

Incorporating Networks in Semantic Understanding of Streetscapes: Contextualising Active Mobility Decisions

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Abstract

Planning for active mobility satisfies many fundamental tenets of good urban design and planning. However, planning for active mobility is a complex endeavour due to numerous local, place-based factors that influence active mobility decisions. Recent advancements in urban data research have demonstrated the effectiveness of deep learning methods in evaluating active mobility potential for urban environments. However, the incorporation of semantic information from deep learning models and street view imagery into spatio-temporal contexts remains a challenge. In particular, knowledge extraction from deep learning models remain an open question for urban planning and decision-making. Towards this issue, we propose a functional deep learning and network science workflow that employs open data from OpenStreetMap and Mapillary to assess factors affecting active mobility decisions and route planning. We demonstrate the generalisability of our analytical workflow through two case studies focusing on urban greenery in Nerima city (Japan), and urban visual complexity in Pasir Ris town (Singapore). Our results reveal clear patterns of heterogeneity in urban streetscapes and identifies unevenness in street infrastructure provision based on destination types. Using this information, we propose specific areas for design intervention to improve active mobility planning. Our workflow is applicable for a diverse range of use cases making it relevant to a wide range stakeholders, not limited to, urban researchers, policy makers, and urban planners.

Keywords: Computer vision, Volunteered Geographic Information, Machine learning, Urban analytics, Walking behaviour

1. Introduction

Active mobility is critical for healthy living and has been recognised as a multi-pronged approach to achieve various planning related goals such as sustainability and successful ageing-in-place (Wong et al., 2018; Tao and Cheng, 2019; Yang, 2020; Yang et al., 2021). In recent

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years, global policymakers have increasingly addressed barriers to active mobility. For example, the Chinese government implemented the ‘Opening and Prohibiting Gated Communities Policy’ in 2016 to prevent the formation of edge communities (Xinhua News Agency, 2016). This effort is followed by the ‘Healthy Cities Initiative’, which is a nationwide health campaign centred around active mobility. Similarly in Europe, active mobility has been a key component of the European Commission’s 2020 climate change strategy, which aims to create active mobility friendly environments, and improve urban mobility for older adults and persons with disabilities (European Commission, 2021). The *15-minute-city* concept which first emerged in the 2015 Paris COP21 conference, advocates for human-centric neighbourhood design where people need not spend more than 15 minutes travelling to urban opportunities (Moreno et al., 2021; Gaglione et al., 2022; Kissfazekas, 2022). Such ideas prompt the human-centric redesign of urban mobility systems and as a corollary underscores the importance of urban environments to encourage active mobility travel.

However, efforts to promote walking and cycling remain a longstanding struggle for policymakers (Hackl et al., 2019). In particular, traditional methods (e.g. residential surveys and geospatial-based studies) to study active mobility continue to be challenged by the complex, and contextually heterogeneous nature of urban environments (Logan et al., 2019; Saxon, 2021; Tang et al., 2021). For example, it is well-known that residential surveys face scalability limitations given that they are time-consuming and costly to administer. On the other hand, while geospatial-based studies help to address some of the shortcomings of residential surveys, they suffer from limitations when generalising to real world phenomenon. For planning practitioners, the mismatch between Euclidean and shortest path distance in the context of planning catchment areas is a well-recognised shortfall (Giles-Corti et al., 2011; Banerjee et al., 2014; Clark et al., 2016; Sun et al., 2018). In addition, the treatment of geographic features as discrete, homogeneous entities is also problematic as previous research have shown that the quality of urban spaces matters as much as quantity (Van Dillen et al., 2012). As active mobility planning becomes increasingly widespread, there is a clear need for scalable and context-based solutions that can be used to examine and assess urban accessibility across varying urban scale and locations. Given the importance of contextual information towards human-centric planning and design, such solutions should ideally account for the close linkage between people’s active mobility decisions and their proximate urban environment.

With these considerations in mind, we propose a deep learning and network-based workflow to extend novel applications and use cases for active mobility studies. In recent years, advancements in computer vision (CV) techniques and street view imagery (SVI) offer opportunities to understand, assess, and explore local street conditions (Dubey et al., 2016; Warburg et al., 2020). For example, recent SVI-based studies have demonstrated that street conditions such as greenery exposure, daylight accessibility, or visual stimulation could improve the likelihood of frequent walking or cycling (Tribby et al., 2017; Hillnhütter, 2021). Notwithstanding the emergent success of SVI-based studies, current approaches face limitations when applied to active mobility planning. Notably, the representation of urban indicators through aggregated indices do not explicitly account for spatial topology inherent in urban systems. In particular, the aggregation of SVI indicators over broad geographic areas abstracts away important local information, limiting the ability to pinpoint target sites for intervention without further study. Moreover, the fine-tuning of grid size is a subjective and tedious process (Fotheringham and Wong, 1991; Mitra and Buliung, 2012; Gao et al., 2021). To avoid this concern, we choose to preserve the spatial fidelity of our analytical results by embedding SVI semantic information

directly into urban networks.

In the subsequent section, we outline current approaches which have employed SVI to improve active mobility planning. Next, we present our methodology, which consists of an automated, open-source, and generalisable workflow using open data to assess active mobility conditions in urban precincts. We introduce our results in the form of a urban greenery and visual complexity case study to evaluate older adult active mobility in Tokyo, Japan and Singapore. Our approach is transferrable to other factors and geographies. Based on our findings, we identify high priority intervention locations to improve active mobility planning. More broadly, our study demonstrates that SVI can be used effectively to improve active mobility analysis and that it is increasingly possible to develop urban streetscape assessment models with deep learning methods. Our analysis can be replicated for any use case, population group, and geographic location, making it relevant to a wide range stakeholders, not limited to, urban researchers, policy makers, and urban planners. A further contribution of the work is that it relies on crowdsourced SVI, a valuable but overlooked source of street-level imagery in the state of the art, being overshadowed by commercial sources such as Google Street View and Baidu.

2. Related Work

Till date, many studies have successfully employed semantic information from street view imagery to improve city planning (Crooks and See, 2022). Deep learning methods fall under a subset of wider approaches which employ SVI to study and improve the planning and design of urban systems (Biljecki and Ito, 2021). In general, SVI studies employing deep learning based methods can be segregated into two domains: 1) studies exploring tangible aspects of urban streetscapes; 2) studies mapping tangible aspects of the built environment to normative user perceptions.

