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Exploring Effective Built Environment Factors for Evaluating Pedestrian Volume in High-Density Areas: A New Finding for the Central Business District in Melbourne, Australia

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Abstract: Previous studies have mostly examined how sustainable cities try to promote non-motorized travel by creating a walking-friendly environment. Such existing studies provide little data that identifies how the built environment affects pedestrian volume in high-density areas. This paper presents a methodology that combines person correlation analysis, stepwise regression, and principal component analysis for exploring the internal correlation and potential impact of built environment variables. To study this relationship, cross-sectional data in the Melbourne central business district were selected. Pearson's correlation coefficient confirmed that visible green ratio and intersection density were not correlated to pedestrian volume. The results from stepwise regression showed that land-use mix degree, public transit stop density, and employment density could be associated with pedestrian volume. Moreover, two principal components were extracted by factor analysis. The result of the first component yielded an internal correlation where land-use and amenities components were positively associated with the pedestrian volume. Component 2 presents parking facilities density, which negatively relates to the pedestrian volume. Based on the results, existing street problems and policy recommendations were put forward to suggest diversifying community service within walking distance, improving the service level of the public transit system, and restricting on-street parking in Melbourne.

Keywords: built environment; pedestrian volume; stepwise regression; principal component analysis; Melbourne



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1. Introduction

Walking and the built environment are considered to be very important aspects for sustainable cities due to their environmental benefits especially when considering that the demand on energy production will inevitably increasing with population growth [1,2]. Scholars and practitioners often consider the built environment variables as a reflection of the urban fabric and a significant component that influences travel behaviour [3,4]. However, the existing body of research has not taken into account the integration effects of land use, street form, facilities density, and the quality of sidewalks with respect to pedestrian volume in the high-density metropolitan areas. Therefore, the present study intends to bridge this research gap by introducing new methods to explore the relationship between built environment variables and pedestrian volume.

This paper aims to identify walking peak periods and to determine the relationship between the built environment factors and the pedestrian volume of 52 pedestrian counting sensors in the Melbourne central business district (CBD). Specifically, the study evaluates the following questions:

- (1) What are the trends of the pedestrian volume in the Melbourne CBD? (If walking occurred in several peak periods, one would expect to categorize and collect the data during the correlation analysis).
- (2) Do all built environment factors under consideration correlate with respect to pedestrian volume during the peak period in a regular grid structured neighbourhood? If not, then can we isolate the irrelevant factor/factors and identify the correlation between built environment factors and pedestrian volume?
- (3) What components comprise the principal component analysis, and do these relate to pedestrian volume within the Melbourne CBD?

Interrelated variables were grouped as the principal component and were evaluated to assess how they relate to the pedestrian volume. Additionally, based on the results, design intervention and policy implementation can be used to increase the walkability in Melbourne's CBD. This study is unique in that it considers the internal relationship for exploring the correlation between built environment variables and pedestrian volume in a high-density area.

2. Literature Review

A great deal of effort has been expended in exploring land use and walking behaviour over the last two decades [4–7]. Mixed land-use is often used as a strategy for operationalizing and promoting non-automobile travel (e.g., walking, cycling or public transit) [8]. A mix-use area usually incorporates banks, restaurants, retail, businesses, working and housing, all close to each other [7]. Greenwald and Boarnet found that land-use affects pedestrian travel behaviour [4]. Ewing et al. highlighted that the single land-use type is not attractive for pedestrians [5]. In addition, Hatamzadeh et al. [6] measured walking behaviour with respect to commuting to work. The results of their research note that higher mixed-use can be an effective policy to promote walking in the city of Rasht, Iran. Based on the body of literature relating to Mixed land-use in supporting pedestrian activity, this paper assumes that land-use mixed degree is a valid variable in walking-related research.

Urban development density influences travel behaviour in the modern city. For example, Kerr et al. highlighted neighbourhood features, such as residential density and intersection density, were related to walking behaviour after the application of logistics regression analyses [9]. Azmi and Ahmad believed that high transit stop density encourages walking between leisure, work, and home [10]. In addition, Laatikainen et al. stated that a significant effect was found with respect to transit stops density for older adults' walking in Helsinki, Finland [11].

An area with high street connectivity offers more potential routes for pedestrians and increases the walkability of neighbourhoods due to a higher intersection density resulting from small block sizes and a flexible street network [5]. Some studies highlighted that intersection density was significantly and positively associated with walking [6,11–14]. Knuiman et al. found evidence from Perth residents in Australia that proves a positive correlation between built environment variables (street connectivity and land-use mixed) and walking frequency [13]. The positive correlation between walking and intersection density was also supported by Laatikainen et al. and Hatamzadeh et al. [6,11]. In addition, Koohsari et al. in a case study conducted in Adelaide, Australia, explored the relationship for adult's walking between transport and street network (intersection density and street integration) [14]. The findings illustrate that around 42% of the association of street integration with walking to transport, can be explained by perceived destination accessibility.

Street trees, sidewalks and pedestrian routes are the built environment component which reflect the quality of a street and influences the walking experience. Yang et al. [15] noted that the visibility of the street's greenery level was positively related to the walking time and walking frequency in older adults, while Rollo et al. highlighted the importance of the quality and effect of green attributes within the overall street scape experience [16]. However, only few studies questioned the positive association between street tree coverage and walking behaviour. For example, Ferrer et al. argued that sidewalk cafes and trees, if

not designed to accommodate pedestrian through movement, can create physical obstacles that narrow the sidewalk, therefore making it difficult for passing pedestrians [17].

Pedestrian volume is defined as the number of pedestrians of a specific location within a certain period [18]. New data sources and methods have stimulated research on pedestrian volume. Responding to the growing demand for transit-oriented development and walkable urbanism in metropolitan areas undergoing urban renewal, previous studies determine the association between pedestrian volume or counts by multiple built environment variables, thus providing evidence to improve the walkability and service level of amenities [19–21].

Hajrasouliha and Yin investigate the impact of geometric connectivity and physical activity on pedestrian volume in Buffalo (NY, USA) in 2014 [19]. Their findings highlight the significant positive correlation between connectivity on pedestrian volume, together with job density and land-use mix. Furthermore, structural equation modelling was used to estimate the correlation between built environment variables and pedestrian volume. Lee et al. established pedestrian volume by the Ordinary least square and Poisson regression in Seoul [20]. This study confirmed the association between the built environment and pedestrian volume in Gangnam, Seoul. In particular, the importance of improving the walking environment and accessibility to the subway system. A further study by Lee et al. analyses the pedestrian volume by regression model and GIS-based built environment variables, with space syntax in Seoul [21]. In Seoul, land-use type, public transit stop accessibility, and sidewalk characteristics often correlate to pedestrian volume. Furthermore, four models were applied to discuss the association between built environment variables and pedestrian volumes in different land-use zones.

