Article

Space Syntax in Analysing Bicycle Commuting Routes in Inner Metropolitan Adelaide

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Abstract: Cycling is a particularly favoured for short urban trips because it is a healthy and environmentally benign activity. As a result, urban mobility, quality of life, and public health are enhanced, while traffic congestion and pollution are decreased. In looking beyond the street network in terms of how it affects cyclists’ behavior choices, Bill Hillier’s (1984) outstanding legacy research on spatial space syntax is investigated in this study. The goal of this study is to determine if an urban area’s street network morphology influences commuters’ inclination to ride their bicycles to work. To further understand the nonlinear consequences of street network geometry on the estimation of cycling to work, a logarithmic-transformed regression model that includes base socioeconomic components, urban form, and street network variables represented by space syntax measure factors is developed. In conclusion, this model determined that bike commuting choice is significantly associated with the centrality index of Connectivity, although this is in combination with socioeconomic factors (age, gender, affluence, housing type, and housing price) and built environment factors (share of commercial, educational activities and distance to the CBD) factors. The findings of this study would be of value to planners and policy makers in support of evidence-based policy formulation to improve the design of bicycle networks in suburban regions.

Keywords: space syntax; street network; cycling; travel behavior; logarithmic-transformed regression; South Australia

1. Introduction

Cycling is an essential mode of transportation that at various times serves as a trip modal choice for exercise and recreation [1]. Although cycling is popular in many countries [2], it is still a niche mode of transportation in many developed nations around the world in terms of the overall percentage of total travels by bicycle versus other modes of transportation. The exceptions are some European Community nations such as Denmark, Germany, and the Netherlands, where population cycling rates are significantly higher than the United States, the United Kingdom, and, in particular, Australia [3].

Longer trips and delays can be the result of efforts to make riding safer or more enjoyable for cyclists. More importantly, if bicycle-specific facilities are only provided in a few locations or segments of networks, at least some cyclists will have to go out of their way to utilize them. As a result, understanding how cyclists’ perceive trade-offs between directness and pleasantness might help with the design and evaluation of cycling infrastructure. Nonetheless, it is worth noting that, in certain cases where travel time has been considered, it is not a significant factor. The amount of physical effort required to pedal, conflict with motor vehicles, and the quality of the environment all affect a cyclist’s propensity to cycle [4]. Improving understanding of what constitutes an optimal bicycle network would facilitate the design of a bicycle network that suits cyclists’ preferences through the selection of routes with the most attractive qualities.
Space Syntax was applied in describing the spatial structure of roadway networks [5]. In space syntax, the spatial pattern or arrangement is thought to have a significant influence on human social interactions. Configuration models quantify the pattern features of the highway network by creating an axial map [5]. The shortest set of axial lines that goes through each convex space and links all axial points is an axial map of the settlement’s open space structure [6,7]. The pattern of how people travel around a city may be anticipated by examining how areas within an urban zone are connected or integrated. To better understand the relationship between urban structure and human movement, the use of space syntax is an effective tool. Cyclist behavior modeling, bicycle route mapping, and wayfinding are all common applications for space syntax in urban environments [8]. By analyzing street network layouts, transportation planners may acquire a better understanding of traffic flow patterns, allowing them to provide a more efficient and practical solution. It is possible that cycling offers greater freedom of route selection than driving [9]. On the other hand, it is constrained by factors such as the directness of the route, the infrastructure of the route, sense of safety, and the purpose and duration of the trip. The space syntax is capable of analyzing some of these constraints and is therefore useful for studies of cycling route selection.

By using space syntax analysis, the calculation of segment angular shift is extremely relevant to analyzing bicycle traffic [10]. Stability in terms of angular reduction or the least amount of angular change is critical for making cycling lanes safe and attractive to cyclists. Cyclists tend to follow a complicated route through an urban area that balances the various features of a network. A common example of this is taking a detour to pass through a more appealing area [11].