Studies assessing the physical condition of urban spaces have a broad spatial coverage, ranging from the micro to macro scale in application. For example, Hara et al. (2012), Serna and Marcotegui (2013), and Najafizadeh and Froehlich (2018) extracted information on sidewalk quality to assess and propose design interventions to improve neighbourhood walkability. Towards understanding the relationship between shading and walkability, Middel et al. (2019) and Szcześniak et al. (2022) examine local conditions such as daylight accessibility in urban intersections and canyons while Zhou et al. (2019) developed an integrated visual walkability index (VWI) to identify walkable environments in the planning and design of healthy cities. As an extension into the temporal dimension, Li et al. (2022) utilised SVI to monitor changes in intersection-level marked crosswalks over a period of 14 years across the United States. Aside from walkability studies, Ito and Biljecki (2021) explore the potential of SVI indicators to assess urban bikeability. On a related note, Ding et al. (2021) show how SVI data can be used to map a network of cycling paths across various cities. Relating to street safety and scenery, Law et al. (2020) investigate frontage quality of streets and demonstrates applications for the Greater London area. These automatic visual assessments of the physical condition of cities can benefit numerous city planning efforts, not limited to, maintenance and large-scale mapping socio-spatial inequalities across urban areas. Aside from physical evaluation of cities, SVI can also be used to measure normative and socio-economic aspect of the urban: evaluating urban vitality (Gebru et al., 2017; Botta et al., 2020), measuring aesthetics of routes (Quercia et al., 2014), and predicting footfall along routes (Basu and Sevtsuk, 2022; Sevtsuk, 2021; Sevtsuk and Kalvo, 2022) . The real-time and long term prediction of urban human activity could benefit emergency planning situations.

Amidst rapid population ageing and an increasing emphasis on healthy cities, another active line of deep learning research investigates the multi-faceted relationship between urban greenery and walkability. Using large scale walking behaviour and SVI data, Lu et al. (2018) established that street greenery is as important as parks for promoting walking behaviour. In a recent study, Yang et al. (2021) show clear non-linearity between street greenery and walking behaviour. This finding is important and indicates that, though street greenery is beneficial, it has limits and does not substitute for good accessibility. In a similar vein, Lu (2019) shows that street greenery acts as a powerful driver to stimulate recreational physical activity, underlying its role in the realisation of healthy cities. On a global scale, Li et al. (2015), Li et al. (2017), Lumnitz et al. (2021), and Wu and Biljecki (2021) demonstrate the wide-scale scalability of deep learning based methods to analyse and map urban greenery across different geographical contexts.

An extension of physical assessment studies are those that aim to correlate tangible built environment indicators with user opinion. For example, Seresinhe et al. (2018), Ye et al. (2019), and Li et al. (2021), employ SVI and user information to qualify the quality of urban streetscenes. The incorporation of human perception could help bridge the gap between objective and normative concerns related to the planning and design of urban spaces.

Previous studies illustrate the increasing plausibility of an SVI oriented workflow for various urban analytical tasks. Our approach expands on previous approaches in three major ways: 1) we demonstrate the feasibility of embedding semantic information directly into urban networks, preserving the spatial fidelity of streetscape semantic information, 2) we employ the topological structure of networks as a basis to integrate SVI information with other open data sources (e.g. points of interest and origin-destination flows from OSM) for analytical purposes, and 3) we show that SVI studies can go a significant step further to optimise active mobility planning and cut across different considerations.

3. Methodology

Active mobility decisions are closely linked to urban environments (Pajares et al., 2021). For our study we adopt an operational definition of urban environments as defined by Silva and Pinho (2010), focusing on how urban environments affects travel choices. In this sense, urban environments can be measured in terms of tangible characteristics that enable or disable people's ability to fulfill daily travel needs. Our computational approach involves a network-based model which associates active mobility characteristics through edge-weighted indicators that are connected by nodes (Boeing, 2017a; Foti et al., 2012).

3.1. Data Selection and Screening

We employ Mapillary's Python Software Development Kit (SDK) to download and access crowdsourced street view imagery. Mapillary is a free, global crowdsourced open platform which provides high resolution SVI for cities and urban regions. Mapillary images are also empowered by a liberal CC-BY-SA 4.0 license which permits users to freely share and adapt images. While image distribution varies, Mapillary's coverage has penetrated most cities around the world with the number of high resolution imagery on the platform doubling from 500 million in April 2019 to 1 billion in December 2019 (Solem, 2019; Ma et al., 2019). The latest access point is provided by Mapillary API Version 4.0 which allows location-based query of image vector tiles. For use case analysis, we choose two sites located in Nerima city, Tokyo, and Pasir Ris estate in Singapore. For each site, we specify a two kilometres sampling radius (based on network distance) and extract two thousand images in each precinct (Figure 1). We

selected these precincts based on factors concerning image availability, residential land-use, and the availability of ageing amenities to support further analysis in our case study, but it is important to note that our study is applicable widely, as suggested by these two disparate study areas.

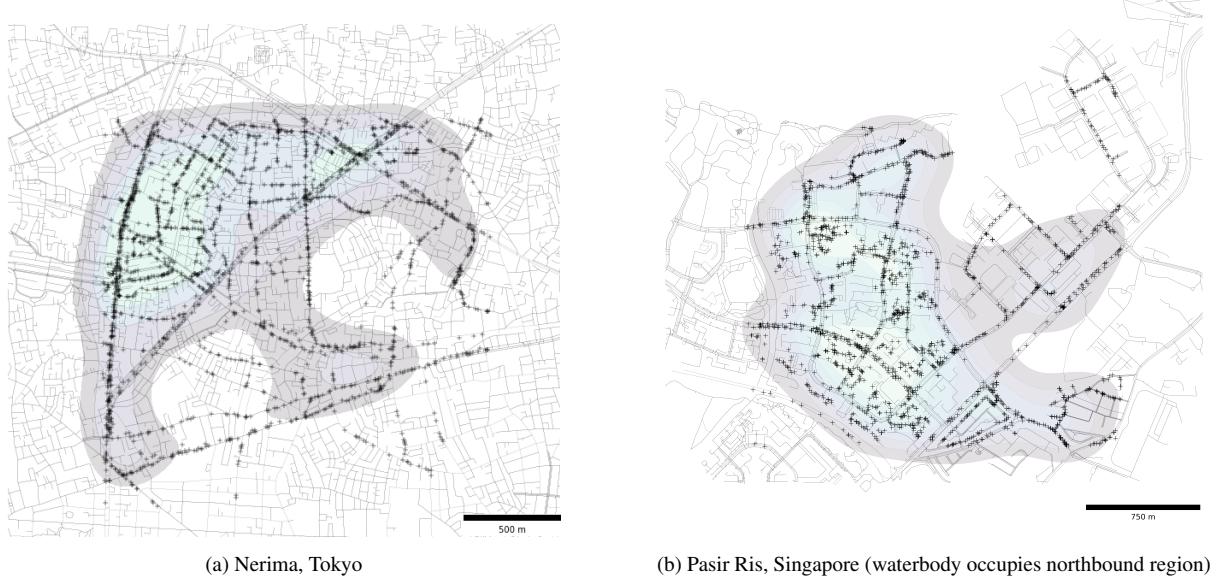


Figure 1: SVI locations and OpenStreetMap network. Data sources: (c) OpenStreetMap and Mapillary contributors.

