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THE IMPACT OF SCALE SELECTION ON THE ASSOCIATION BETWEEN THE 5DS AND WALKING BEHAVIOUR: A GIS-BASED ANALYSIS IN PUTRAJAYA CITY

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ABSTRACT

Neighbourhood-built environment has been shown to impact walking behaviour in terms of density, diversity, design, destination accessibility, and distance to transit, or so-called the "5 Ds". However, the uncertainty in the magnitude of this link remains problematic, partly because of how geographic boundaries are operationalized. This study examines appropriate geographical units for calculating GIS walkability indices in a tropical context. Using data from Putrajaya city, the impact of four commonly used spatial definitions (240, 400, 600, and 1000-meter network buffers) on the association between the 5 Ds and walking volume was investigated, based on GIS measures of 2392 catchment buffers and observations from 123 gates. The negative binomial regression revealed that indices representing land use compositions demonstrated sensitivity to the delineation of boundaries and exhibited a robust relationship at broader spatial extents. In contrast, street-related measures such as connectivity and distance sustained a stronger association even at smaller scales. Moreover, the 600-meter network scale may be the most appropriate for identifying the association between the 5 Ds combination and pedestrian counts in residential neighbourhoods. The study recommends prioritizing walkability indices that incorporate distances to various facilities as indicators of walkability, as this approach can provide a more effective explanation for walking within small buffers.

1. INTRODUCTION

The built environment within a neighbourhood plays a crucial role in shaping residents' walking habits. Due to its immediate influence, numerous studies have investigated the relationship between neighbourhood design and walking behaviour. Researchers have identified key factors influencing walkability, such as population density, residential density, land-use diversity, street connectivity, destination accessibility, and proximity to public transit. Findings consistently demonstrate that higher densities and diversity, greater connectivity, shorter distances to destinations, and easy access to public transportation are all positively associated with increased walking and pedestrian volume (Frank et al., 2005; Marshall et al., 2009; Frank et al., 2010; Grasser et al., 2017; Habibian & Hosseinzadeh, 2018; Tao et al., 2020; Gao et al., 2020). These factors have been combined into a comprehensive framework known as the 5Ds (Density, Design, Diversity, Destinations, and Distance to transit), often operationalized using Geographic Information Systems (GIS) (Cervero & Kockelman, 1997; Ewing & Cervero, 2010).

The use of a 5Ds - GIS-based measures has advanced the assessment of walkability and yielded novel insights into the relationship between the built environment of a neighbourhood and walking behaviour (Koohsari et al.,2014). This approach offers more cost-effective and expeditious assessment tool than traditional field-based audits, as it leverages readily available secondary data. However, it is essential to recognize that GIS-based measures are sensitive to scale and boundary location, referred to as the Modifiable Areal Unit Problem (MAUP) (Fotheringham & Wong, 1991). The MAUP describes the subjective decisions made in defining the boundaries and delineation of areas when reporting contextual effects, which pose a significant methodological challenge when defining the concept of a "neighbourhood" for walkability research (Brownson et al., 2009; Villanueva et al., 2014). In this sense, neighbourhood refers to the geographical area within which environmental attributes relating to walking are investigated.

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The selection of geographic boundaries to measure the built environment concerning walking is a multifaceted process that may produce diverse outcomes (C. Lee & Moudon, 2006; Learnihan et al., 2011). For example, Mavoa et al. (2019) utilized several neighbourhood definitions, including administrative boundaries and road network buffers of varying sizes (500, 800, 1000, and 1500 meters). The findings revealed that the choice of neighbourhood definition can influence the detection or absence of an association between the built environment and physical activity among adults, including walking. Additionally, the study suggests that a neighbourhood delineation that is suitable for one built environment measure may not be appropriate for other measures. For instance, the impact of street connectivity and destination accessibility were less likely to be detected at smaller scales (less than 800m), whereas residential density and land use mix were more impactful at the same geographic unit.

In a similar study, Gehrke and Wang (2020) investigated the impact of the built environment on travel mode choice and explored the effects of scale selection and zonal configuration in defining neighbourhoods. The study found that the associations were influenced by the scale extent chosen to reflect the built environment's connection to walking. The land use mix indices showed a stronger association with walking at a smaller spatial extent (400-800-meters network buffer), while the density and network connectivity indices showed a stronger association with walking as spatial scale increased (1200-1600-meters network buffer). In a different study, Wei et al. (2016) found that, with the 800-m network buffer defined as the neighbourhood, the walkability index (a combination of intersection density, land use mix, and residential density) can alone explain about 15% of the variance of physical activity, including walking. However, Clark and Scott (2014) found that the 200-meter buffer had the highest variance explained by built environment factors, such as density, land use mix, and connectivity, while the 400-meter buffer had the weakest association.

Other studies tried to explore the impact of age group on this association. For example, Villanueva et al (2014) used several age groups within varying neighbourhood buffers (200 m, 400 m, 800 m, and 1600 m). The results showed that although only the 200 m buffer was able to explain the walking behaviour of younger adults (aged 18-29 years), neighbourhood walkability was positively associated with walking regardless of life stage and geographic unit. In contrast, Mitra and Buliung (2012)found that the buffer size had a significant impact on children's walking behaviour to school at 400 m, while Van Loon et al. (2014)British Columbia and the surrounding lower mainland region (n=366 found this effect at a larger buffer size (1600 m).