The findings drawn from the literature review indicate that built environment variables influence the walking frequency, walking time and walking distance. While pedestrian volume studies have examined the relationship between the walking environment and pedestrian activity. Many of these nonetheless have their limitations, which can be divided into the following aspects.

First, the research by Jiao et al. suggests that the entropy index is a valid method to measure land-use evenness rather than land-use diversity, hence previous studies often only paid attention to the land-use mix evenness by the entropy measure, rather than land-use diversity [22].

Second, unlike the majority of the existing research, the internal correlation between built environment variable was ignored. The potential correlation between public transit stop density, walkable environment, and amenities has not been considered in the quantitative process. According to this background, the collective impact from the built environment to pedestrian volume needs to be considered when analysing the CBD.

Furthermore, the benefits of the regular grid-like neighbourhood were discussed in previous studies. Considering the features of the grid-like pattern, the empirical study based on the data set in Melbourne CBD helps to provide a more informed understanding of the relationship between pedestrian volume and built environment variables.

3. Methods and Data

3.1. Study Area

The present study utilises Melbourne's CBD as a case study. Melbourne is Australia's second-largest city and the capital city of the State of Victoria, with an estimated resident population of 183,756 in 2020 [23]. Melbourne CBD is centrally located in the Local Government Area (LGA) of the City of Melbourne, which is one of 31 Local Government areas in the greater Melbourne metropolitan area. In terms of the central business district, the dominant 200 m × 200 m grid defining the CBD covers an area of roughly 1.0 miles × 0.5 miles or 1.87 km × 0.95 km when considering street width, with the major north-south and east-west streets being 30 m wide (Figure 1). The 2018 Melbourne CBD's basic map in Figure 1 lists urban texture and blocks with ID. In Figure 1, major blocks measure 200 m × 200 m, with the Hoddle grid establishing a further subdivision on the east-west axis dividing each

major block into two $94\text{ m} \times 200\text{ m}$ half blocks separated by a 12-m lane and yielding a total of 75 blocks (NB Blocks 001, and 007 are significantly larger with the former being oriented approximately 30° off the orientation of the Hoddle grid and acknowledging the extension of the city beyond the CBD on a different axis). The development density of CBD is higher than in other suburbs. Melbourne CBD has a pedestrian-and transit-friendly environment according to the pedestrian-and transit-friendly neighbourhood standard by Ewing [12]. Therefore, the investigation of Melbourne's CBD provides a better understanding of the relationship between the built environment and pedestrian volume in high-density areas.



Figure 1. Hoddle grids pattern with block ID in the Melbourne CBD in 2018.

Many studies assumed that the buffer zone of transit-related research is between 400 m to 800 m [24,25]. Furthermore, the research by Gori et al. [25] agreed that the maximum distance for pedestrian-friendly walking was an 800 m radius or 10 min walking time. Similarly, Hatamzadeh et al. [26] found that 0.25 miles (approximately 402 m) is the sensitive distance for walking to school. This study defines the 500-m buffer area around the pedestrian counting sensors to catch the built environment variables (Figure 2). Moreover, Figure 2 shows 52 pedestrian volume counting sensors and the 500-m buffer area in the Melbourne CBD. For our analysis, we included the latest observation of built environment variables and pedestrian volume from the pedestrian counting system 2018 [27]. The pedestrian counting system is a platform to collect and publish pedestrian volume data in Melbourne CBD, which contains 77 sensors in 2020. However, in the data set of 2018, only 52 blocks of data were available in the pedestrian counting system platform. According to this background, 52 sensors cross-sectional data was applied to the study. Therefore, the red dots in Figure 2 highlight the locations of 52 sensors.

Furthermore, red bubbles show the 500-m buffer zone, which centred on the red dots. The base layout of Figure 2 comes from the Melbourne CBD map in 2018. The Melbourne CBD's pedestrian volume and built environment variables are derived from the pedestrian volume counting system and Melbourne's Census of Land Use and Employment 2018. The data collection methodology of built environment variables is presented in Section 3.3.

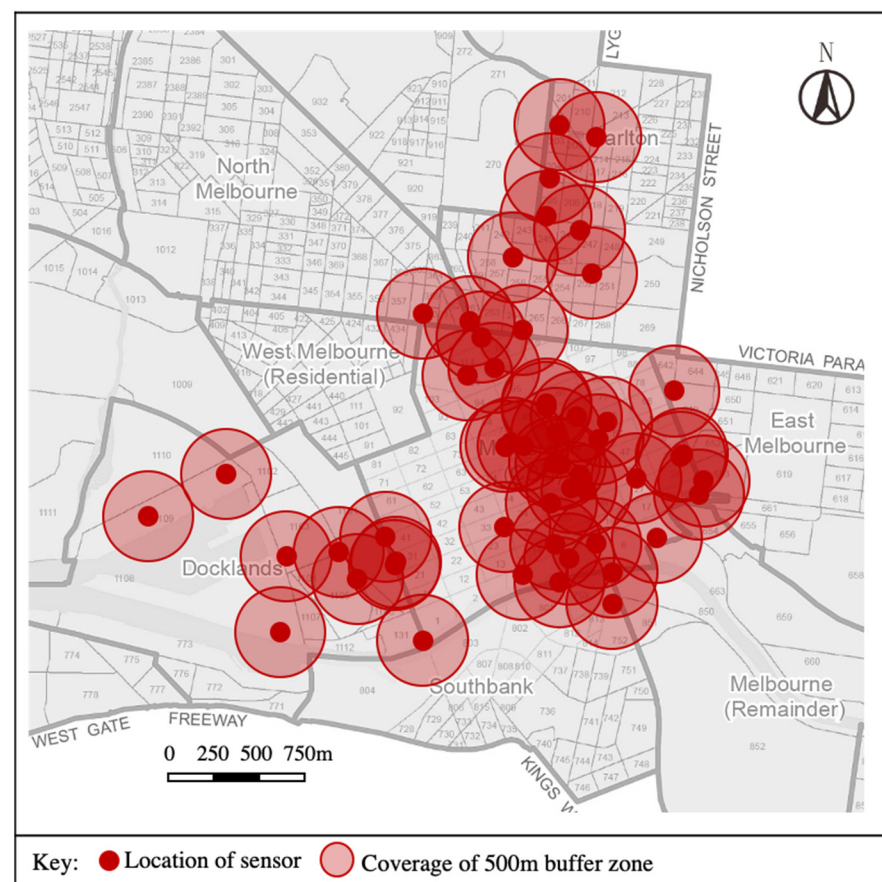


Figure 2. Location of sensors and buffer zone in the Melbourne CBD. Source: Own elaboration.