We proceed to manually screen images to determine their suitability for inclusion. The challenges of working with crowdsourced imagery are documented by previous studies (Alvarez Leon and Quinn, 2019; Mahabir et al., 2020). Accordingly, we exclude images for the following main reasons: 1) quality (blurred or discoloured images); 2) narrow field of view (images with high degree of visual obstruction); 3) routes that are not accessible by pedestrians (e.g. highways or train tracks); 4) indoor environments. The selection process resulted in a final set of 3,777 geo-tagged images. The manual screening process of 4,000 images took a single researcher approximately three hours to complete. Though tedious, this should not pose a problem for practitioners to implement across multiple sites of interest. An overview of the image screening process is enumerated in Table 1.

3.2. Model Architecture

The landscape of deep learning is evolving at a rapid pace and there are as many deep learning model architectures as there are cities in the world. A recent comprehensive review of semantic segmentation datasets and models by Garcia-Garcia et al. (2017) found the "DeepLab" model architecture to be the most consistent and robust performer across all RGB channel datasets. We follow their recommendation and adopt the approach taken by Bulo et al. (2018) which consists of a DeepLabV3 segmentation head (Chen et al., 2017) trained on top of a WideResNet-38 model (Zagoruyko and Komodakis, 2016). The training procedure proceeds in a two-step manner. First, training hyper parameters (e.g. batch size, learning rate, image size) are optimised with the smaller (5000 images) Cityscapes SVI dataset (Cordts et al., 2016). To account for under-represented classes, a class-uniform oversampling strategy was further employed. Subsequently, the tuned settings were applied to the larger Mapillary Vistas (global research edition) dataset (Neuhold et al., 2017), training with 18,000 images and validating on

Table 1: Image screening process

Site	Nerima, Tokyo		Pasir Ris, Singapore	
	No. of Images	%	No. of Images	%
Initial Set	2000	100	2000	100
Excluded	74	3.7	149	7.5
<i>Poor Quality / Limited FOV¹</i>	16	0.8	52	2.6
<i>Obstruction</i>	11	0.6	16	0.8
<i>Indoor Image</i>	21	1.1	18	0.9
<i>Inaccessible (e.g. Highway)</i>	26	1.2	63	3.2
Final Set	1926	96.3	1851	92.5

¹ Heavily slanted, poorly lit, or images with narrow camera aperture were excluded.

2,000 images, yielding state of the art results with a mean Intersection over Union (mIoU) of 53.12%.

The wide residual network architecture employs larger layer depth to promote the learning of useful feature representations in each layer. This helps to mitigate well known issues such as the "diminishing feature reuse" problem which is commonly seen in narrow and deep model architectures. In addition, DeepLabV3 is well suited for segmentation of urban scenes as it is able to segment objects across multiple scales. The model achieves this through multiple atrous convolution layers that translates to an expansion in the effective receptive field for feature learning. Last but not least, the implementation by Bulo et al. (2018) offer several advantages over the original implementation. One notable change is the in-place activated batch normalisation layer which allows for significant memory savings through layer integration (up to 50%) at low (0.8-2%) computational overhead.

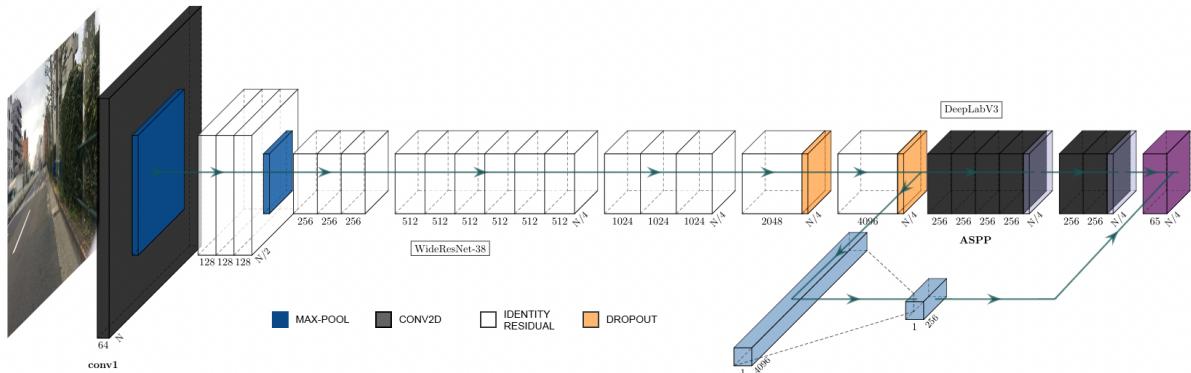


Figure 2: WideResNet-38 + DeepLabV3 schematic.

Our model is trained on the Mapillary Version 1.2 validation dataset which comprises of 65 semantic classes (Neuhold et al., 2017). Figure 3 displays examples of model predictions. As shown, the predicted image masks display a high degree of visual fidelity in mapping out objects in the original image. In some cases, the model manages to pick out street elements such as fences and manholes which are challenging for humans to spot.

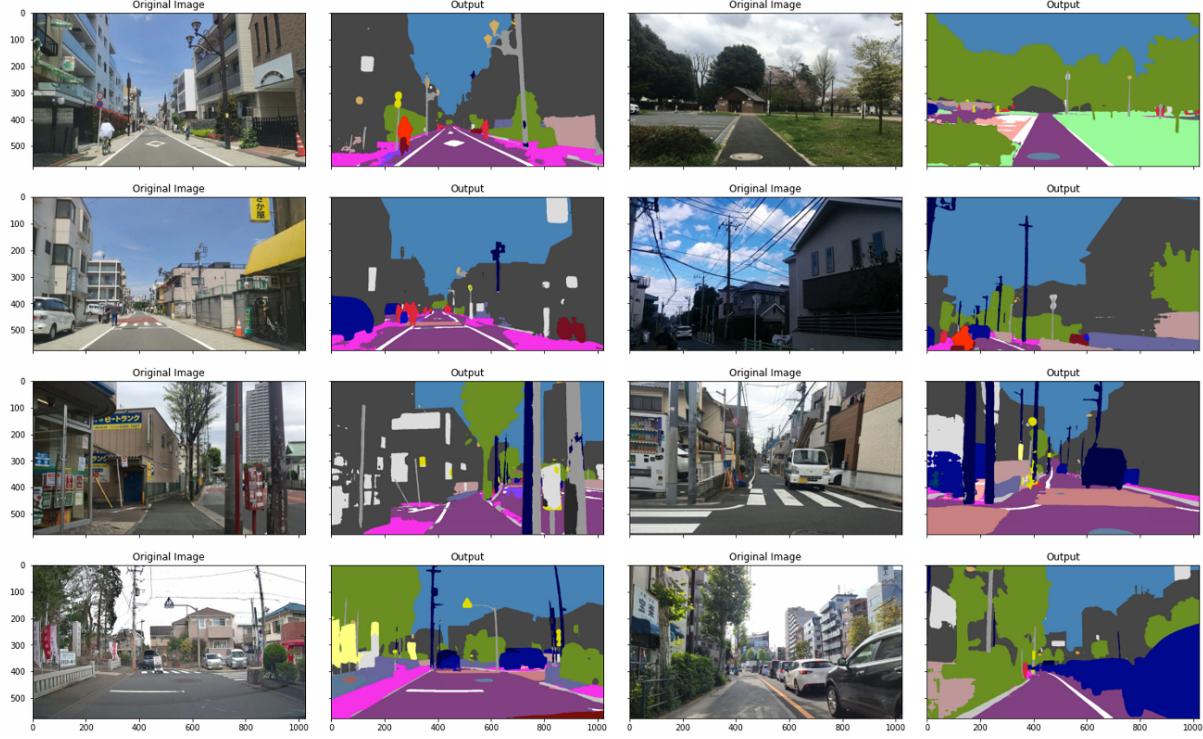


Figure 3: Examples of segmentation mask outputs.