However, the lack of standardization may pose a serious challenge when it comes to comparing and combining evidence across studies (Learnihan et al., 2011). In addition, selecting the most relevant geographic scales within which built environments can affect walking behaviour is a significant step in translating research into urban design and public health practice (Javad et al., 2013). For instance, evidence showing that proximity to commercial retail or open spaces within a neighbourhood is associated with more walking is useful but not sufficient for urban designers or environmental policy makers. Information on the optimal distance that these facilities need to be located from residents for better walkable design is crucial. In other words, a better understanding of the geographic scales and distances at which built environments influence walking may better inform urban design and policy interventions (Koohsari et al., 2013; Learnihan et al., 2011).

In an effort to define an optimal geographical neighbourhood, the aforementioned studies generally propose that larger scales are more suitable for detecting the influence of the 5 Ds of the built environment on walking behaviour (Mavoa et al., 2019; Gehrke & Clifton, 2014). However, in the context of Malaysia, this perspective prompts an intriguing inquiry due to the tendency for unfavourable weather conditions to lead to shorter distances being walked (Ramakreshnan et al., 2020). Consequently, this factor results in a smaller buffer of investigation. The reported walking distances of 200 meters and 240 meters in Malaysia by Azmi and Karim (2011) and Qureshi (2016), respectively, are notably shorter compared to the commonly employed 400m and 600m distances often used as benchmarks in research related to public health, transportation, and urban planning. This distinction holds regardless of walking type or population characteristics (Moudon et al., 2006; Feng et al., 2010).

Given these considerations, this study aims to provide insights into the impact of the 5Ds of the built environment on pedestrian volume at multiple network buffers. Of particular significance is its focus on Malaysia, where shorter walking distances, influenced by the tropical climate, present unique challenges for promoting active transportation. Understanding these associations in such contexts is vital for informing research regarding neighbourhood walkability and the size of geographical units that should be applied to calculate GIS walkability indices. This will be relevant for researchers, practitioners, and policymakers who aim to promote healthy neighbourhood environments and encourage physical activity.

2. METHODOLOGY

This study adopts a quantitative approach based on cross-sectional data to understand the influence of scale variation on the association between the 5Ds of the built environment and walking volume. Data were collected from various sources (as described under each heading below) and operationalized using GIS. Subsequently, the data were linked to the geographic locations of 2,392 housing units within the study area, and compared across four different geographical scales (240m, 400m, 600m, and 1000m).

2.1 Study site

The study was conducted in Putrajaya, Malaysia's new federal government administrative centre situated 25 kilometres south of Kuala Lumpur. According to the Department of Statistics (https://www.dosm.gov.my), the estimated population of Putrajaya is

113,832.However, Putrajaya was chosen due to the abundance of micro-level features that actively promote walkability, such as walkways, crosswalks, street lighting, street furniture, and greenery (Azmi & Karim, 2012). This is a critical aspect for this study because it allows for effective control of the influence of micro-level features, enabling a more isolated examination of the specific role played by the 5Ds (macro-level features) in promoting walkability.

This study focuses on two residential precincts, Precinct 9, Precinct 11 (see Figure 1a). The selection assumed that neighbourhoods with higher density are likely to have denser commercial land use and more recreational sites, given the adequate population to support such amenities. The study analysed a total of 2,393 housing units across the two precincts (Figure 1b).

2.2 Neighbourhood unit

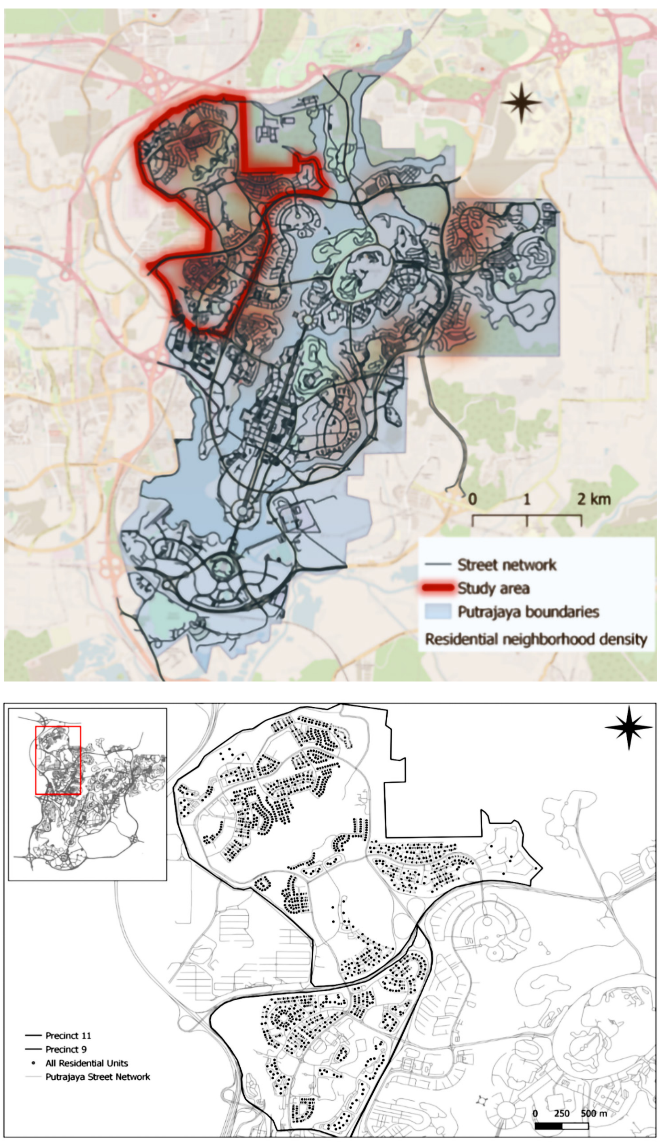


***Figure 1**: a) Heatmap illustrating the distribution of residential density in Putrajaya city, demonstrating a notable concentration of high residential density in the study area. Data was obtained from PLAN Malaysia. b) Spatial Distribution of the 2392 Housing Units included in this study (P 9.11).*