3.2. Study Design

Since the study's objective is to identify the relationship between built environment variables and pedestrian volume, this paper presents a new methodology that combines stepwise regression and principal component analysis for illustrating the correlation and internal operation between built environment factors and pedestrian volume.

The flow diagram in Figure 3 illustrates the methodology and includes four parts. In the data preparation process, we first extract the factors of pedestrian volume and built environment variables from a different database. In the second step, the Pearson correlation coefficient identifies the association between built environment factors and pedestrian volume. In the third step, stepwise regression is applied to evaluate the order of importance of variables and to select a valuable subset of variables [28]. The correlation coefficient tests the linear relationship between built environment variables and pedestrian volume in the peak period. The next step in the process involves factor analysis and principal component analysis. The factor analysis with a varimax rotation is used to reduce the dimensionality of the datasets, increase interpretability, minimize information loss, and extract the principal component [29]. The principal component analysis results can identify the internal correlation between the principal component and pedestrian volume. The final result and further recommendations were based on the comparison of stepwise regression and principal component analysis.

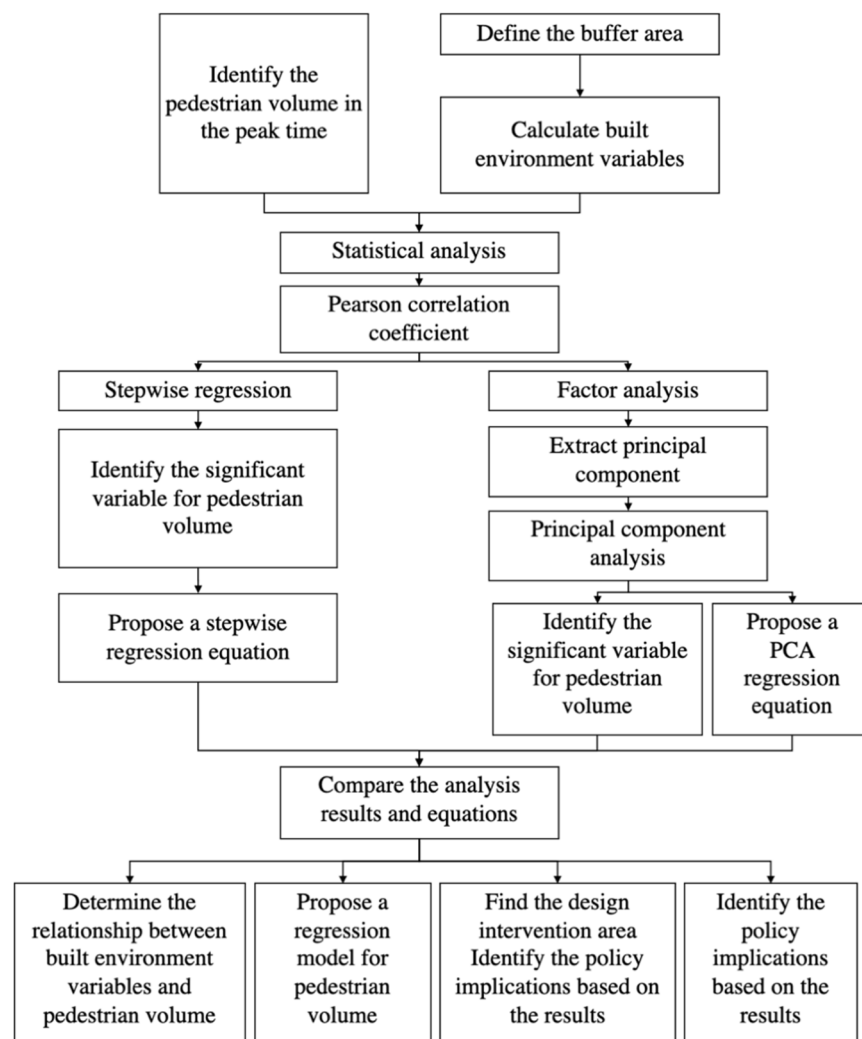


Figure 3. Flowchart of method. Source: Own elaboration.

3.3. Data Collection

In this study, unapplied cross-sectional data was included in the data collection. For example, Cervero and Kockelman [8] conceptualized the factors of development density, land-use diversity, and street network design as the 3Ds and examined the correlation between these 3Ds and travel behaviour. Ewing and Cervero [1] expanded the 3Ds with destination accessibility and distance to transit. In our paper, the factors of land-use mix degree, employment density, intersection density, public transit stop density, parking facility density, visible green ratio, and restaurant seating density were used to measure the built environment of the buffer zones around the sensors.

This study defines land-use mixed degree as the diversity of land use type. Jiao et al. identified the difference between land-use diversity, land-use evenness and land-use balance by several common-use measures [22]. They argued that the entropy index only relates to the land-use evenness rather than land-use diversity. Shannon diversity index is a commonly used and valid method to measure land-use mix diversity [30–33]. The land-use mix degree function as given below:

$$\text{LUMD} = - \sum_{i=1}^n P_i \ln P_i \quad (1)$$

where, LUMD is the land-use mix degree of sensor i , P_i is the number of land-use type of sensor i . The land use dataset of Melbourne's CBD was collected from the Census of

Land Use and Employment in 2018 [34]. In addition, the classification standard of land use codes was based on the Australian and New Zealand Standard Industrial Classification.

Employment density is the number of employments around the pedestrian counting sensors within a buffer zone. The function of employment density is as follows:

$$ED = FTEMS_i / A_i \quad (2)$$

where, ED is the employment density of sensor i , $FTEMS_i$ is the number of full-time equivalent members of staff within the buffer zone around sensor i , A_i is the area of the buffer zone around sensor i . The employment statistics, or the number of jobs of a given area was collected based on the Census of Land Use and Employment in 2018 [34].

Intersection density is the number of intersections measured within a buffer area of pedestrian counting sensors. Intersection density refers to Equation (3):

$$ID = \beta_i * I_i / A_i \quad (3)$$

where, ID is the intersection density of sensor i ; β_i is the intersection density coefficient of the buffer zone around sensor i ; I_i is the number of three-way or four-way intersection of the buffer zone around sensor i ; A_i is the area of the buffer zone around sensor i . Google Earth and Open Street Map provided the street networks with all intersections within the Melbourne CBD. The intersection density coefficient was based on the penalty in Table 1 of intersection density by Walk Score Methodology [35]. Table 1 gives the adjusted coefficient for the intersection density and public transit stop density. It shows that there are different coefficients with different intersection density values, distance to the sensor, and transportation mode. The value of the coefficient comes from the finding of Walk score methodology.