3.3. Computing Active Mobility Indicators

The segmentation process was conducted on a Nvidia Geforce RTX 3090 GPU which took slightly less than two hours to segment all images ($N=3777$). We adopt a similar computational approach to previous work (Section 2) and compute indices as the pixel ratio between classes of interest and the total number of pixels for each image (Hara et al., 2012; Li et al., 2015; Zhou et al., 2019). Previous studies have demonstrated a strong positive relationship between urban greenery and active mobility (Tsai et al., 2019; Vich et al., 2019; Heikinheimo et al., 2020). Urban visual complexity of urban environments play an important role in influencing active mobility decisions (Johansson et al., 2016; Bornioli et al., 2019). Visual complexity has been recognised as a core component of urban design and refers to the amount of sensory information perceivable per unit time during travel (Ewing and Handy, 2009; Rapoport, 2013). Empirical evidence suggests that too much urban complexity might result in sensory overload for users (Cassarino et al., 2018; Grassini et al., 2019), while too little urban complexity might result in dull environments (Marshall, 2012; Desouza and Flanery, 2013). It is hence important to measure the amount of visual complexity, especially for highly dense urban environments. In this instance, we employ Shannon's theory of information entropy (Shannon, 2001) to measure the visual complexity of street view imagery. Intuitively, the indicator measures the amount of information in images where scenes with high number of visual elements (e.g. street infrastructure) that are proportionately distributed, correspond to high levels of visual complexity. Readers interested in the confluence of complexity and urban design are referred to (Boeing, 2018). As a caveat, we did not include other popular indicators such as sidewalk accessibility (e.g obstacles on pavements) and sky view factor. Street obstacle occurrences are often discrete and non-linear, limiting their interpretation to interpolation along networks. In addition, crowdsourced SVI images are not guaranteed to offer a clear, consistent view of sidewalks, making this use case unsuitable. On the other hand, while sky view factor (SVF) offers a natu-

Table 2: List of computed indices, definition, formula, and explanation

Indices	Definition	Formula	Explanation	Range
Green View Index	Visual extent of urban greenery for pedestrians	$G_i = \frac{G_n}{T_n}$	G_n is the no. of vegetation pixels T_n is the total number of pixels	[0, 1)
Visual Complexity Index	Visual extent of urban complexity for pedestrians	$C_i = - \sum_{i=1}^K P(x_i)(\log_b P(x_i))$	$P(x_i)$ is class probability for i-th class over K possible classes	[0, 6.02 [*])

^{*} Based on max entropy of K=65 classes with equal probability; can be interpreted as white noise. Maximum complexity empirically from our image set is 2.466 with 11 observable classes.

ral continuous interpretation along networks, it has been empirically shown to exhibit complex relationship with active mobility decision making (Li et al., 2018; Basu and Sevtsuk, 2022; Sevtsuk and Kalvo, 2022). Not discounting the importance of SVF, interpretations should be supported by further empirical and contextual data. Building on this understanding, we specify exposure to urban greenery and visual complexity as our target indicators of interest for use case analysis. Table 2 specifies the list of computed indices.

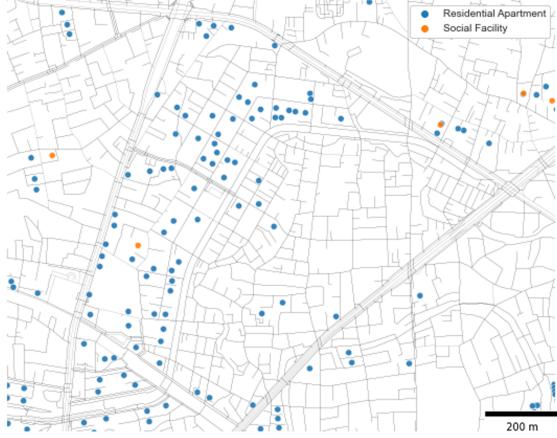
For case study analysis, we extract geometric features from OpenStreetMap (OSM). OSM is an open collaborative mapping platform that hosts the most comprehensive crowdsourced collection of urban geometric features, not limited to, building footprints, amenities, and street networks. We preprocess and automate network accessibility analysis with OSMNx (Boeing, 2017b) and Pandana (Foti et al., 2012).

4. Results

4.1. Case Study: Urban Greenery Exposure

There are many possible use cases for active mobility. We choose to focus on population ageing since it is an existential problem for society. Active mobility is an important strategy to improve population health and promote successful ageing in place (Loo and Lam, 2012; Hou et al., 2020; Song et al., 2020). With these considerations, we choose an urban precinct in Tokyo, Japan in the midst of rapid population ageing. Nerima is one of 23 special wards located in the Tokyo Metropolitan Region with a population count of 381,000 (Nerima City Hall, 2022). Currently, more than one-fifth of residents are aged 65 and above. Nerima is primarily a residential district and hosts a wide range of amenities for older adults. For our analysis, we pick five amenities within close proximity to residential apartments: clinics, social facilities, restaurants, libraries, and community centres. Figure 4 shows one possible combination of origin-destination (OD) flows between residential apartments and social facilities, and walking time throughout the network.

We proceed by embedding green view index (GVI) into the network. First, nodes with SVI information are geo-located and embedded into the street network. Subsequently, SVI information is distributed to all other nodes in the network based on a distance threshold and linear weight decay over edge distance (Foti et al., 2012). As a technical note, distance threshold will vary depending on data density as well as across different application and use cases. Figure 5a, the greenest regions of the neighbourhood lies along the western corridor and are located close to residential areas. However, a visual observation shows that the distribution of urban greenery among residential areas is quite uneven. For example, residential apartments located northbound enjoy less greenery.

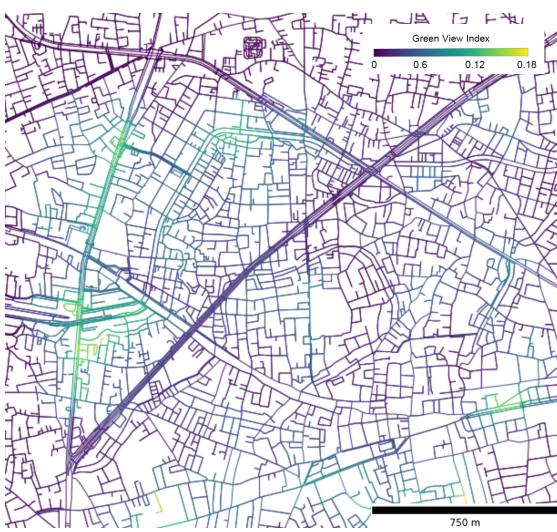


(a) Origin and Destination Locations.