The distances selected for the study were informed by various sources: Qureshi (2016) and Azmi & Karim (2011) suggest that pedestrians in Putrajaya typically walk up to 240 meters before resorting to driving. However, 400 meters and 600 meters are commonly used in public health, transportation, and urban planning research in addition, the structure plan of Putrajaya adopts 400 meters (or 5 minutes) as a walkable distance to community facilities. However, some trips may exceed 1000 meters (Houston, 2014). The distances conceptualization is summarized in table1.

In this study, neighbourhood borders were delineated by applying multi-buffer network areas around each housing unit within precincts 9 and 11, encompassing semi-detached and high-rise, high-density units. Buffers with radii of 240, 400, 600, and 1000 meters were created around each unit using the QNEAT3 extension within the QGIS program, as illustrated in Figure 2. Road network data, including pedestrian-only paths, was sourced from Open Street Map (OSM), while inaccessible streets were excluded from analysis.

***Table 1:** Conceptualization of selected distances.*

Distance	Description	Source	Example
240 meters	Average distance pedestrians in Putrajaya walk before driving.	Qureshi, 2016, pp3; Azmi & Karim, 2011	Optimized bus stop locations for walking access (Taplin & Sun, 2019)
400 meters	Commonly used walkable distance in research studies for public health, transportation, and urban planning Walkable distance to community facilities as per the Structure Plan of Putrajaya	Moudon et al., 2006; Feng et al., 2010, Azmi & Karim, 2011	Walking accessibility to neighbourhood open space in Hong Kong (Tang et al., 2020)
600 meters	Commonly used walkable distance in walkability studies for public health, transportation, and urban planning	Moudon et al., 2006; Feng et al., 2010	Walking threshold in Zhejiang University, China (Mu & Lao, 2022)
≥1000 meters	Possible distance for some pedestrian trips	Houston, 2014	Community Life Circle (15min-CLC) in Shanghai (Wu et al., 2021)

2.3 Data collection

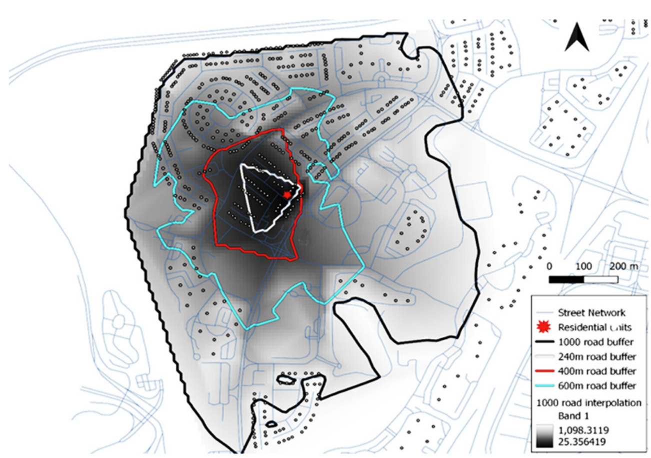


***Figure 2:** Neighbourhood Boundaries for a Residential Unit in Precinct 9 with Road Data from Open Street Map (OSM).*

2.3.1 Pedestrian count

This study models pedestrian count as a function of the 5Ds of the built environment, validated by prior research (Penn et al., 1998; Raford & Ragland, 2004; Liu & Griswold, 2009; Ewing et al., 2016; Sanders et al., 2017; Park et al., 2019; Singleton et al., 2021), achieving significant model fits (R^2 or pseudo-R^2 = 0.98, 0.77, 0.75, 0.52, 0.76, 0.71, 0.49 respectively). Using a modified version of Penn and Dalton's (1994) protocol, 123 observation gates were placed on tertiary and residential streets with pedestrian walkways.

Counts were taken by stationary observers at the midpoint of each street segment during three observation periods (morning 8-10 a.m., evening 4-6 p.m., and 6-8 p.m.) over two weekdays and one weekend day per area, resulting in 30 minutes of observation per segment. Observations were made in similar weather conditions between August and September 2021, avoiding rainy days, with an average maximum daytime temperature of 32.0°C (89.6°F). The mean pedestrian volume for each street segment was calculated and aggregated by observation time slots. An interpolation process estimated values for remaining areas, and results were clipped to predefined neighborhoods, with data exported as CSV for statistical analysis.

2.3.2 5Ds of built environment

Five built environment attributes—Density, Diversity, Design, Destination accessibility, and Distance to transit—were calculated for each unit within four scale definitions (240, 400, 600, and 1000 meters). Data on density and diversity came from the Integrated Land Use Planning Information System (I-Plan Geoportal) 2022, provided by the Department of Town and Country Planning of Malaysia. The main shapefile contained land cover information categorized into 38 classes, which were reclassified into five land uses: residential, commercial, recreational, education, and institutions. These land uses were then clipped to the catchments across different scales.

2.3.2.1 Density

was presented by two measures: net residential density (the number of residences unit per residential hectares), and Residential land use density (the ratio of residential land use to the total catchment area).