Table 1. Adjust coefficients of intersection density and public transit stop density.

		Adjust Coefficients
Intersection density coefficient (β_i)	Intersection per buffer zone	
	Over 20	1.000
	15 to 20	0.990
	12 to 15	0.980
	9 to 12	0.970
	6 to 9	0.960
Distance decay coefficient (σ_j)	Under 6	0.950
	Distance to the sensor (meter)	
	Less than 300	1.000
	300 to 500	0.975
Service level coefficient (ω_j)	500 to 1000	0.750
	Transportation means	
	Heavy/light rail	2.000
	Ferry/cable car/tram	1.500
	Bus	1.000

Source: Walk score methodology [35].

Public transit stop density relates to the number of stops, service level, and distance decay. The data was collected from the various network maps in Public Transport Victoria and City Mapper platform. The distance decay coefficient and service level coefficient (Table 1) of public transport were provided by Walk Score Methodology [35]. In the measure of public transit stop density, the distance decay of stations and service level of travel mode was different. Walk Score Methodology concludes the distance decay by walking speed from 300 m (5 min walking distance) to 1000-m (15 min walking distance). The equation of public transit stop density refers to Equation (4):

$$PTSD = \sum_{i=1}^n \sigma_i * \omega_i * PTS_i / A_i \quad (4)$$

where, PTSD is the public transit stops density of sensor i , σ_i is the distance decay function coefficient (Table 1), ω_i is the service level coefficient of public transportation (Table 1), PTS_i is the number of public transit stops (includes bus, tram, train, and V/line) of sensor i , A_i is the area of the buffer zone around sensor i .

Parking facility density reflects the number of parking space (includes on-street parking and off-street parking facilities) available around the pedestrian counting sensors within a 500 m buffer area (refer to Equation (5)). The information about parking spaces was based on the dataset in Census of Land Use and Employment 2018 [34]. The following equation can calculate the density of parking facility:

$$PFD = PF_i / A_i \quad (5)$$

where, PFD is the parking facility density of sensor i , PF_i is the number of parking facilities of sensor i , A_i is the area of the buffer zone around the sensor i .

The visible green ratio reflects the street-side greenery at the human scale. Figure 4 gives the location of sensors as red dot and blue dot. In particular, we selected blue dots as samples to show the collection process of visible green ratio. First, the original street views of each sensor were captured by the Google Street View based on an adult's visual field. Second, the green pixels were extracted in Photoshop 2020. The calculation equation was proposed by Li et al. [36]. This study applies the green pixels and total pixels into Equation (6) to measure the visible green ratio of each sensor in Melbourne's CBD.

$$VGR = G_i / P_i \quad (6)$$

where, In Equation (6), VGR is the visible green ratio of sensor i , G_i is the total green pixel of the street image of sensor i , P_i is the total pixel of the street image of sensor i .

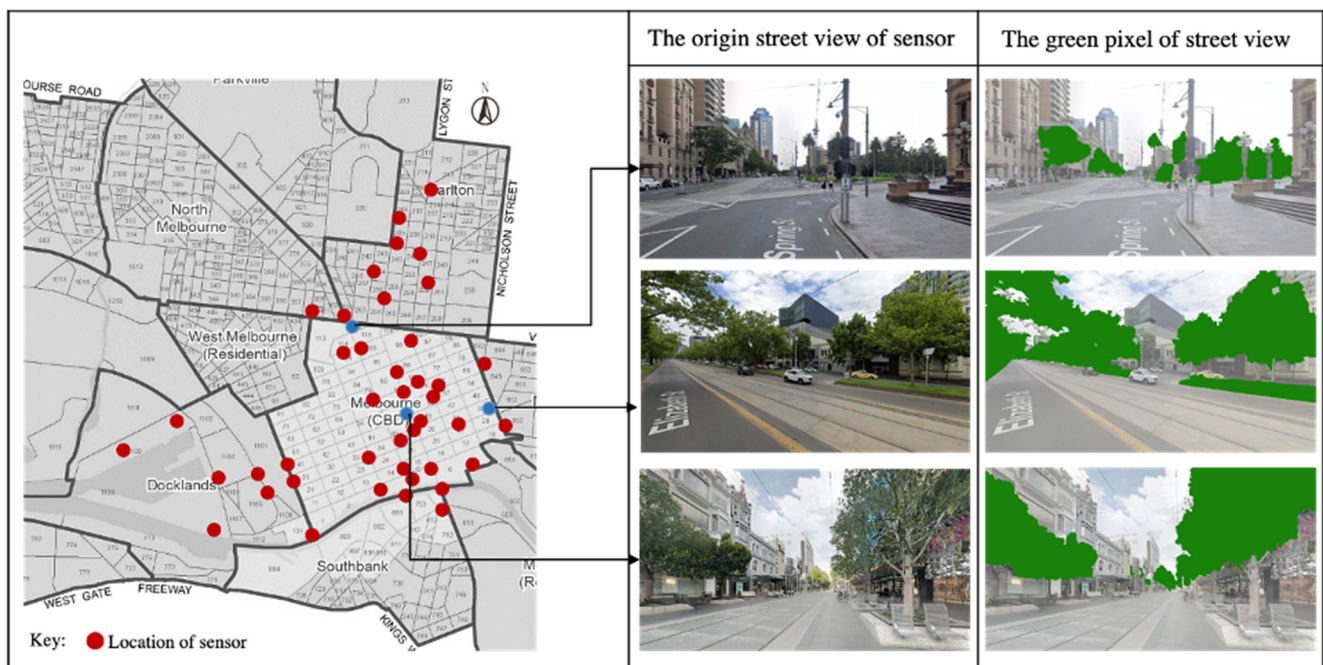


Figure 4. Sampled street view of visible green ratio. Source: Own elaboration based on the Google earth street views.

Restaurant seating density is the number of seats of the Café, restaurant, bistro around sensors within a 500-m buffer area and refers to Equation (7):

$$RSD = R_i / A_i \quad (7)$$

where, RSD is the number of seats in the restaurants around the sensor i , R_i is the number of seats in restaurants around the sensor i , A_i is the area of the buffer zone around sensor i . The information about the number of seats in restaurants is based on the data resource of Census of Land Use and Employment 2018 [34].