To examine the factors that influence cycling to work, Ashley and Banister utilized UK census data and built a model in relation to existing urban areas that incorporated rider profiles, trip distances, the availability of cycling infrastructure, and car ownership rates [12]. A focus on cycling routes in existing urban areas is preferable because major modification to the layout of the road network, such as through developing cycling right-of-way routes through developed urban areas, is costly and therefore less practical [13]. Nelson and Allen (1997) used census data from 18 locations in the United States to estimate work trip cycle mode splits based on weather, topography, the number of college students and the number of per capita miles of bikeway infrastructure [14]. They observed that providing good bikeway facilities resulted in a higher percentage of persons riding their bikes to work. Cyclists prefer routes with specialized cycling facilities and those that provided destination-based amenities such as parking and recreation facilities [15,16]. However, for off-road cycling infrastructure, where it is shared with pedestrians, it is important that the distribution of available space between pedestrians and cyclists is carefully designed because when the bicycle lane is over-dimensional, it has a substantial impact on pedestrian safety perceptions [17]. Philips et al. (2017) developed a hybrid spatial microsimulation model based on simulated data utilizing the Monte Carlo sampling technique to build a synthetic population of humans as part of a model-based policy indicator. The model was put to the test in the United Kingdom, where it was used to assess people’s ability to travel by bicycle [18].

Campisi et al. (2020) created a decision-making tool for building bicycle lanes based on numerous variables such as cost, location, and safety. This approach may gather, consolidate, and combine many types of data at various levels in order to control all stages of an infrastructure project’s implementation [19]. In most current transportation modeling practices, variables such as transportation demand, distance measurements, and route capacities are all included, but variables like cognitive ease of route finding, route directness, and smoothness, which may be critical for built-environment bike-ability, are rarely included. Rather, more refined and user-friendly methods for projecting bicycle route selection based on urban street network layout would be beneficial from both a traffic planning and a user perspective [20]. In this regard, speed and directness are considered to be important factors in the route choosing behavior of a cyclist [16].
There have been few studies on the efficacy of policies and initiatives used to encourage residents to use green transportation, such as cycling in South Australia [21,22]. In order to increase the number of people who cycle, safety measures such as bike lanes and signage must be improved [23]. In South Australia, efforts to promote cycling should focus on making it simple for individuals to cycle to work. Most importantly, additional methodologically sound studies to determine the effects of deterrents to cycling should be conducted [24]. The study of street design features that affect cycling behavior in South Australia is particularly scarce, and only a handful of these studies have used space syntax research techniques.

This research could aid in the understanding of the influence of road network design on the choice of bike routes for commuting in Australia’s cities and towns. This research makes use of a space syntax approach to determine the relationship between street network design and data on commutes to work. Inner suburbs around Adelaide’s metropolitan area were selected because they had a higher percentage of cyclists because of the high quality of the built environment and proximity to workplaces.

This study examined how optimizing urban form, street network design and geometry can improve cycling conditions. A mix of GIS and Space Syntax is one such tool for navigating bike lanes and paths in urban areas. Consequently, the key research question is in investigating the effect of street network geometry in determining an individual’s decision to commute by bike in Adelaide’s inner suburbs.

The innovation of this paper is in providing a methodology for developing a better understanding of the patterns of work trip cycling based on a mix of metrics drawn from space syntax theory on a fine-grained scale. The study results contribute to developing a theory and an understanding of how street networks are designed in response to user behaviour and how street network layout facilitates cycling. In addition, this is the first time that a large-scale morphological analysis of Adelaide’s street network has been done in relation to how effectively it facilitates cycling. This research utilized the smallest available geographical units (SA1 level), thereby allowing a fine-grained analysis of potential cycling routes across a large part of the Adelaide metropolitan region.

The rest of the article is structured as follows. Section 2 describes the methods and conceptual framework, providing an explanation of space syntax and how space syntax measures were applied to determine connectivity, depth, and other configuration attributes of the street network. The case study area is then introduced, and then the collection of secondary data and its processing are described. Next, Section 3 presents the analysis of data, i.e., the outcomes of applying space syntax to quantify the street network geometry, and the results of regression models and its associated variables. Finally, in Section 4, we discuss the results of our modeling and describe how the findings are consistent with previous studies. We also discuss the implications for both theory and practice and present some directions for future research on cycling networks.

2. Method

2.1. Space Syntax

The space syntax rooted in Graph theory [5] is a collection of techniques to study the patterns of spatial configuration, as it relates to the distribution of buildings, which reflects human activities. Hence, space syntax is a pertinent methodology for describing human behavior and social activities from the perspective of space configuration [5].