2.3.2.2 Diversity

was calculated by two land use mix indexes as following:

- *Entropy index:* was computed based on Frank' formula (Frank et al., 2010) considering five land uses: residential, commercial, office, institutional /education, and recreation, the index was calculated using the next formula:

$$\textit{Entropy Index} = -\sum_{i=1}^{n}\left[\left(\frac{P_{ij}}{P_j}\right)\ln\left(\frac{P_{ij}}{P_j}\right)\right]/\ln n$$ were

n: Number of land-use clusters.

Pij: Number of property assessment units i in zone j.

Pj: Sum of property assessment units 1 to, n in zone j.

Entropy Index varies between 0 and 1 where:

0 = Maximum specialization.

1 = Maximum diversification

- *Herfindahl-Hirschman Index:* H-HI was calculated by summing the squared proportions of each land use category, where the high value of HHI indicates a low level of land use mix and vice-versa,

H-H Index = $$p_1^2 + p_2^2 + \cdots + p_n^2$$ were

Pi: Percentage of land use type i

n: Total number of land uses

2.3.2.3 Design

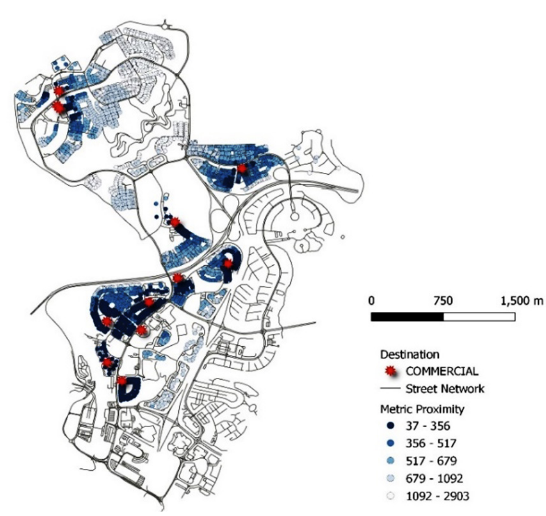
Design was presented by three measures: 1. street connectivity (number of true intersections / km2 of land area) 2. Street density (the total length of streets per unit area); 3. Block size (the Total land area / Number of blocks).

2.3.2.4 Destination accessibility

Including transit**,** was measured as a street network distance from a housing unit to the closest destination of a specific type (along the street). The data on the location of facilities was obtained from map of Putrajaya land uses. while data on the street network used to calculate distances was obtained from Putrajaya's OSM (Open Street Map). Multiple processes were used to measure network distances.

The first step was to use the Qneat3 plugin to perform an interpolation analysis within Q-GIS to convert the vectorial maps of the destinations into a single network distance raster containing information about network distances to the destinations. This process was

repeated for each destination to gain an understanding of each



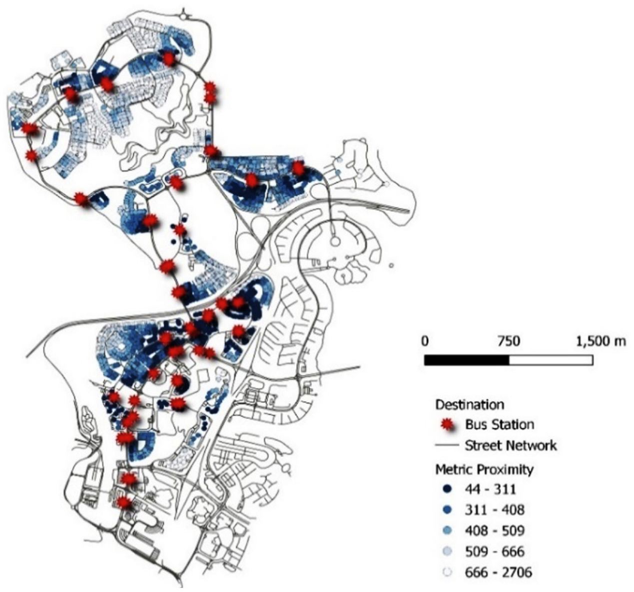


Figure 3: *Conversion of network distance raster values to points using sample raster values to calculate distances to commercial, transport.*

accessibility grouping, The second step was to compute the network distance between each residential unit and the nearest destination by converting the network distance raster values to points using the sample raster values. This process produced maps containing residential points weighted according to the distances (Figure 3). The next histogram illustrates the distribution of distances in the studied area (Figure 4).

2.3.3 Data analysis

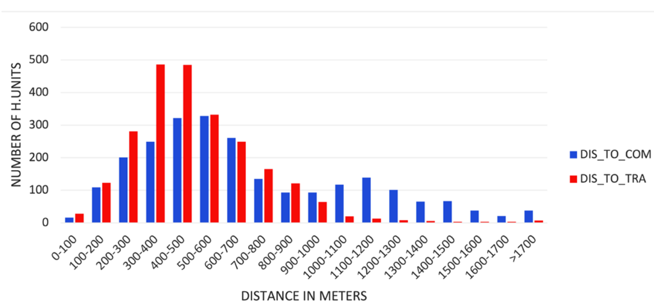


Figure 4: The resulting histogram displays the mean distances to commercial and transport des

This study first used Spearman's Correlation Coefficient to define the correlation between the attributes of the built environment, namely Density, Diversity, Design, and Destination accessibility, at the selected scales of analysis: 240, 400, 600, and 1000 meters. However, certain sub-variables were omitted from the analysis based on the correlation results. Additionally, a correlation coefficient matrix was used to determine the relationship between pedestrian counts at four different scales of analysis (240, 400, 600, and 1000 meters) and the four considered walkability indices: the Frank index, the Habibian index, and the urban walkability index.