The polylines of the pedestrian volume of 52 counting sensors in the Melbourne CBD were presented in Figure 5. The pedestrian volume of sensors was based on the dataset in the Melbourne pedestrian counting system. In Figure 5, most of the walking travels occurred in the morning (6:00 to 10:00), noontime (11:00 to 15:00), and evening peak time (16:00 to 20:00). Therefore, this study categorized the pedestrian volume of each sensor into three groups as morning-peak pedestrian volume, noontime-peak pedestrian volume, and evening-peak pedestrian volume.

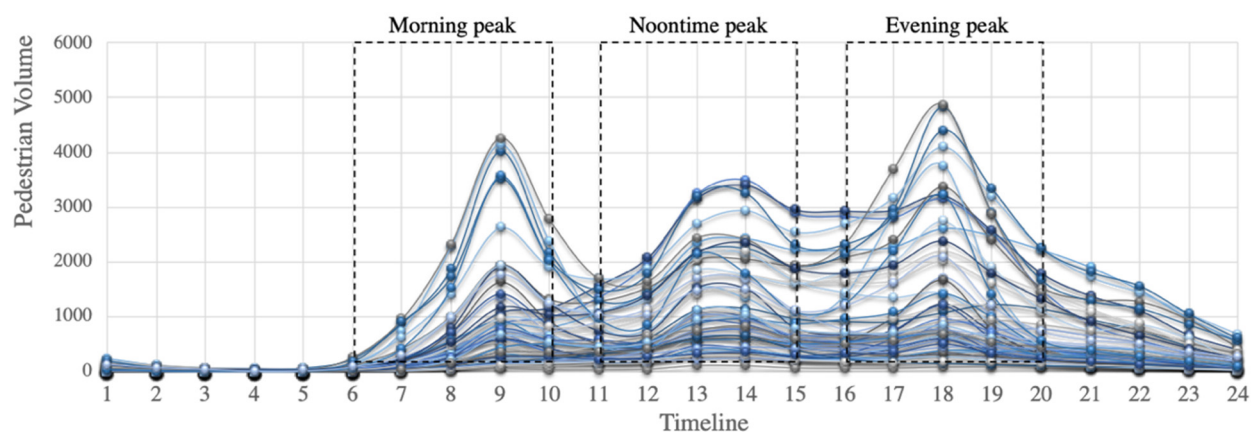


Figure 5. Pedestrian volume of 52 sensors in the Melbourne CBD. Source: Own elaboration based on the pedestrian counting system 2018 [34].

Table 2 provides the descriptive analysis of the independent variables of the built environment and dependent variables of pedestrian volume in the different peak period. Of the 77 pedestrian counting sensors in the Melbourne CBD, we excluded 25 sensors because they had missing data in 2018. As shown in Table 2, the independent variables were land-use mix degree, employment density, parking facility density, intersection density, public transit stop density, visible green ratio, and restaurant seating density. All variables were measured within the 500-m buffer from the central location of pedestrian counting sensors in the Melbourne CBD. Furthermore, the minimum pedestrian volume was far higher than the maximum volume in the peak periods. Due to excluding outlying data from the analysis, each peak period's pedestrian volume was collected based on the Trim mean function, hence calculating the mean taken by excluding a percentage of data points from the pedestrian volume dataset's bottom tails.

Table 2. Descriptive analysis of all of the variables.

		Obs.	Mean.	S.D.	Min	Max
Built environment variables	Land-use mix degree	52	1.558	0.269	0.958	2.186
	Employment density	52	35.121	23.779	1.700	95.492
	Parking facility density	52	8.613	4.399	1.398	20.152
	Intersection density	52	0.034	0.011	0.010	0.054
	Public transit stop density	52	0.141	0.048	0.038	0.214
	Visible green ratio	52	0.200	0.112	0.002	0.450
	Restaurant seating density	52	17.847	11.061	1.950	53.640
Pedestrian volume	Morning	52	594.465	668.648	13.000	3973.000
	Noontime	52	1070.119	849.471	51.000	3628.000
	Evening	52	1124.539	1014.242	68.000	4631.000

4. Results

4.1. Summary of Correlation and Stepwise Regression

Table 3 shows correlation between built environment density and pedestrian volume in different peak periods, where the land-use mix degree is related to the employment density, public transit stop density, and restaurant seating density. Also, employment density is associated with land-use mix degree, public transit stop density, parking facility density, and restaurant seating density. A high restaurant seating density area in the Melbourne CBD is associated with a high level of land-use mix degree, employment density, parking facility density, intersection density, and public transit stop density. A strong association of land-use mix degree, employment density, public transit stop density, restaurant seating density, coincided with the pedestrian volume noon-peak period as showed in Table 3. It was therefore decided that the best dependent variable of the pedestrian volume correlates with the noon-peak group.

Table 3. Pearson correlation coefficient.

	Pedestrian Volume		
	Morning Peak (6:00 to 10:00)	Noon Peak (11:00 to 15:00)	Evening Peak (16:00 to 20:00)
Land–use mix degree	0.510 **	0.723 **	0.659 **
Employment density	0.285 *	0.279 *	0.239
Parking facility density	−0.128	−0.304 *	−0.263
Intersection density	−0.153	0.099	0.021
Public transit stop density	0.388 **	0.627 **	0.556 **
Visible green ratio	−0.168	−0.066	−0.130
Restaurant seating density	−0.061	0.335 *	0.261

Note: Sample amount (N) is 52; * $p < 0.05$, ** $p < 0.01$.

This study uses stepwise regression to gain insights into the relationship between built environment variables and pedestrian volume in the peak time. Table 4 illustrates the main characteristics of the built environment variables and pedestrian volume. In Table 4, R^2 is 0.668. This indicates that about 66.80% variation of pedestrian volume in the noontime peak is based on the built environment variables. In this model, F is 32.203, and the p -value of constant is 0.000 (less than 0.050), which means at least one variable correlates to the pedestrian volume. The value of VIF of the variable is less than 5.00, which verifies that the model does not have multicollinearity. The datasets do not self-correlate due to the D–W value is 1.891. Built environment variables showed different correlations with pedestrian volume in Melbourne CBD.

Overall, land–use mix diversity, public transit stop density, employment density showed different correlations with pedestrian volume. Both variables of land–use mix degree and public transit stop density significantly and positively correlate to the pedestrian volume in the noon-peak time due to the regression coefficient being 1930.980 and 8114.663, t values are 6.169 and 4.375, and p values are lower than 0.01 (Table 4). In contrast, the regression coefficient and t value of employment density are −11.379 and −0.333, which means a negative association between employment density and pedestrian volume in Melbourne CBD.

Table 4. Results of stepwise regression.

