

Research Paper

A city is not a tree: a multi-city study on street network and urban life

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HIGHLIGHTS

- Christopher Alexander's urban structural theory was tested empirically in four cities.
- Urban life was measured using Twitter, POI, and walking behavior data.
- Urban structure was measured using graph-analytics of street network data.
- Semilattice-shaped networks, measured in Meshedness Coefficient, is conducive to life.
- The same cannot be found for networks of "Living Structure" measured in Ht Index.

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ABSTRACT

Christopher Alexander, a British-American scholar, famously differentiated an old (natural) city from a new (planned) one in structure. The former resembles a "semilattice", or a complex system encompassing many interconnected sub-systems. The latter is shaped in a graph-theoretical "tree", which lacks the structural complexity as its sub-systems are compartmentalized into a single hierarchy. This structural distinction can explain, or perhaps determine "the patina of life" in old urban districts and the lack of such in new ones. Alexander's idea, although widely influential, remains contested for its lack of empirical support. Subsequent literature failed to distinguish the structural differences between the old and new cities in systematic ways, nor is his asserted structure-life relationship verified with rigor. This study aims to test Alexander's urban structural theory under a comprehensive research framework. We translated his constructs and premises into a mathematically testable form. The structural qualities of an urban street network, conceived as "semilattice", "complex network" and "living structure", were measured using graph-topological indicators. Urban life was captured using a combination of Twitter activities, Point-Of-Interests, and walking trips, aggregated at the district level. The structure-life relationship was tested statistically, after controlling for urban form and socio-demographic confounders, including land use, density, block size, parks, income, age, and demographics. This research design was implemented in London, New York, Hong Kong, and Gdansk. Our results support Alexander's early works that an old urban district contains more "semilattice" than new ones. This quality can be captured by Meshedness Coefficient, a graph-network indicator for a semilattice-shaped street network and a strong predictor for urban life. The same cannot be observed for "complex network" with consistency, and we found no independent associations between "living structure" and life, contrary to existing literature. The study shed light on the hidden relationships between urban spatial structure and behaviors, in both the virtual and physical world. We uncovered the British-American predilection of Alexander's theory, which is well-supported by observations

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in London and New York yet less so in Hong Kong or Gdansk, suggesting the need for a locally-sensitive approach. The analytical tools developed can be of value for planning research and practice.

1. Introduction

Christopher Alexander, a British-American scholar, formulated the relationship between urban structure and life in an article “*A City Is Not a Tree*” (Alexander, 1965). A natural (old) city differs from a planned (new) one by structure: the former is shaped like a “semilattice”, a mathematical term for a complex system encompassing large numbers of interconnected sub-systems; whereas the latter is structured in a graph-theoretic “tree”, compartmentalized into a single hierarchy. This structural difference explains why, or perhaps determines that a planned city lacks “the patina of life” and it is “entirely unsuccessful from a human point of view” (Alexander, 1965, p.1). He went on to assert a (lively) city cannot be planned, at least not in the modernist manner, since “they (the planners) cannot encompass the complexity of a semilattice in any convenient mental form” (ibid. p.16). Alexander’s structure-life theory was revisited and updated continuously throughout his career, such as “*Notes on the Synthesis of Form*” (Alexander, 1966), “*A Pattern Language*” (Alexander, 1977), “*A New Theory of Urban Design*” (Alexander, 1987) and more recently, “*The Nature of Order*” (Alexander, 2002), yet its key message remained largely consistent.

Alexander’s idea is of lasting influences over the last half-a-century. “*A City Is Not A Tree*”, along with “*A Pattern Language*” and “*A New Theory of Urban Design*” were listed among Cuthbert’s 40 classic urban design texts (Cuthbert, 2007), widely cited, taught, and followed by two generations of researchers and practitioners. Alexander was credited, in part, of inspiring New Urbanism, an urban design movement advocating for interconnected, compact network of streets over the fragmented cul-de-sacs, or dead-ends in the suburbs (Katz, 1993; Park and Newman, 2017). His work is often compared with Walter Christaller’s Central Place Theory of the quantity, the size and the location of human settlements in the discipline of economic geography (Brush, 1966), and the “Deep Structure” in Bill Hillier’s Space Syntax Theory, referring to the typological depth of urban spatial networks (Hillier, 1989; Davis, 2021). Alexander is considered by Michael Batty, an urban spatial data scientist, as “path-breaking” in revealing the complexity and diversity as the essential features of urban live (Batty, 2006; 2015); he is also regarded as “one of the founders of the emerging science of complex networks” by urban science scholar Luis Bettencourt (2016, p.48).

The scientific rigor of Alexander’s work remains contested. Stephen Marshall (2012) criticized “*A City Is Not A Tree*” as rooted in analogies and thought experiments, which have not been tested in systematic ways, while subsequent researchers tend to simply cite Alexander in outline without critical scrutiny. Gabriel and Quillien (2019) consider Alexander and the architectural and urban planning community largely failed to find scientific explanations for his intuitions to be taken seriously outside of the arts. Such failure, noted by Michael Mehaffy (2019), owes much to the artist-architects’ obsession in creating newness for its own sake. Dovey and Pafka (2016) argued that the pseudo-scientific tendencies of Alexander matters less, under the pretext that urban design knowledge is broader and cannot be reduced to numbers. Alexander’s structure-life relationship was rarely proven or falsified in empirical literature. A search of scholarly work published in the wake of Alexander yielded a trio of papers which tested his ideas partially (Mohajeri, French, & Batty, 2013; Jiang and Ren, 2019; de Rijke et al., 2020). Their findings were insufficient to settle the disputes in literature. Questions remained whether the asserted structural difference can be observed consistently between the natural (old) and planned (new) cities? Which Alexandrian structural qualities (and their mathematical expressions) are predictive of urban life? And to what extent is Alexander’s theory applicable across cultures and societies?