Secondly, the association between built environment attributes and walking volume was modelled using negative binomial regression (NBR) to account for the positively skewed count data. The pedestrian volume of each catchment area was measured as the mean number of walkers in different street segments within the area.

This study uses z-scores of all exposure measures to rescale the heterogeneous units of data and allow comparison between models. Therefore, coefficients represent the deviation from the data centre (mean), and exponential beta (Exp-b) values were added to standardize the interpretation of coefficients.

3. RESULTS

3.1 Descriptive summary

A total of 2393 housing units were included in the final analysis. The walking volume and 5Ds attributes surrounding each unit were aggregated across four scales. As described in Table 2, different scale changes had varying impacts on the study variables. Pedestrian volume, represented by the average workday/weekend pedestrian count, increased significantly as the scale of analysis increased, from 18.43 pedestrians per catchment area at 240m to 279.93 pedestrians per catchment area at 1000m. Similarly, diversity measures such as the entropy index of mixed land use increased with scale expansion, owing to the inclusion of more land uses in the catchment area.

On the other hand, density measures such as gross residential density decreased as the scale of analysis increased, going from a mean of 10.46 units per hectare at 240m to 4.76 units per hectare at 1000m. A similar pattern was observed for design measures; for instance, at the 240m scale, there were 5.13 intersections per unit, while at the 1000m scale, 4.65 intersections per unit could be found.

Regarding destination accessibility, the network distance to various types of destinations (schools, recreation areas, commercial centres, offices, and bus stops) remained consistent across all scales of analysis, with an average value of around 700 meters. This consistency is expected because the distances were measured based on fixed number of destinations. This implies that an increase in catchment size does not lead to any changes in the distances from the housing unit to the intended destination.

Table 2: Descriptive statistics of dependent and independent variables (stratified by scale).

		Scales of analysis											
		240M			**400M**			**600M**			**1000M**		
Variables	Sub-variables	Total (n = 2393)			Total (n = 2393)			Total (n = 2393)			Total (n = 2393)		
		Mean	Median	SD	Mean	Median	SD	Mean	Median	SD	Mean	Median	SD
Density													
	Gross Residential density	10.46	10.44	4.52	8.82	8.78	3.92	7.31	7.10	3.28	4.76	4.72	1.54
	Residential land ratio	0.43	.42	.11	0.37	0.38	0.09	0.33	0.33	0.08	0.26	0.25	0.051
Diversity													
	Entropy index	.00	.05	1.00	0.77	0.77	0.07	0.79	0.79	0.080	0.82	0.84	0.07
	H_H index	3670.81	3580.06	894.6	3305.98	3312.60	558.60	2971.50	2978.36	423.21	2598.09	2481.37	315.34
Design													
	Intersection density	5.13	4.35	2.98	4.99	4.38	2.18	4.78	4.31	1.57	4.65	3.98	1.87
	Street density	263.99	251.09	56.70	257.76	253.49	46.68	241.74	246.58	34.67	223.15	221.85	34.21
	Block size	828.67	173.26	3103.89	818.64	213.99	3091.47	606.92	268.54	2240.50	431.70	377.35	212.73
Destination accessibility													
	Network distance to school	744.97	722.92	357.45	744.97	722.92	357.45	744.97	722.92	357.45	744.97	722.92	357.45
	Network distance to recreation	364.35	306.58	260.70	364.35	306.58	260.70	364.35	306.58	260.70	364.35	306.58	260.70
	Network distance to commerce	700.03	589.58	400.24	700.03	589.58	400.24	700.03	589.58	400.24	700.03	589.58	400.24
	Network distance to offices	913.23	848.25	443.25	913.23	848.25	443.25	913.23	848.25	443.25	913.23	848.25	443.25
	Network distance to transport	495.65	454.04	238.51	495.65	454.04	238.51	495.65	454.04	238.51	495.65	454.04	238.51
	Average distance	643.65	586.38	243.99	643.65	586.38	243.99	643.65	586.38	243.99	643.65	586.38	243.99
Pedestrian volume													
	Average_ workday/ weekend pedestrians	18.43	12.00	17.63	50.46	37.00	44.87	111.43	80.00	99.05	279.93	215.00	196.43

3.2 The impact of MAUP

The study examined the relationship between 5Ds attributes (Density, Diversity, Design, Destination accessibility, and Distance to transit) measured at four geographical scales (240, 400, 600, and 1000 meters) and walking volume to assess the effects of the Modifiable Areal Unit Problem (MAUP). Correlation analysis revealed fluctuations in land use measures as the scale changed. For instance, measures of density (net and gross residential density) and the entropy index of land use showed a shift in coefficient direction from 240 to 1000 meters (Table 3), likely due to limited land use variation in smaller buffers.

Walking volume negatively correlated with the average distance to all destinations, including commercial areas and schools, but showed a weaker association with parks and bus stops. This suggests that in Putrajaya, people prioritize walking to commercial destinations over recreational destinations or bus stops, with peak correlation observed within the 400 to 600-meter range (Table 3) . For design measures, street connectivity metrics showed a consistently increasing correlation with walking volume as the scale expanded, with the strongest association observed at 1000 meters.