	Unstandardized Coefficients		Standardized Coefficients	t	p	VIF	R ²	Adjust. R ²
	B	Std. Error	Beta					
Constant	−2710.893	417.483		−6.493	0.000 **			
Land–use mix diversity	1930.980	313.004	0.640	6.169	0.000 **	1.555	0.668	0.647
Public transit stop density	8114.663	1854.990	0.476	4.375	0.000 **	1.667		
Employment density	−11.379	3.671	−0.333	−3.099	0.003 **	1.710		

Note: Dependent variable is Noon–peak–PV; D–W value is 1.891; ** $p < 0.01$; $F(3.48) = 32.203$, $p = 0.00$.

4.2. Result of Factor Analysis

Factor analysis has been used in this study to increase the interpretability of the correlation between built environment variables and pedestrian volume before the application of principal component analysis. The Kaiser-Meyer-Olkin (KMO) and Bartlett's test were used to verify the dataset's adequacy for factor analysis [37]. According to the acceptable value range of Measure of Sampling Adequacy by Kaiser [37], the minimum eligible value is 0.500, and the p -value should be less than 0.050, which pass the Bartlett test. The KMO and Bartlett test results report that the datasets of built environment variables are suitable to run the principal component analysis and factor analysis because the value of KMO is 0.609 (the minimum acceptable value for KMO is 0.600). The significant value (p -value = 0.000) of Bartlett's test is less than 0.050.

To explore the potential connection between independent variables, the rotation of the factor improves the reliability of the factor and simplify the factor structures. Tables 5–7 illustrate the results of factor analysis in the principal component analysis.

Table 5 gives the initial eigenvalues and rotation sums of squared loadings of components. Due to the eigenvalue of component 1 to component 3 are 2.911, 1.269, and 1.129 and higher than 1.000, three principal components were extracted in the factor analysis. The cumulative rate of component 1 to component 3 is 75.994%. Compared with the component's variance explained rate in initial eigenvalues, variance explained rates in the rotation sums of squared loadings after redistribution were all over 19.000%.

Table 5. Total variance explained.

	Initial Eigenvalues			Rotation Sums of Squared Loadings		
	Total	Variance Explained Rate (%)	Cumulative (%)	Total	Variance Explained Rate (%)	Cumulative (%)
Component 1	2.911	41.737	41.737	2.441	34.871	34.871
Component 2	1.269	18.122	59.858	1.500	21.428	56.299
Component 3	1.129	16.136	75.994	1.379	19.695	75.994
Component 4	0.801	11.442	87.436			
Component 5	0.387	5.528	92.964			
Component 6	0.302	4.313	97.278			
Component 7	0.191	2.722	100.000			

Note: Extraction method is principal component analysis.

Table 6 displays the rotated component matrix of built environment variables and principal components in the factor analysis. First, in Table 6, there is a positive association among land–use mix degree, employment density, public transit stop density, and restaurant seating density with component 1 because the load coefficient of variables was 0.860, 0.708, 0.847, and 0.632 and higher than 0.600. According to this, component 1 was named diversity of land use and amenities. Second, due to the load coefficient of intersection density and visible green ratio were 0.701 and 0.796, component 2 was named 'walking friendly'. Furthermore, only the association between component 3 and parking facility density was found in Table 6. Therefore, component 3 was named 'vehicle parking friendly'.

Table 6. Rotated component matrix.

	Component 1	Component 2	Component 3
	Diversity of Land Use and Amenities	Walking Friendly	Vehicle Parking Friendly
Land–use mix degree	0.860	−0.160	−0.055
Employment density	0.708	0.231	0.504
Parking facility density	−0.041	−0.098	0.962
Intersection density	0.275	0.701	−0.107
Public transit stop density	0.847	0.254	−0.095
Visible green ratio	−0.077	0.796	0.043
Restaurant seating density	0.632	0.471	0.416

Note: Extraction method is principal component analysis; Rotation method is Varimax with Kaiser Normalization; Rotation converged in 3 iterations.

To measure the principal component by built environment variables, Table 7 illustrates the component score coefficient matrix. In Table 7, the weights for each variable were provided for the calculation process. After the factor analysis, this study applied the principal components to the further analysis in Section 4.3.

Table 7. Component score coefficient matrix.

	Component 1	Component 2	Component 3
	Diversity of Land Use and Amenities	Walking Friendly	Vehicle Parking Friendly
Land–use mix degree	0.459	−0.289	−0.145
Employment density	0.235	0.017	0.292
Parking facility density	−0.119	−0.092	0.745
Intersection density	0.003	0.481	−0.135
Public transit stop density	0.373	0.022	−0.185
Visible green ratio	−0.207	0.621	0.021
Restaurant seating density	0.160	0.217	0.228

Note: Extraction method is principal component analysis; Rotation method is Varimax with Kaiser Normalization.

4.3. Result of Principal Component Analysis

The literature review has noted the importance of the internal effects of built environment variables. However, very few studies examined how the variables affect each other and how they correlate to the pedestrian volume as different sets. The principal component analysis is a way to reduce the dimensionality of datasets, increase interpretability, and minimize information loss. The built environment variables, categorized into three principal components and the principal component analysis results, is summarized in Table 8.

Table 8 illustrates the results of principal component analysis. As shown in Table 8, R^2 is 0.641, which means about 64.10% of Melbourne's variation of pedestrian volume can be explained by components 1, 2, and 3. The model passed the F-test, and at least one component correlated to the noon–peak pedestrian volume due to the F value is 28.520, and the p -value of constant is 0.00 (less than 0.05). Also, samples' collinearity and self-correlation did not show because the value of VIF (1.00) is less than 5.00, and the D–W value is 1.847 and around 2.00.

Overall, these results of principal component analysis present the correlation between component 1 and 3. In Table 8, there is a clear positive correlation (standard coefficient = 0.735 and $p = 0.00 < 0.01$) between component 1 (diversity of land use and amenities) and pedestrian volume.

Table 8. Result of principal component analysis.

	Unstandardized Coefficients		Standardized Coefficients	t	p	VIF	R ²	Adjust R ²
	B	Std. Error	Beta					
Constant	0.019	0.001		14.988	0.00 **	—		
Component 1 (diversity of land use and amenities)	0.011	0.001	0.735	8.494	0.001 **	1.000	0.641	0.618
Component 2 (walking friendly)	−0.001	0.001	−0.089	−1.030	0.308	1.000		
Component 3 (vehicle parking friendly)	−0.005	0.001	−0.304	−3.515	0.001 **	1.000		

Note: Dependent variable is Noon-peak-PV; D-W value is 1.847; ** $p < 0.010$; $F(3,48) = 28.520$, $p = 0.000$.