The space syntax analysis was conducted on a segment graph or an axial graph [25]. Using a linear network to represent the road system, an axial graph can be constructed to show the road network’s open spaces in detail. The segment graph shows a finer granularity, which considers each part between the nodes, and in addition to the topological distance with the same weight for each turn, it can also calculate the minimum angular distance [25,26]. It is important to remember that the terms “shortest path” and “shortest distance” refer to graph-based concepts, not geometric network equivalents. In this case,
the topological distance is represented by the number of edges between two different nodes [27].

The relative importance of each street segment can be calculated using the Graph theory and the space syntax technique. As it turns out, centrality refers to the systemic hierarchy of accessibility. To measure centrality, measurement of detailed features include the following: Connectivity; Choice; Integration and Depth [28].

The Connectivity of a line is determined by the number of other lines that are immediately connected to it [29]. Thus, a node’s degree is the number of edges that pass through it. Choice measures the shortest routes between all of the network’s edges [7,30]. Choice illustrates how many ways lines in a network can cross each other. It refers to the level of ease with which a traveler wishes to move from one location within a region to another. Higher numbers indicate a greater potential for through-movement throughout the network, while lower numbers indicate a reduced potential for through-movement within the network. Using Integration, the distance between any two elements can be determined using only the axial measurements, selection, and length of the shortest path between them. For this function, an angular change parameter was created in conjunction with segment analysis. The Depth between two spaces in the graph is defined as the minimum number of syntax steps required to reach one to the other [31].

2.2. Study Area

Adelaide is the capital of South Australia and Australia’s fifth-most populated city (with a population of over 1.4 million people) residing in a land area of 3259.8 km² [21]. The Strategic Plan for South Australia has set a number of ambitious goals for the state’s future prosperity. Cycling, according to the State Government, is critical to achieving several goals outlined in the Strategic Plan. In South Australia, cycling has risen to the fourth most popular recreational activity, with over a third of the people cycling at least once annually. International cycling events, such as the Tour Down Under, have attracted large numbers of tourists to the state, resulting in the strengthening of tourism. More than 2100 km of bicycle routes have been planned and implemented as part of the Bikedirect network in the Adelaide metropolitan area. The South Australian Government’s Bike Ed project has trained over 30,000 primary school students in bicycle safely. This, combined with South Australia’s ideal climate and geography, has led to a revival in the South Australia’s vibrant cycling culture [22,32].

Despite the above-mentioned strategic goals and initiatives, the percentage of people who cycle to work (for the first or entire route) is relatively low, with female commuters accounting for around one-third of male commuters (Table 1). The inner suburban area of the Adelaide metropolitan region (within a radius of 10 km from CBD) was chosen for this study because it has a comparatively larger percentage of people cycling to work, as illustrated in Figure 1. This region has a population of 620,769 people (2016) and a population density of 2622 people per km². In addition, the average price of a home in this region is $3918.5 per square meter as of 2016 [33]. However, for modeling purposes, only 822 tracts with nonzero cyclists were chosen.

Table 1. Percentage of people using a bike, Journey to Work [33].

| Region                  | Commuting Cycling | No. of Employed People | Commuting Cycling (Percent) |
|-------------------------|-------------------|------------------------|-----------------------------|
|                         | Male  | Female | Total | Male  | Female | Total | Men | Women | Total |
| Greater Adelaide Metropolitan | 4368  | 1144   | 5512  | 334,036 | 222,691 | 556,727 | 1.31 | 0.51  | 0.99  |
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Figure 1. Location of selected area and frequency of cycle commuting for each census tract (left). Connectivity, Choice and Integration measures for a typical census tract (right). Source: Authors.

2.3. Data

A set of sociodemographic and physical data were collected from secondary sources. The GIS data was sourced from the Government of South Australia’s open source data “Data.sa.gov.au” [34], and open street map (OSM). The data on housing prices originated from the South Australian cadastral database called the Integrated Land Information System (SAILIS) [35]. Based on the refined GIS map analysis, a detailed axial map of the path and cycle network was made using the ESRI ArcGIS 10.8.1 and Depthmap X version 0.5 [36]. Different measures of space syntax were then captured at both the global and local (in different directions as named R3, R5, and R7) scales. The goal of the combined space syntax and GIS was to analyze parameters that should be important for people deciding their preferred mode of transport. The ‘Journey to work’ data was collected from the Australian Bureau of Statistics (ABS) which was combined with socioeconomic profile data [32]. The optimal unit of analysis is the geographic level of SA1 with an average population of 447. The rationale for the selection of small geographic units was to tailor the analysis to a fine grained approach in order to achieve greater significance [18,37].