Table 3: *The correlation between 5Ds measures and walking volume across the scales of analysis.*

	Scale of analysis			
Built environment attributes	**240m**	**400m**	**600m**	**1000m**
Gross Residential density	-0.244**	-0.192**	0.033**	0.479**
Residential land ratio	-0.188**	-0.263**	-0.144**	-0.09**
Intersection density	0.242**	0.31**	0.376**	0.651**
Street density	0.243**	0.256**	0.327**	0.645**
Block size	0.1*	0.145**	0.084**	0.488**
Entropy index	-0.02	-0.002	0.161**	0.414**
H_H index	-0.263**	-0.257**	-0.239**	-0.453**
distance to offices	-0.161**	-0.273**	-0.275**	-0.239**
distance to school	-0.198**	-0.33**	-0.312**	-0.333**
distance to recreation	-0.23**	-0.118*	-0.06*	-0.017**
distance to commerce	-0.37**	-0.457**	-0.49**	-0.403**
distance to transport	-0.128	-0.103*	-0.039**	-0.057**
Average distance	-0.371**	-0.486**	-0.473**	-0.422**

Correlation is significant at ** $p<0.01$. * $p<0.05$, $p>0.05$ level (2-tailed)

3.3 Impact of 5Ds

A negative binomial model was used to evaluate the impact of the combined 5Ds on walking volume across various scales. The fully adjusted models (see Table 4) show significant likelihood ratio statistics (772.9, 923.9, 1070.4, 1051.0), indicating a robust fit compared to a null model with only intercept terms. Model 3, with a likelihood ratio of 1070.4 and 10 degrees of freedom (df), had the highest value, and a McFadden's R^2 of 0.049, highlighting the significant impact of the 5Ds at a 600-meter scale.

Analysing each attribute separately, the average distance to all destinations consistently negatively impacted walking volume at all scales (240, 400, 600, 1000 meters), with coefficients of -0.651, -0.799, -0.867, and -0.626, respectively. At the 600-meter scale, an increase of one unit from the mean distance results in a -0.867 decrease in pedestrian traffic, indicating shorter distances to destinations like recreation, schools, and retail increase pedestrian volume at the neighbourhood level.

Street density had a consistently positive impact on walking volume at all scales (240, 400, 600, 1000 meters), with coefficients of 0.312, 0.252, 0.162, and 0.310, respectively (see Table 4). At the 240-meter scale, an increase of one unit in street density is associated with an increase of 0.312 pedestrians. Additionally, the number of intersections positively impacted walking volume, especially at the 600-meter scale, where an increase of one unit in its mean is associated with a 0.170 increase in pedestrian count. These results show that neighbourhoods with longer and more connected streets are more pedestrian-friendly.

Regarding density constructs, the residential land ratio consistently showed a positive impact on walking volume across all scales (240, 400, 600, and 1000 meters), with coefficient values of 0.168, 0.422, 0.465, and 0.231, respectively (see Table 4). At the 600-meter scale, increasing one unit from the mean residential land ratio contributes 0.465 more pedestrians. This indicates that denser residential lands are associated with more walking activity, as high density leads to compact land development, more diverse land uses, and shorter travel distances between origins and destinations.

Table 4: *Negative binomial regression model results for pedestrian counts*

		Model.1 (240m)			Model.2 (400m)			Model.3 (600m)			Model.4 (1000m)		
		Coef. (Std. Error) B	**Exp (B)**	**Wald Chi-Square**	**Coef. (Std. Error) B**	**Exp (B)**	**Wald Chi-Square**	**Coef. (Std. Error) B**	**Exp (B)**	**Wald Chi-Square**	**Coef. (Std. Error) B**	**Exp (B)**	**Wald Chi-Square**
Constant		**2.738***** (0.0213)	15.452		**3.721***** (0.0208)	41.299		**4.487***** (0.0206)	88.829		**5.414***** (0.0205)	224.550	
5ds	Residential land ratio	**0.168***** (0.0479)	1.183	12.303	**0.422***** (0.0393)	1.525	114.961	**0.465***** (0.0370)	1.592	157.946	**0.231***** (0.0357)	1.259	41.840
	Gross Residential density	**-0.219***** (0.0301)	0.803	52.913	**-0.390***** (0.0370)	0.677	111.095	**-0.327***** (0.0446)	0.721	53.664	**-0.192***** (0.0393)	0.825	23.954
	Intersection density	-0.052* (0.0403)	0.949	1.666	0.081** (0.0408)	1.084	3.955	**0.170***** (0.0481)	1.186	12.513	0.095* (0.0743)	1.099	1.626
	Street density	**0.312***** (0.0379)	1.366	67.647	**0.252***** (0.0390)	1.286	41.495	**0.162***** (0.0472)	1.176	11.763	**0.310***** (0.0684)	1.363	20.528
	Block size	0.040* (0.0298)	1.041	1.840	-0.055** (0.0268)	0.947	4.155	**-0.123***** (0.0232)	0.885	28.022	**-0.107**** (0.0424)	0.898	6.382
	Entropy index	**-0.180***** (0.0354)	0.835	26.023	**-0.142***** (0.0298)	0.868	22.649	**0.094***** (0.0364)	1.098	6.639	**0.142**** (0.0617)	1.133	5.330
	H-H index	**-0.680***** (0.0590)	0.507	132.996	**-0.637***** (0.0434)	0.529	216.002	**-0.305***** (0.0420)	0.737	52.942	**-0.381***** (0.0613)	0.683	38.625
	Distance to commerce	**0.335***** (0.0448)	1.398	55.940	**0.362***** (0.0494)	1.437	53.768	**0.343***** (0.0517)	1.409	44.004	**0.496***** (0.0570)	1.642	75.754
	Distance to transport	**0.231***** (0.0330)	1.260	48.984	**0.417***** (0.0335)	1.517	155.169	**0.525***** (0.0322)	1.690	266.105	**0.173***** (0.0301)	1.189	32.914
	Average distance	**-0.651***** (0.0469)	0.521	192.508	**-0.799***** (0.0457)	0.450	304.829	**-0.867***** (0.0463)	0.420	350.343	**-0.626***** (0.0482)	0.535	168.395
Likelihood ratio statistic (df)		772.9(10)			923.9(10)			1070.4(10)			1051.0(10)		
AIC		18108.911			22697.922			26317.153			30719.574		
BIC		18172.495			22761.505			26380.736			30783.153		
McFadden's R		0.03 3			0.041			0.049			0.047		
N. of observations		2393			2393			2393			2393		