The finding supports the benefits of mix-use design. A mix-use environment can promote walking in people's daily travel. Due to the standardized coefficient is -0.089 and p value higher than 0.050 , the relationship between component 2 (walking-friendly) and pedestrian volume was not found. In addition, the value of component 3 reflects the vehicle parking spaces supply. The standard coefficient of component 3 is -0.304 and p value lower than 0.010 . A negative correlation was found between component 3 and pedestrian volume.

5. Discussion and Design Intervention

This study explores the correlation between built environment variables and pedestrian volume in the high-density area. The analysis of datasets presents some general characteristics of variables. The data pre-process examined three peak periods of walking, which means most walking occurred in the noontime peak (11:00 to 15:00). The finding of Pearson's correlation coefficient indicates that land-use mix degree and public transit stop density had a positive correlation to the pedestrian volume in the three different peak period. On the other hand, pedestrian volume in the morning peak received a negative effect on parking facility density.

The factor analysis aims to extract the principal components from the built environment variable. The results of factor analysis showed different aspects of principal components. About 64.70% of the variation of pedestrian volume in Melbourne can be explained by components 1, 2, and 3. Meanwhile, variables of land-use mix degree, employment density, public transit stop density, and the restaurant seating density were all positively related to component 1. Intersection density and visible green ratio directly related to component 2, and parking facility density correlated to component 3. Following the principal component and built environment variables, three principal components were named 'diversity of land use and amenities', 'walking friendly', and 'vehicle parking friendly'.

The principal component analysis highlights that pedestrian volume received a positive effect on component 1, which means the diversity of land use and amenities were positively related to pedestrian volume. Component 2 reflects the quality and comfort level of the walking environment in the given area. Previous studies assumed that greenery level and high intersection density promotes walking travel. However, component 2 and pedestrian volume are uncorrelated in this study. Although the visible green ratio and intersection density do not correlate to the pedestrian volume, a walkable environment with sidewalk trees and small to medium length of blocks may affect walking behaviour potentially. The present study agrees that the mix-use design of neighbourhoods and diversity of amenities support walking travel. In addition, a rational arrangement of public transit stops also promotes walking.

Parking facility density was a critical factor that was associated with walking in some studies. However, a negative relationship between vehicle parking friendly components (component 3) and pedestrian volume was also found in Melbourne CBD. The findings

suggest that parking facility density negatively associates with pedestrian volume in the Melbourne CBD. With the increase of parking facility density, on-street parking spaces may create a physical obstruction that narrows the sidewalk, making it difficult to walk in high-density areas. In addition, commuters using motor vehicle travel mode will often try to park as close as possible to their destination and thereby increase congestion while also impacting pedestrian movement and safety along sidewalks.

Figure 6 gives the framework of this study, which illustrates the research methods and the results. Comparing stepwise regression and principal component analysis, we highlighted the correlation between multiple built environment variables with pedestrian volume in the regular grid structure of Melbourne's CBD. The relationship between built environment variables and the pedestrian volume provides based research that can help decision making and spatial planning. Some suggestions for decision making were listed in Figure 6. First, diversifying community services is a new strategy to promote walking in a high-density area; Second increasing the service provision of the public transportation system; Third increasing the supply of employment opportunities; Fourth by improving the public transit system, the pedestrian volume between public transit stops and workplaces may be increased. These may in turn benefit the promotion of walking. Also, restricting the supply of on-street parking may help to control the dependence on car use.

With regards to spatial planning, mixed-use design and transit-oriented development are necessary, especially for urban renewal projects in high-density metropolitan areas. According to the findings in this research, design indicators such as suitable walkable distances (approximately 5 min walking distance) with respect to work, recreation, and shopping proximities for commutes are an important consideration for improved walkability within high-density areas such as Melbourne's CBD.