SEIFA (socioeconomic indexes for areas) measures of IER (Index of Economic Resources) were used, as defined by the ABS [38]. The IER index measures a neighbourhood’s overall access to economic resources, which a high IER score indicates. There may be many high-income households and owner-occupier properties in a neighborhood with high IER amounts [38]. The datasets used to build the exclusive bicycle network database for this study are illustrated in Figure 2.
3. Results

3.1. Correlation Analysis

Because the purpose of this paper was to test the effect of the space syntax variables on commuting by bike, a correlation test was applied to find pair-wise associations between each space syntax measure and cycling. First, the spatial syntax of all census areas studied was measured. Space syntax measurements for all links within the census area were estimated. Ten indices were measured for each link, which can be divided into four categories: Connectivity, Depth, Integration, and Choice. The census area values were then aggregated using a Mean function. The amount of the syntax space index in each census tract is the average of measurements of all links within the tract. The measurement results are illustrated in Figure 3.

![Diagram of Cycling Network Database](image)

**Figure 2.** Cycling network database. Source: Authors.

**Figure 3.** Distribution of space syntax measures for studied neighbourhoods (SA1). For all graphs, the X-axis shows the value of the measure and the Y-axis shows the frequency. Source: Authors.

As illustrated in Figure 3, the distribution of measures is close to a normal distribution for most indices and presents a good basis for modeling. Note that outliers were removed for analysis. However, while there are significant correlations between many of the pairs of space syntax measures, only the measures with the strongest correlations were selected as dependent variables in the modeling process. The Correlation Matrix (Figure 4) displays the coefficients of correlation between variables. Each cell in the table represents the relationship between the two variables.

The following measurements are strongly correlated with commuting by bicycle: Connectivity (r = +0.26); Global depth (r = −0.32); and Integrated global (r = −0.29). Therefore, only these three measures are used for regression modeling. This matrix also demonstrates that Global depth and Global integration work in the same direction as opposed to Connectivity. Moreover, these two are strongly correlated with each other (r = +0.51), limiting their capacity to be included in the model simultaneously.

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3.2. Logarithmic-Transformed Regression

The dependent variable’s logarithmic (natural) form is used in the model. When there is a nonlinear connection between the independent and dependent variables, or when the values of the dependent variable are severely skewed, this technique is advised [39]. Another important benefit of the natural log is in creating a constant elasticity model [39]. When the regression coefficients change across space, it is also advised to employ alternative approaches such as geographically weighted regression (GWR) [40,41]. However, before utilizing these approaches, it is important to assess the spatial autocorrelation of each variable in the dataset [42].

The dependent variable in the regression model is the share of employees that cycle to work. The explanatory variables are a combination of socioeconomic and street network geometry in a continuous fashion that each is expected to influence the share of trips by cycling. Only the most influential factors were selected whilst controlling for co-linearity among the studied variables.

The space syntax measures that were measured and illustrated in Figure 1 previously were entered into the primary model. The hotter colours (i.e., the redder spectrum) represent higher Connectivity whilst the cooler colours (i.e., the blue end of the spectrum) represent lesser Connectivity. The descriptive statistics of the significant variables extracted from the analysed database are provided in Table 2.
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Figure 4. Correlation matrix of the studied variables. Source: Authors.
Table 2. Descriptive Statistics of explanatory variables. Source: Authors.

| Variable name   | Description                                      | Count | Mean  | Std  | Min  | Max  |
|-----------------|---------------------------------------------------|-------|-------|------|------|------|
| E_M25_34        | Number of male workers aged 25 to 34              | 822   | 26.35 | 16.05| 8    | 186  |
| IER_Index       | SEIFA advantage                                  | 822   | 4.71  | 2.43 | 1    | 10   |
| LnCmmrcl        | Commercial area (Ln)                              | 822   | 5.13  | 3.81 | 1    | 12.34|
| LnEducnl        | Educational area (Ln)                             | 822   | 3.10  | 3.57 | 1    | 13.17|
| AvgP_Price      | Average housing value multiplied (per $1000)      | 822   | 4.11  | 0.86 | 2.13 | 9.56 |
| Sep_H           | Number of separated houses                       | 822   | 93.82 | 29.72| 0    | 131  |
| CBD_dummy       | CBD area = 1, other = 0                           | 822   | 0.43  | 0.49 | 0    | 1    |
| Connectivity    | Space Syntax: Connectivity                       | 822   | 3.58  | 0.77 | 1    | 6    |
| Bike            | Number of workers cycled to work                  | 822   | 5.95  | 3.07 | 3    | 22   |

