhou et al., 2022).

Regarding the neighborhood environment, our results for Amsterdam aligned with a nationwide Dutch study by Wang et al. (2021), who found that pronounced land-use mix was only positively associated with the walking duration at weekends. Diversity of land-use not only means more opportunities to carry out active travel but also provides a variety of utilitarian destinations (including recreational facilities) (Kamruzzaman et al., 2016; Shigematsu et al., 2009). Therefore, diverse land-use may be more attractive to pedestrians at weekends for leisure purposes. Additionally, the positive relationship between distance to the train station and walking duration was congruent with earlier studies (Kamruzzaman et al., 2016; Lu et al., 2018; Sarker et al., 2019). It seems that the transit station within walking distance stimulates people's walking. Alternatively, those who live far from the train station may transfer across modes to reach the nearest train station resulting in more walking (van Kampen et al., 2021).

Confirming an earlier study (Koo et al., 2021), our model comparisons showed that street features combined with built environmental variables that are typically studied contributed to explaining pedestrians' walking levels. However, SV characteristics appeared to be of more relevance to the walking duration on weekends. Our results supported Alfonzo's (2005) hierarchy hypothesis that walking needs are supported by the physical environment at different levels (e.g., neighborhoods vs. streetscapes). Motivations to walk on weekdays appeared to depend more on functionally oriented neighborhood features, while weekend walking appeared to be positively affected by small-scale streetscape environmental features (e.g., streetscape greenery for recreation) (Alfonzo, 2005; Koo et al., 2021).

Our results support evidenced-based policymaking to promote walking. First, environmental interventions should be more tailored to the experienced streetscape setting rather than only focusing on traditional land-use aspects (e.g., land-use mix). Urban planners are encouraged to supply more street greenery, especially at places attracting a surplus of pedestrians on weekends. Obstacles such as individual standing walls should be reduced to create more aesthetically appealing and walking-friendly urban environments. Another intervention strategy to stimulate walking could be separating motorized lanes and sidewalks by employing green belts that support pedestrians' perception of safety. Second, as we showed in our analyses, we advise not only relying on the principle "the more, the merrier" because environmental interventions may only be effective until a threshold value is reached. For example, it is common practice to assume that population density promotes walking behavior monotonically. However, our findings and others (Lu et al., 2019; Cheng et al., 2020) suggest that restricting over-crowded walking environments is a means to promote walking.

5. Strengths and limitations

The present study added to the limited evidence supporting the impact of SV-derived built environments on walking behavior. To the best of our knowledge, this study was one of the first European transport-related studies to rely on deep learning algorithms to analyze SV images to identify street-level characteristics of the urban built environment with high reliability. An additional strength was to assess the possible non-linear associations (Hasan et al., 2021; Koo et al., 2021; Li et al., 2018). As recommended elsewhere (Gao et al., 2020; Wang et al., 2021), a distinction was made between weekdays and weekends, allowing us to disintermediate walking behaviors associated with the built environment but could potentially vary temporally.

The present study was subject to a number of limitations. First, our study focused on pedestrian mobility, possibly limiting generalizability to populations who do not walk for personal or transportation-related reasons. The moderate sample size may limit the statistical ability to identify weak correlations and hinder further data stratification by trip purpose (MacCallum et al., 1999; Wang et al., 2021). We thus urge future studies to assess how SV environmental features are associated with different walking purposes. Second, walking duration data relied on self-reporting and was thus prone to reporting errors (Wasfi et al., 2016), a problem inherent in all self-reported survey data (Howard, 1980). Third, compared to manually carried out neighborhood audits (e.g., Ewing et al., 2016; Ewing & Handy, 2009; Hajrasouliha & Yin, 2014; Steinmetz-Wood et al., 2019), our computational approach only included a limited number of automatically extracted SV environmental features. Despite its city-wide applicability, our models did not control for the proportion of windows on the street, enclosure and street safety facilities, and the dominant building colors possibly be associated with walking behavior (Ewing et al., 2016; Ewing & Handy, 2009; Wang et al., 2022). Fourth, we cannot exclude that the ratio of pixels per SV element may have biased the analyses. For example, we may have observed a higher percentage of SV-derived people because persons were simply closer to the camera. Future studies should implement deep learning approaches for object counting to address this potential observational uncertainty (Yin et al., 2015; Jiang et al., 2021). Fifth, our SV data (2016–2019) and travel survey (2014–2017) were temporally not perfectly aligned, which could have affected our results. Closely related, streetscapes are dynamic, and their appearance may depend on the time of the day. For example, more cars likely appear in an image during peak hours. Sixth, compared to more finely granular residential address information (Wang et al., 2021), our PC4 areas were moderately large but may better represent the typical neighborhood activity space. More critical than the neighborhood size are uncertainties arising from people's day-to-day mobility and environmental exposure beyond their residential neighborhoods (Birenboim et al., 2021). How this limitation has influenced our models remains unclear. Fifth, due to a lack of data on peoples' location and travel mode preferences, self-selection effects might be at play and might affect the reported associations (van Wee, 2009). Finally, the cross-sectional nature of our data was susceptible to reverse causality, also a limitation in many previous studies (Bunds et al., 2019; Gao et al., 2020; Yang et al., 2021).

6. Conclusion

This study explored the non-linear associations between SV-derived environments and the walking duration of pedestrians in Amsterdam. The results suggested that streetscape features, particularly cars and individual standing walls, were negatively associated with pedestrians' walking duration, while street greenery showed inverse patterns between weekdays and weekends. We also found that environment-walking associations differed between weekdays and weekends; however, evidence that these associations were non-linear was limited. Positive non-linear associations were found only in the case of weekday SV-derived people, including after adjusting for other neighborhood characteristics (e.g., address density, land-use mix, and street connectivity). We conclude that transport policy-makers and urban planners should take account of the specific characteristics of street environments to promote walking and recommend further longitudinal studies.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

I have shared the links of the open data that used in our manuscript in the references.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.landurbplan.2023.104752.

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