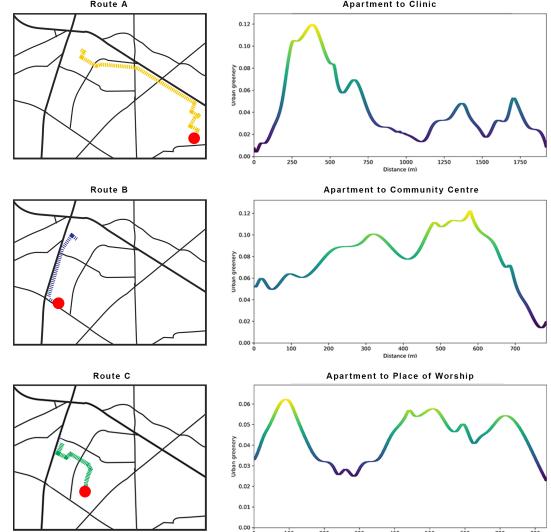


(b) Network Accessibility (walking time).

Figure 4: Example of origin-destination accessibility computation. Source: (c) OpenStreetMap contributors.



(a) Linear interpolation of GVI.



(b) Sample routes (red circle marks end).

Figure 5: GVI is unevenly distributed and appears to cluster along arterial roads at Nerima, Tokyo. Along sample routes, GVI tends to peak when traversing along arterial roads and is relatively lower for streets within residential neighbourhoods.

Ideally, urban greenery should be placed along paths where most users travel. While the number of possible paths in a network is possibly intractable (O^N where N is trip length), previous studies on older adult mobility have noted that travel patterns are highly correlated with destination type and availability (Loo and Lam, 2012; Lorenzo et al., 2012; Loo et al., 2017; Szeto et al., 2017; Wong et al., 2018; Song et al., 2020; Hou et al., 2020). On this basis, we scope our analysis to routes based on key amenities: clinics, social facilities, restaurants, libraries, and community centres. We chose these amenities based on OSM data availability and empirical evidence from earlier mentioned studies. However, the analysis conducted is extendable to any points of interest.

Figure 6 shows the relationship between the distribution of trips across all residential apartments to the nearest target amenity type and greenery. For pragmatic considerations, we report the top three shortest paths for each OD pair. This assumption makes reasonable sense as we

expect people to prioritise the shortest route while having some flexibility in their routing path. From Figure 6 we observe several notable patterns. First, the average exposure to greenery is higher on average for trips to community centres, social facilities, and restaurants. This finding is not surprising given that leisure related trips and urban greenery are often found to be jointly correlated with active travel. On the other hand, trips to clinics and libraries have less exposure to urban greenery which could signify a gap in urban greenery coverage since urban greenery can play a significant role in improving physical, social, and mental health for older adults. For example, a visual observation shows that trips to clinics experience significantly lesser greenery than trips to community centres. A two-sample Kolmogorov–Smirnov test validates the statistical significance of this comparison (value = 0.688, p-value = 4.43E-41).

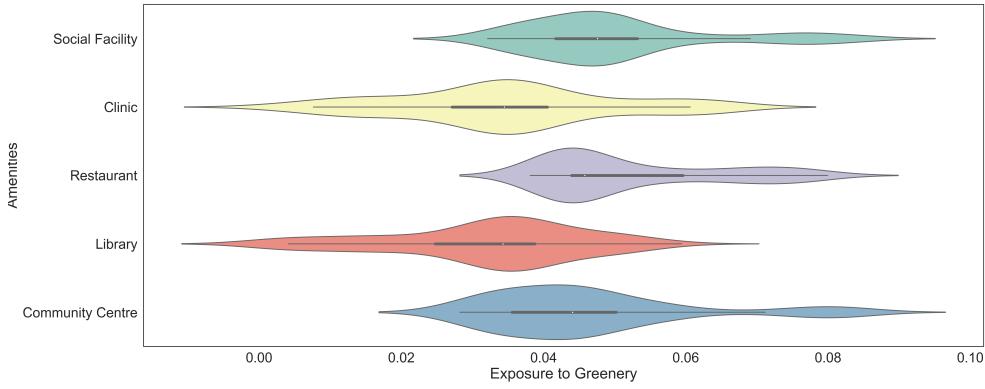


Figure 6: Distribution of greenery exposure exhibit clear differences across different amenity types. Mean greenery exposure for trips to clinics and libraries is significantly lower relative to trips towards social facilities, restaurants, and community centres.

Next we adopt a network topological approach to investigate urban greenery provision. Preferably, routes that are most commonly used by residents to access amenities should have higher greenery coverage than less frequently used routes. Based on shortest paths between all origin (residential locations) and destination (amenities) pairs, we aggregated the number of times each edge is traversed and plot the results. Our analysis is similar to the conventional computation of betweenness centrality in graphs but is applied to edges instead of vertices (Agryzkov et al., 2019; Sevtsuk, 2021). In addition, each edge is coloured by the average greenery exposure (accounting for edge length) to indicate the degree of greenery exposure along routes. Figure 7 shows the most commonly travelled edges between residential apartments and amenities.

The width of an edge indicates its spatial importance in the network. Edges with thicker margins correspond to street segments with many shortest paths (between OD pairs) traversing through them, vice versa. Looking at Figure 7, we can observe that street segments such as A and C have high greenery exposure but have fewer paths routing through them. On the other hand, street segments such as B experience the most movement traffic but have the lowest greenery exposure compared to other areas. Our findings suggest that the distribution of urban greenery in Nerima, Tokyo is currently not optimal and residents could benefit from efforts to increase greenery at targeted streets.