According to Table 3, all of the characteristics included in the above models have been shown to be statistically significant (CI = 95%), and these were used as a basis for calculating bicycle trips for work commuting. The values of VIF (<5) proves that the selected variables have no co-linearity. The addition of built environment measures and street geometry parameters for the Connectivity measurement increased the explanatory power and overall quality of the model. The goodness of fit measurements of the final model (adjusted R-square of 0.500) demonstrates how the physical features contribute to the model’s power in explaining the behavior of commuters by bicycle. These indicators, as part of the evaluation of the street network for cycling, provide a more complete assessment and, when cycling behavior is considered in the journey prediction model, results in greater accuracy.

Table 3. OLS Regression Results. Source: Authors.

| Variable       | Coef.   | Std. Err. | t-Statistic | p > |t| | [0.025 | 0.975 | VIF | Elasticity |
|----------------|---------|-----------|-------------|-----|---|---------|-------|------|-----|-----------|
| const          | −0.891  | 0.114     | −7.844      | 0   | −1.113 | −0.668 |        |      | 2.118 | 0.5       |
| E_M25_34       | 0.005   | 0.001     | 4.089       | 0   | 0.003  | 0.008  | 2.118  | 0.5  |
| IER_Index      | 0.050   | 0.007     | 7.271       | 0   | 0.036  | 0.063  | 1.063  | 5.0  |
| LnCmmrcl       | 0.008   | 0.004     | 2.061       | 0.04| 0      | 0.017  | 1.762  | 0.008|
| LnEducnl       | 0.011   | 0.004     | 2.682       | 0.007| 0.003  | 0.018  | 2.431  | 0.011|
| AvgP_Price     | 0.020   | 0.021     | 9.627       | 0   | 0.163  | 0.246  | 1.030  | 2.04 |
| Sep_H          | −0.001  | 0         | −9.853      | 0   | −0.002 | −0.001 | 1.271  | −1.0 |
| CBD_dummy      | 0.262   | 0.036     | 7.312       | 0   | 0.192  | 0.333  | 2.006  | -    |
| Connectivity   | 0.077   | 0.019     | 4.119       | 0   | 0.04   | 0.114  | 2.429  | 7.7  |
| R-squared      | 0.505   |            |             |     |        |        | 2.623  |      |
| Adj. R-squared | 0.500   |            |             |     |        |        | 0.269  |      |
| F-statistic    | 103.5   |            |             |     |        |        | −0.049 |      |
| Prob (F-statistic) | 1.53 × 10−118 |            |             |     |        |        | 2.757  |      |
| Log-Likelihood | −408.74 |            |             |     |        |        | 1.940  |      |
| AIC            | 835.5   |            |             |     |        |        | 2.356  |      |
| BIC            | 877.9   |            |             |     |        |        | 0.308  |      |

The model included three types of variables: socioeconomics (represented by age group, gender, dwelling type, SEIFA affluence index and housing value); built environment (represented by the presence of commercial and educational land use, and distance from CBD); and street network geometry (represented by network Connectivity). According to the elasticity result [39], the most powerful factors are Connectivity (7.7%), IER index (5.0%) and average housing price (2.0%).

Commuters are more likely to ride their bicycle to work if there is greater intensity of commercial and educational activities in their area. It is also demonstrated that for commuters located on the perimeter of the CBD, the propensity to cycle to the workplace decreases. This finding is consistent with the cycling literature confirming the overall higher quality of infrastructure in the CBD in facilitating cycling [43] and cycling safety [44]. The average residential property price in a neighborhood appears to have a major role in
explaining variations in work-related cycling. This variable is thought to be a proxy for some neighborhood quality characteristics. The higher the median property value in the neighborhood, the higher the share of cycling to work. A study by Liu and Shi (2017) in the United States demonstrated that the distance between home and bicycle facilities/networks has a significant positive impact on average property value, confirming the preference of households for a high-quality bicycle infrastructure [45]. Conversely, proximity to cycling infrastructure can reduce privacy and a sense of security from crime, leading to a decrease in home values [43,46]. A Canadian study reported that changes in home values due to the deployment of bicycle lanes vary widely depending on the location and type of cycling facilities [47]. As noted by Flanagan et al. (2016), investment in cycling could be the catalyst to breaking down the historical borders of socioeconomic imbalances [48].