Standard errors are in parenthesis *** p<0.01, ** p<0.05, * p<0.1.

Conversely, residential density measured as the average number of units per hectare negatively impacts walking volume at all scales, with coefficients of -0.219, -0.390, -0.327, and -0.192. This suggests that increasing the number of housing units is associated with a decrease in pedestrian numbers. The disparity might be due to methodological differences, as housing units are evenly distributed across the neighbourhood, making it harder to detect variations.

Table 3 also shows that the H-H index consistently negatively impacts pedestrian traffic volume across all scales (240, 400, 600, and 1000 meters), with coefficients of -0.680, -0.637, -0.305, and -0.381, respectively. For example, an increase of one unit in the mean H-H index results in a decrease of -0.680 pedestrians at the 240-meter scale. The H-H index measures the concentration of land use mix, where lower values indicate higher diversity, suggesting that increased land use mix correlates with higher pedestrian activity. The entropy index shows a consistent but weaker negative impact on pedestrian traffic volume. At the 1000-meter scale, an increase of one degree in the mean entropy index is associated with a decrease of 0.142 pedestrians (see Table 2).

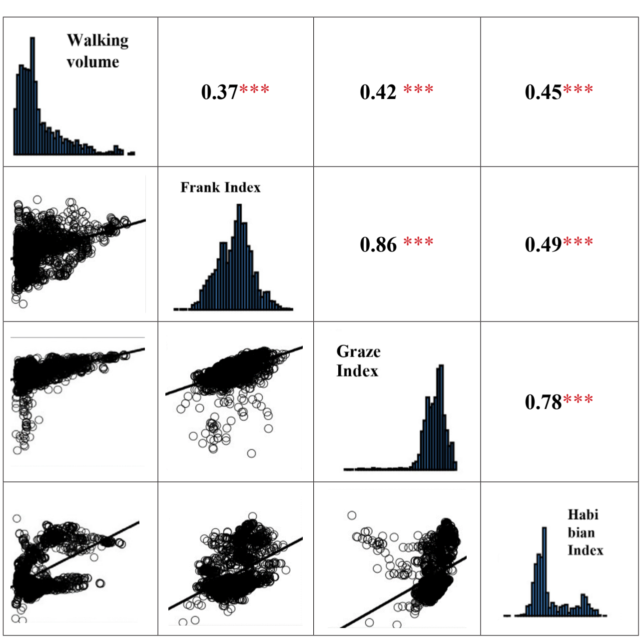
4. DISCUSSION

The results revealed that the direction and relationship of walkability variables and walking volume depend on the scale of the built environment under examination. Specifically, indices representing land use compositions demonstrated sensitivity to the delineation of boundaries and exhibited a robust relationship at a broader spatial extent. In contrast, street-related measures such as connectivity and distance, sustained a stronger association even at smaller scales. The study also suggested that a 600-meter network scale may be the most appropriate for identifying the association between 5Ds combination and pedestrian counts in residential neighbourhoods.

These findings have specific significance for assessing neighbourhood walkability in tropical environments. Unpleasant weather conditions often lead to shorter walking distances (Ramakreshnan et al., 2020), resulting in a smaller buffer of investigation. Selecting the best walkability assessment combinations, such as the Walkability Index (Frank et al., 2010), Urban Walkability Index (Glazier et al., 2012), or Habibian's Walkability Index (Habibian & Hosseinzadeh, 2018) (see Table 5), need to account for their individual components and weights to fit the scale of the analysis. As proven by this study, some built environment components, namely land use mix and density, do not reflect the real level of pedestrian volume at small scales. Therefore, combinations prioritizing street-related measures, such as connectivity and distances to various facilities, as indicators of walkability, may offer a more effective explanation for walking within small buffers. To illustrate this, when comparing these indexes using a 400 m network buffer, the commonly used Frank Index (primarily a combination of 3 land use component and street connectivity, see table 1) exhibited weaker associations with walking volume ($r = 0.37$, $p < 0.01$) (Figure 5) compared to the other two indexes, which prioritizing proximity components (Urban Walkability Index: $r = 0.42$, Habibian's Walkability Index: $r = 0.45$, $p < 0.01$)

Table 5: *Conceptualization of included walkability indices based on 5Ds combination*