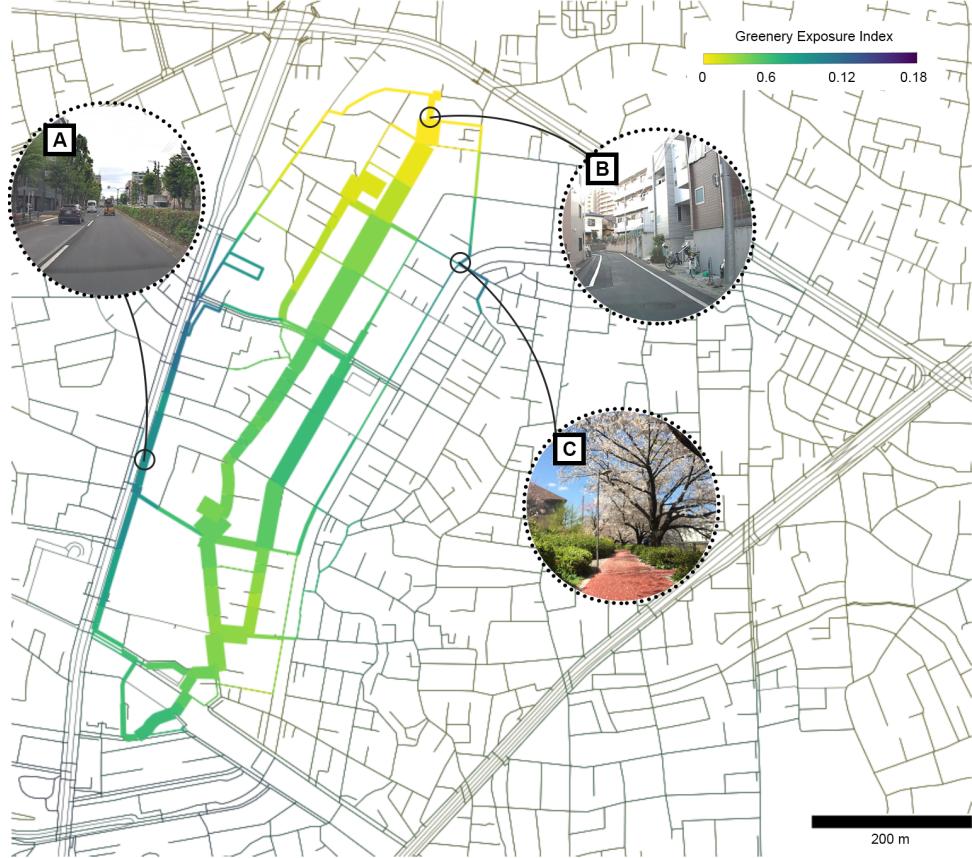


Figure 7: Network showing most used paths weighted by network betweenness and coloured by greenery exposure along edges. Despite being a route traversed often by residents to various amenities, site B has low greenery exposure relative to site A which appears to be a car-oriented street.

4.2. Case Study: Urban Visual Complexity

Given the close relationship between complexity and willingness to walk/cycle, it is important to measure the amount of visual complexity for dense urban environments. Visual complexity depends on many elements, not limited to, buildings, street furniture, traffic signage, human activity, and urban greenery (Gehl, 1987; Arnold et al., 1980; Jacobs et al., 1993; Botta et al., 2020; Ernawati, 2021). Streetscapes with more visual elements (e.g. street infrastructure) correspond to higher levels of visual complexity while scenes with less visual elements have lower visual complexity. In this regard, SVI provides an intuitive way to understand urban visual complexity of streetscapes.

Building on these considerations, we choose for our analysis, a dense urban residential district in Pasir Ris, Singapore. Pasir Ris is a mature town with total population of 144,610 residents and population density of 9615 people per km² (Department of Statistics, 2021). The residential population is young compared to other planning areas in Singapore with only 12% of its population aged 65 and above. To examine active mobility patterns among a younger demographic, we specify a mix of recreational (cafes, community centres) and essential (banks, places for worship, clinics, schools) amenities to generate OD trips. We follow a similar approach to the previous case study and embed visual complexity into the network through linear interpolation. One technical note for data pre-processing is that visual complexity is highly sensitive to image availability and areas with complexity of zero correspond to null instances. In other words, a value of zero for complexity implies that an image is filled entirely with only

one class. However, it is highly unlikely that urban scenes display only one visual class (e.g. all building or all sky). Therefore, we adopt an additional step to assign areas with null instances the mean complexity value for the entire site. This is a reasonable assumption as we found complexity values to be normally distributed across the site.

Figure 8a shows consistent patterns of visual complexity ($\mu = 0.79, \sigma = \pm 0.32$) throughout Pasir Ris estate. Notably, edges with high visual complexity are mainly situated within housing estates where footpaths and car parks are located. On the other hand, areas with low visual complexity tend to fall along roads along the residential estate periphery. The derived patterns confirm the close correspondence between travel speed and visual complexity (Ewing and Handy, 2009). Overall, our findings suggest evidence of a meticulously planned urban neighbourhood in Pasir Ris, Singapore.

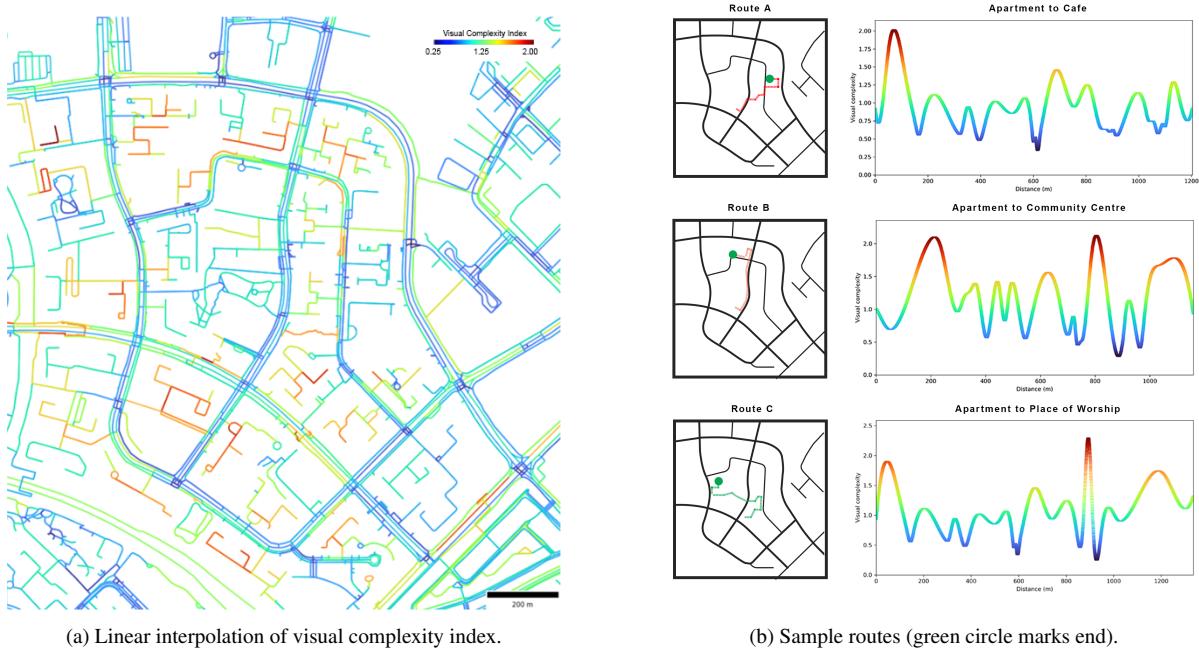


Figure 8: Visual complexity distribution at Pasir Ris is well balanced with high complexity within estates and low visual complexity along axial roads. Along sample routes, visual complexity exposure tends to peak within residential neighbourhoods.