Commuters in inner Adelaide areas with a better socioeconomic profile, as measured by the IER index for advantage, take a greater percentage of work trips by bicycle, demonstrating the favorable effects of increased cycling. One possible explanation is that a bigger proportion of white-collar jobs is concentrated in the CBD and inner suburbs, making commute distances shorter. It is worth noting that the average distance traveled to work in Australia is 16.5 kilometres [33]. On the other hand, the share of separate houses is associated with a lower share of cycling to work. It is likely that separate dwellings have higher car ownership and usage and hence are less likely to have residents commuting by bicycle. A key finding from the model was that the greater the share of employed males in the age group of 25 to 34 years of age in a neighborhood, then the higher the likelihood of using bicycles to work in that neighborhood. This result backs previous research on the favorable effects of gender and age on cycling [49].

Examining the metrics of space syntax identifies Connectivity of the street network at the neighborhood scale which has a positive effect on the proportion of people that cycle. This finding shows that the propensity to cycle is dependent on the impedance of movement and that the geometry of the street network geometry has a significant influence on the choice of cycling for commuting.

4. Discussion and Conclusions
Overall, this study determined that bicycle commuting flows are significantly associated with centrality indices, although this is in combination with other socioeconomic and built environment factors [24]. In response to the research question, this study has enhanced knowledge of tools evaluate the performance of street networks in facilitating cycling, using inner metropolitan Adelaide as a case study, by utilizing the axial-based street metrics of Connectivity. Rather than using traditional simple measures such as intersection or road density, the study focused on topological distances within a defined urban area. In practice, this technique has demonstrated a capability in analyzing and assessing the performance of street network’s spatial and hierarchical structural properties as they relate to cycling activity [50]. The holistic model developed, consisting of factors that include socioeconomics, urban form, and street network geometry attributes, was demonstrated to have moderate explanatory power (Adj. R-squared: 0.500) in describing the variations in commuter cycling. Overall, the findings of this study indicate that street network design and layout should be considered for behavioural models targeting cycling commuter journeys because commuter cycling potential is more appropriately assessed with this technique than with the traffic activity zones in traditional traffic engineering models [10].

The finding on street network morphology supports similar literature, such as the study by Ozbil et al. [51], which assessed the impact of local integration of cycling. In addition, the studies by Schepers et al. [52], and Rybarczyk et al. [53] investigated the impacts of integration (at the metropolitan level) on cycling. Similarly, Schepers et al. [52]
discovered that (local) integration within a 100-m radius of the trip makers’ neighbourhood between origin and destination had a negative relationship with commuter cyclist’s travel.

Other findings, such as the favorable effects of a high density built environment and greater intensity of commercial/educational activities and home value (as a proxy for neighborhood quality) on cycling share, are consistent with previous studies [43], and partially show the potential of cycling infrastructure as an indicator and facilitator of gentrification [54]. According to Ewing et al. [55], there is a substantial link between cycling preference and increased urban density. In a similar study, Parkin et al. [56] discovered that urban density (as measured by proximity to work sites) was associated with the percentage of people who cycled.

As previously stated, this study solely evaluated the inner suburbs of metropolitan Adelaide, which constitute one-third of the region’s street network. A further study could extend to include all of the Adelaide metropolitan region. Similarly, this study solely looked at data for commuter trips. The conclusions of this study are based on the 2016 ABS household census survey [33]; however, additional new research is needed to determine the effects on cycling behaviour during the COVID-19 pandemic. It should be emphasized that only commuting cycling trips were simulated; further research is required to determine the role of space syntax of street networks on non-commuter-based cycling [8]. The proposed model in this research can be improved by including additional variables on individual perceptions that reflect the perceptual barriers of different social groups to cycling, in a similar vein as the work undertaken by Dill and McNiel [57] in the United States. Further refinement of the model could be achieved with more comprehensive segmentation of cycling commuters by gender, age, job status, occupation, and education level.

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