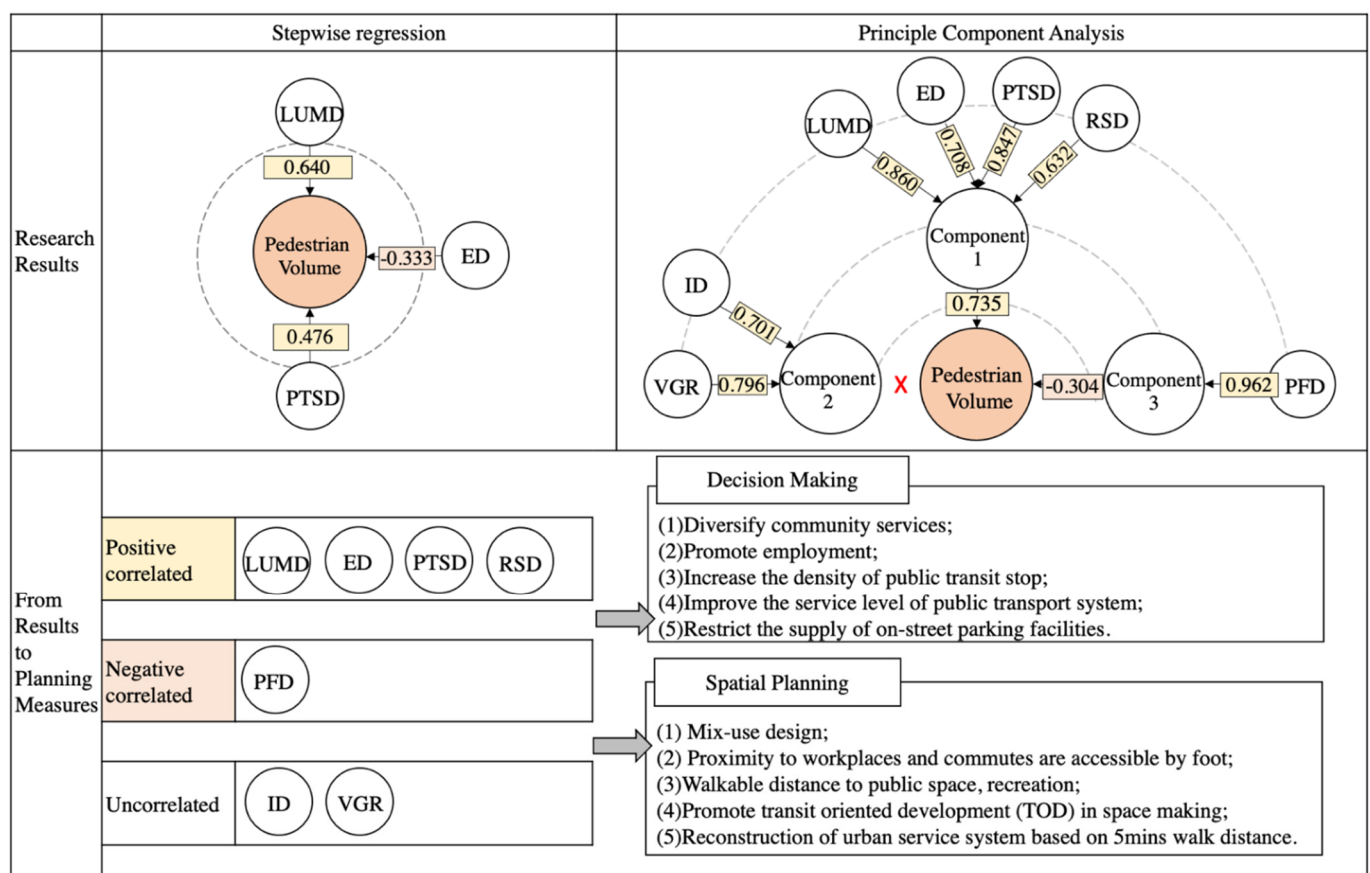


Figure 6. Research results and potential implementation strategies.

This study contributes a framework to exploring the association between the built environment and pedestrian volume in the high-density area. In addition, existing street problems and potential improvement of walkability in Melbourne CBD can be identified in this study (Figure 7). Figure 7 shows the intervention areas with the low land-use mixed degree, employment density, public transit stop density, and restaurant seating density. The darker circles in Figure 7 present the intervention areas with low diversity of land use and amenities. Urban design considerations in Melbourne's CBD should focus not only on the neighbourhood's layout and urban fabric in the intervention area in Figure 7 but also on the integrity of amenities.

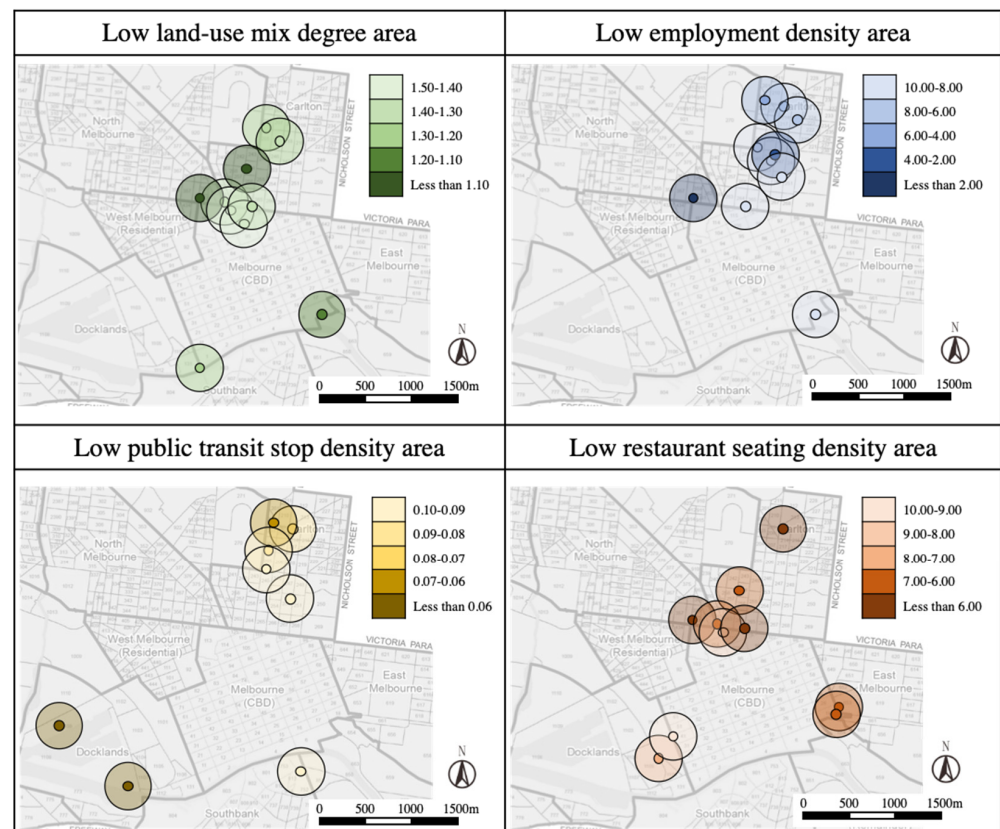


Figure 7. Design intervention areas. Source: Own elaboration.

6. Conclusions

This study contributes to understanding the factors affecting pedestrian volume in high-density areas. The characteristics of the dataset were illustrated. Secondly, land-use mix degree, employment density, public transit stop density, and restaurant seating density correlate with the pedestrian volume in the correlation analysis. As the result of further study, only two variables (land-use mix degree and public transit stop density) are related to the pedestrian volume according to the results of stepwise regression. The factor analysis extracts the principal components from the built environment variables and understands the correlation of different components. Three principal components were extracted and represent the different aspects of the built environment of Melbourne's CBD. Component 1 presents the diversity of land use and amenities and associate with the pedestrian volume in the peak period. Component 3 is the reflection of vehicle parking friendly (density of parking facilities), which is negatively associated with the pedestrian volume.

Previous studies assumed that the quality of the walking environment is often associated with walking. However, this study indicates that walking environments do not always correlate with the pedestrian volume, which may have to do with the regular grid design of the street configuration, and possibly a limitation on route choice within the

specific case study area as defined by the pedestrian sensors. The visible green ratio and intersection density loaded onto Component 2 reflect the quality of the walking environment. Pedestrian volume and Component 2 do not correlate with each other. However, this result may vary depending on the season and changes in the weather, which have not been factored into this study. In addition, the sensor array is not able to differentiate between pedestrian route selection or opportunities for pedestrian route choice.

Together these results provide valuable insights into how the built environment variables were grouped as different components and how the components were associated with the pedestrian volume in the high-density area. In addition, this study provides various suggestions for planners to help create a walkable environment and promote walking travel in Melbourne's CBD. This research has its limitations. The dataset was collected around the sensors of pedestrian counting system in the Melbourne CBD; hence further studies are required to process data gathered from the surrounding suburban areas in order to validate the results presented in the paper. This study provides a path to analysing the correlation between the pedestrian volume and built environment variables. More variables explaining pedestrian volume attributes such as the impact of topography on pedestrian route selection, or variations in weather and season could be incorporated and assessed in further studies. In addition, the research can be extended to include other case study cities presenting a range of street patterns, both regular and irregular grid/morphology structures, in order to better understanding the correlation between built environment variables and pedestrian volume with respect to improving the walkability in a variety of high-density areas.

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