GIS-based index	Author	Measures	Operational way	formula
Frank's walkability index	(Frank et al., 2005) (Frank et al., 2010)	-Net residential density -Intersection density -Land use mix -Retail floor area ratio	z- score	Walkability = (2 ×z-intersection density) + (Z-net residential density) + (Z-retail floor area ratio) + (Z-Entropy index)
Habibian's walkability index	(Habibian & Hosseinzadeh, 2018)	-Design indices -Diversity indices -Density indices -Destination indices	Linear regression, correlation analysis, principal components analysis, Z-score	Walkability = $\beta 1Z1j + \beta 2Z2j + \beta 3Z3j + \beta 4Z4jw$
Urban walkability index	(Glazier et al., 2012)	-Dwelling density -Population density -Proximity to retails and services -Street connectivity	Factor analysis; Principal components analysis	Walkability = $\ell 1$(Dwelling density) + $\ell 2$(Population density) + $\ell 3$(Street connectivity) + $\ell 4$(Availability of all retail and services) [ℓ is the value of factor loading]



When examining the impact of each component of the 5Ds on walking volume, shorter distances to destinations such as recreation, schools, and retail locations are associated with increased pedestrian volume at the neighbourhood level. This association is most prominent at the 600-meter scale, indicating that interventions aimed at increasing destination accessibility within this distance range could have a significant impact on promoting walking behaviour in our study area. However, these findings challenge prior studies that suggested 200 and 240 meters as the threshold distance for Putrajaya residents to walk before choosing to drive (Azmi & Karim, 2011; Qureshi, 2016, respectively), this disparity can primarily be attributed to the mismatch between objective and perceived methods of assessing distances (Koohsari et al., 2014).

The study also asserted that commercial destinations, such as retail stores and grocery markets, have a stronger impact on walking volume than transportation destinations, such as bus stops, at all geographical scales. This suggests that incorporating transport destinations as a neighbourhood walkability index, should consider the land-use zone (e.g. residential, commercial, industrial) (S. Lee et al., 2020), thus, researchers on residential neighbourhood may reconsider the emphasis on transportation infrastructure in assessing walkability, and instead prioritize the assessment of neighbourhoods distances to a variety of commercial destinations.

When we look at design measures, intersection density showed a stronger positive impact on walking volume than street density and block size at all scales, specifically at the 600-meter street network buffer. Consistent with previous research (Ellis et al., 2015; Molaei et al., 2021), our study suggest that intersection density offers the best measure of connectivity related to walking activity when using the footpath network. Although each measure of connectivity captures slightly different aspects of the broader concept, indeed, intersection density is the measure most closely associated with walkability. Additionally, the 600m network buffer (which equates to a 7–8-minute walk) around residential addresses is far more predictive of active travel in residential neighbourhoods. This implies that people living in areas with a higher density of connected footpaths within a 600m radius around their home are more likely to engage in active travel.

On the other hand, land use-related measures such as residential density and land use mix showed a fluctuating pattern across scales. The impact of residential density peaked at a scale of 600m, whereas the entropy index had a greater impact at the largest scales (1000m). These results are similar to those of Wei et al.s' (2016) study, which confirmed the validity of scales in the range of 800m to 1600m network buffer in detecting the association between land use mix and walking. The limitations of disaggregated land use measures in predicting walking at small scales have been noted in previous studies (Gehrke & Clifton, 2014; Clark & Scott, 2014; Gehrke & Wang, 2020; Liao et al., 2020). However, the impact of land use mix measured using the Herfindahl-Hirschman Index (HH) was impactful at the smallest scale (240m).

In general, the HH index tends to be more sensitive to changes in the dominance of specific land uses, while the entropy index is more sensitive to changes in the evenness of land use distribution. In this context, the dominance of certain land use types (e.g., commercial and retail) has a stronger influence on walking activity than the evenness of the distribution of land uses. This could explain why the HH index has a stronger impact on pedestrian traffic volume than the entropy index. This suggests that methodological differences in land use measurement could impact the association between land use mix and walking behaviour. Moreover, it highlights the importance of carefully considering the spatial scale when measuring land use-related factors that influence walking behaviour.

This study has two limitations. Firstly, the maximum buffer scale was 1000m, yet the regression analysis indicates that larger scales may alter the association between the built environment and walking. As demonstrated, the impact of most 5Ds and syntactic metrics on walking volume increased with scale, suggesting that scales beyond 1000m could be appropriate for detecting these associations. However, previous research indicates that expanding the scale may reduce heterogeneity which may lead to difficulty in detecting an effect (Dollman et al., 2009; Thornton et al., 2012). Secondly, regarding exposure variable data, the study did not differentiate between residents and visitors or between types of walking (utilitarian vs. recreational), which is critical as different motivations for walking may result in different associations with the built environment. Additionally, pedestrian data were interpolated in Q-GIS, potentially introducing estimation errors due to predicting values from limited sample points.

5. CONCLUSION

This study investigates how the definition of a neighbourhood can impacts the magnitude of associations between built environment attributes and walking volume. The study found that while the association was consistent across various scales for all built environment measures, smaller neighbourhoods were less likely to exhibit these associations. Notably, the most suitable neighbourhood definitions for detecting associations were the 600-m road network buffers. These findings highlight the importance of considering the appropriate geographical scale when conducting research on the built environment and walking within residential neighbourhood. It also emphasizes the need for further evidence to identify the most appropriate neighbourhood scales for different built environment measures, outcome measures, scales, and neighbourhood definitions. Given the difficulty in identifying a single optimal neighbourhood definition, future work should aim to identify a range of appropriate neighbourhood definitions to accommodate the diverse nature of communities. Furthermore, future research should incorporate a greater range of scales, particularly larger scales (>600), to enhance our understanding of the relationship between built environment attributes and walking. This will enable the development of more effective interventions that promote physical activity, enhance community well-being and help address the rising public health concerns of physical inactivity and sedentary lifestyles.

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