As previously established, routes with well-balanced visual complexity (i.e., not too high or too low) are perceived as being ideal for active mobility. It is hence important to quantify the amount of visual complexity for targeted daily trip destinations. Figure 9 illustrates the distribution of visual complexity across trips from public housing apartments to the nearest target amenity type. Each row corresponds to an amenity type while each column translates to the mean visual complexity for the respective decile range.

We proceed to highlight several observations. First, visual complexity exposure is on the whole higher for trips to cafes, clinics, and community centres. This makes intuitive sense as cafes, clinics, and community centres are highly localised services and likely to be embedded within residential neighbourhoods. Another interesting observation we identified is the presence of distinct clusters based on visual complexity distribution. With the caveat that classifications tend to be complex and may be subjective, we found three patterns/clusters that have intuitive explanations:

Macro, Localised Amenities Amenities such as clinics and community centres serve the en-

tire urban precinct (macro) and can be found throughout the residential district. Trips are characterised by a well-spread, balanced range for visual complexity..

Macro, Peripheral Amenities Banking facilities in Pasir Ris are located at the periphery of the housing estate (along a primary arterial road). The distribution is characterised by consistent low visual complexity. For example, almost 90% of trips have mean value below the site average.

Meso/Micro, Localised Amenities Another identifiable distribution pattern is that for places of worship, schools, and cafes which show higher than average visual complexity. These amenities serve the meso and micro urban scales are located within residential estates that have high visual complexity.

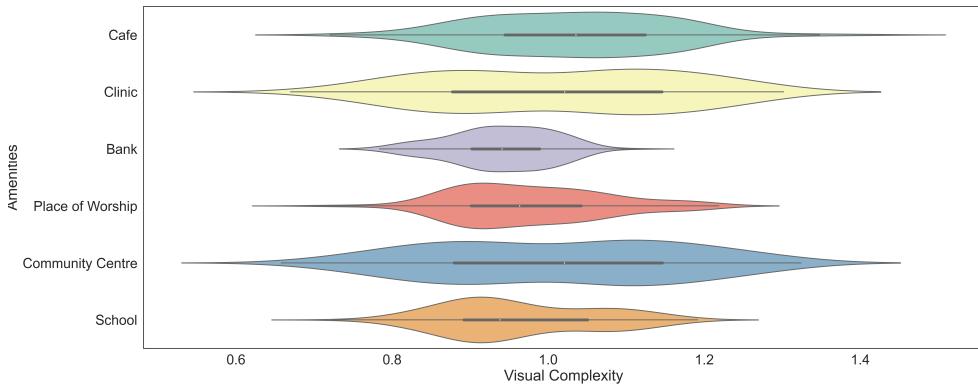


Figure 9: Distinct clusters can be recognised from the distribution variance between amenity types. Centralised amenities such as clinics and community centres exhibit the highest distribution variance since they are embedded within residential estates. On the other hand, banks have the lowest distribution variance as they are located at the site periphery (main road) where visual complexity is consistently low.

Overall, our finding indicates interesting patterns about visual complexity among travel to different amenity types. The varying patterns suggest that visual complexity is highly informative of user travel experience and its incorporation should benefit active mobility planning.

Lastly, we look into a place-based analysis of visual complexity and network edge importance. As illustrated in Figure 10, commonly used path generally have balanced visual complexity values throughout Pasir Ris. However, our analysis identified one well-used primary arterial road running from west to east of the site with strikingly high visual complexity (three standard deviations above the mean). A closer inspection of the site via Mapillary revealed many banners and traffic signs along the site. High visual complexity from ‘urban visual clutter’ has been found to be associated with higher traffic accident risk for pedestrians and drivers (Oviedo-Trespalacios et al., 2017; Tapiro et al., 2020). Our findings suggests that efforts to reduce the amount of visual stimuli at sites with high visual complexity could help to improve traffic safety and promote active mobility at Pasir Ris estate.

5. Discussion

An important gap in current active mobility research is limited understanding of how contextual information from streetscapes can contribute to planning efforts. Network-based SVI

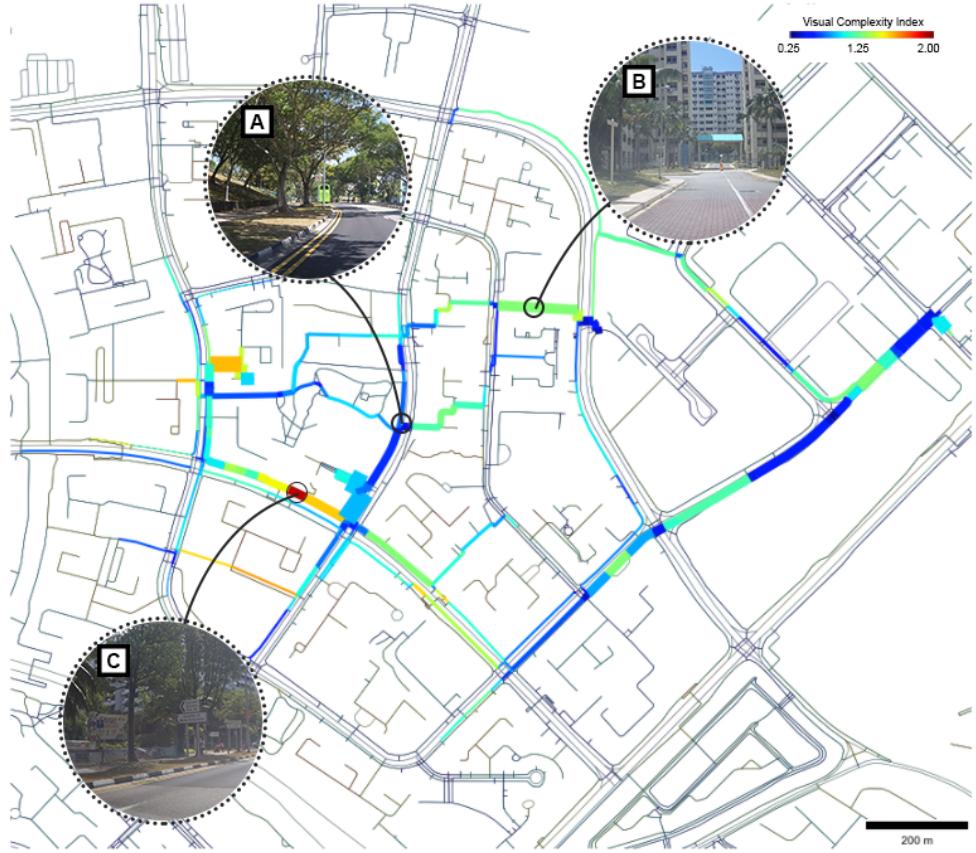


Figure 10: Network showing most used path weighted by network betweenness and coloured by visual complexity along edges. Sites within residential estates (e.g. Site B) tend to have higher visual complexity. Despite being located on an arterial road, Site C exhibits high visual complexity due to a large number of advertisements and traffic signs.

studies value-add to existing active mobility studies by allowing high resolution, context-based information to be incorporated into local planning decisions. In this work, we demonstrate that the combination of methods established in the fields of urban network science and deep learning can provide insight on this issue. By accounting for semantic information, it is possible to propose localised intervention measures and understand how streetscapes contribute to active mobility experiences for various use cases, population groups, and locations. Subject to data availability, our analysis can be replicated at any urban scale and is generalisable across urban contexts.

Our findings have four broad ranging implications for ongoing active mobility studies. First, it allows us to abstract away from our view of cities and urban areas as aggregated and static instances in space and time. As mentioned by Batty (2021), the Covid-19 pandemic has laid bare tensions and problems with urban analytical approaches treating urban phenomenon with a cross-sectional lens. For instance, the increasing dynamism and uncertainties associated with complex urban systems have challenged the validity of methods with low temporal frequency (e.g. population surveys at 5 or 10 year intervals). In particular, we have seen how presumably immovable patterns of urban mobility (such as the 9 to 5 rush hour) fade into oblivion. Subject to data availability, SVI-based studies can be implemented for any time period/interval and image collection for target sites can be completed within hours. Such analytical methods provide a powerful mechanism to monitor, detect, and compare urban change over time and addresses current gaps for evidence-based planning (Yap et al., 2022).

Second, we see crowdsourced SVI datasets like Mapillary playing an increasingly important role in global street view analysis. Compared to images from proprietary datasets (e.g. Baidu or Google), Mapillary images offer the following benefits: 1) hosted on a free and open platform which promotes liberal use and ownership, 2) images might be available for areas not covered by proprietary alternatives. In addition, images are high quality and vetted for quality, privacy, and consistency during the upload process (e.g. Mapillary automatically applies a CV pre-processing algorithm on each upload). Last but not least, the liberal license allows global deep learning datasets such as Mapillary Vistas (Neuhold et al., 2017) to be created and shared with the community.

Third, our findings extend applications related to the incorporation of visual semantic information of urban environments into networks. For active mobility studies, a paradox is often drawn between the need to contextualise interventions and the need to replicate analyses at numerous locations. However, geospatial computations are computationally expensive and scalability has been a longstanding area of research in geospatial-based studies (Lai et al., 2018; Murakami et al., 2019). Network-based methods are well-defined and developed, allowing for highly efficient data processing. This allows us to tap into the wealth of analytical tools, functionalities, and highly optimised workflows that have been developed in the network sciences (Liang and Kang, 2021; Liu and Biljecki, 2022). Moving forward, we expect networks to continue to grow in importance as a fundamental component of urban systems. A recent study by Zhang et al. (2022) demonstrates the utility of networks to evaluate optimality of active mobility trips. As the amount of urban data is expected to increase significantly in the foreseeable future, novel analytical methods to understand complex urban systems will likely demand near real-time learning and prediction to better support evidence-based planning and decision making (Kandt and Batty, 2021).

Last but not least, it is important to stress that the push towards more powerful analytical capabilities should not neglect the emancipatory goals of planning. As forewarned by Boeing et al. (2021), urban data and analytics warrant serious consequences for representativeness, privacy, and equity. The estimation of popularity of street segments based on network topology allows urban planners and practitioners to pinpoint highly accurate intervention sites without compromising user privacy. It is also transparent and straightforward to extend the method to promote equitable planning. For example, network POIs can be readily augmented with aggregated information (e.g. assigning higher importance values to rental housing units) to promote more equitable planning outcomes. To ensure representativeness, network estimates should be extended and calibrated with actual travel flow data where available. Analytical methods should thus be practiced with mindful criticality to avoid unintended consequences.

On limitations, data concerns and usability remain forefront. On usability, the lack of accessible tools continue to challenge our ability to conduct open science and reason with the complexity of our urban environments (Harris et al., 2017; Boeing, 2020; Poorthuis and Zook, 2020; Arribas-Bel et al., 2021; Anselin and Rey, 2022; Boeing et al., 2022). In particular, a significant chasm remains between the complex problems faced daily by planning professionals and the software solutions available to them. We believe that practitioners should not need to master a dozen software interfaces to solve a single task. On the bright side, all software and models used in our workflow are mature software with good documentation, clear installation instructions, and easy to follow tutorials. Nonetheless, there is a need for more integrative software solutions that recognise the multidimensional nature of urban problems (Yap et al., 2022).

Another key challenge is data availability. The analysis is dependant on the availability of

street view imagery as well as geospatial information of points of interest from OpenStreetMap. At present, extending the study to areas with poor data coverage is not possible without manual data collection. The unequal distribution continues to pose challenges for comparative studies in lesser developed regions (Ma et al., 2019; Mahabir et al., 2020). Another limitation is the noisiness of crowdsourced street view data. For example, images may be taken from vehicles, on bicycles, or via walking which provide various vantage points. There is currently also no standardised and automated way to check for unsuitable images aside from manual inspection (Juhász and Hochmair, 2016).

6. Conclusion

Bringing together innovations from the fields of network science and deep learning, we demonstrate the feasibility of an open analytical workflow which can produce interesting insights for active mobility studies. Towards realising healthy cities, our approach affirms the importance of semantic information from streetscapes for contextualising active mobility planning and decision-making.

The development of network-based SVI use cases and applications in active mobility studies is still in its early phases. Further research opportunities for active mobility include augmenting network analyses with open building data. Buildings share an intimate relationship with road networks, and are as much as networks, indicative of the hierarchical processes inherent in urban systems. On that note, the increasing availability and accessibility of large scale, high quality global building morphology indicators and footprints presents unique opportunities to improve our multi-scalar understanding of complex urban networks (Biljecki and Chow, 2022). Another area for further research includes bridging gaps in data distribution and inequality. More specifically, network-based structures can be used to fill existing data gaps by mapping relationship across correlated urban indicators. For example, one direction could be to employ semi-supervised learning algorithms (e.g. graph convolutional networks (GNNs) or generative adversarial networks (GANs)) for data translation tasks (Xu et al., 2018a,b; You et al., 2020; Wu and Biljecki, 2022; Zhao et al., 2022; Wang and Biljecki, 2022). Such learning have demonstrated huge potential to fill data gaps in under-represented regions. Last but not least, the increasing popularity of 360 degree panoramic street view imagery present opportunities to develop better contextual understanding of urban environments for active mobility. As an example, slope and surface pavement material could be assessed to determine risk of fallibility along routes. In this regard, this work is a novel attempt to bridge recent developments in network sciences and deep learning research, and contributes to the growing body of research underlying the potential of SVI to improve planning and design of cites. An additional contribution of this work is its use of crowdsourced SVI, an overlooked but growing and valuable source that we believe will become more common in urban studies in the future. Our work shows that for some use cases in urban studies, volunteered geographic information such as Mapillary can rival commercial sources such as Google Street View.

Amidst rapid urbanisation and population ageing, active mobility concerns will continue to grow in prominence. Moving forward, the integration between deep learning methods and network sciences provides opportunities to address new analytical demands that reflect rising uncertainties and dynamism in the study of complex urban systems.

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