This study aims to test Alexander’s urban structural theory under a

comprehensive research framework. Our objectives are to 1) test whether there are systematic structural differences between old and new cities or urban districts, 2) statistically examine the structure-life relationships, 3) test the generalizability of his theory across geographical and cultural context. A cross-sectional research design was adopted in 168 urban districts in four cities: London, New York, Hong Kong, and Gdansk. The spatial structure of street networks in each district was measured using a trio of graph-network indicators, operationalized according to Alexander’s three major constructs: “semilattice”, “complex network”, and “living structure”. Urban life was measured using a combination of social media data, Point-Of-Interests (POI), and walking trips. The asserted structure-life relationships were tested using statistical control for urban form and socio-demographic confounders.

2. Relevant works

Recent advancement in street network and urban data analytics supports the revisiting of Alexander. His conception of urban structure has inspired a large body of quantitative literature, covering the field of mathematics, transport, geography, and urban sciences. His construct of urban life has also been captured by a wave of literature using “urban new data” obtained from social media platforms, mobile devices, and POIs, etc., although his key premises have rarely been tested empirically. Relevant literature is summarized in Fig. 1.

2.1. Urban structure and network analysis

“Semilattice” and “tree” were proposed by Alexander (1965) to describe the complexity of an urban system and the degree of overlapping of its sub-systems. At first, he presented the semilattice-tree dichotomy in set theory, which was later replaced with graph theory by Harary and Rockey (1976), the two mathematicians advocating for the graph-representation of urban structures using “links” and “nodes”, which has since become the mainstream approach. “Semilattice” can be measured by counting the number of loops in a network, and it can be conveniently computed using Meshedness Coefficient, a graph-theoretical indicator measuring the number of loops in a network as a proportion of the maximum allowable number (Buhl et al., 2004). The “tree” quality, in contrast, implies the lack of structural complexity and the absence of overlapping among sub-systems. It has been captured by the Treeness Indicator, defined as the ratio between the length of street segments not within a loop and those of the entire network (Xie and Levinson, 2007).

“Complex network” appeared in “*Notes on the Synthesis of Form*” (Alexander, 1966) and later in “*A Pattern Language*” (Alexander, 1977), referring to the convoluted, non-trivial features found in real-world networks. It has since been operationalized into many graph-topological indicators. Examples include Betweenness Centrality, a measure representing the role of a “node” in connecting others in its surroundings (Freeman, 1977), Closeness Centrality, the sum of the lengths of the shortest paths from a “node” to the rest (Rodrigue, Comtois and Slack, 2016), and many others such as Proximity and Integration (Porta, Crucitti and Latora, 2006). Alternative indicators were developed in transport literature to measure the complexity of a transportation network, including the proportion of three-way / four-way road intersections, cul-de-sacs (dead-end), or the average block size (Kerr et al., 2007). To date, complex network” remains an active domain of scientific research.

“Living structure” was coined in “*The Nature of Orders*” (Alexander, 2002), referring to a structure containing overlapping details across many levels of scale to form a coherent whole. Alexander regarded the

“living structure” as both a physical phenomenon and a philosophical view fundamental to life and beauty. His listed 15 qualitative properties from “levels of scale” to “contrast” to describe a “living structure”, and his list was substantiated by Nikos Salingaros (2018) using fractals, a concept for objects of repetitive patterns at increasing and decreasing scales. A mathematical classification of the “living structure” was given by Jiang and Yin (2014) based on the head/tail breaks, a method of dividing elements of a network into the “head” and “tail” using the arithmetic mean of a designated data value. This division continues until the distribution of “head” is no longer heavy-tailed. This method was further developed into the H_i Index, an indicator capturing the degree of skewed distribution of a network’s property, or “far more small things than large ones” (Jiang and Ren, 2019).

2.2. Urban life

Urban life, synonymously referred to as vitality, vibrancy, or liveness, is often viewed as an attribute of a place. As an outcome measure, urban life has been captured by a wave of recent literature in the domain of urban planning and geography. For example, Yue and Zhu (2019) measured urban vitality in Wuhan, China using social network review data, and they found vitality in association with density, mixed use, and accessibility indicators such as Betweenness Centrality and Closeness Centrality. Long and Huang (2017) studied POI and web-based review data and concluded that urban block size is negatively associated with urban commercial vitality. Alternatively, urban life has been measured using mobile phone data (de Nadai et al. 2016) or social media activities (Franca et al., 2015; Chen et al., 2019).

A more robust measure of urban life, which recently flourished in the field of urban studies, is to combine multiple evidence from both the virtual and the real world. Huang et al. (2021), for instance, studied the perception of city images using both geo-coded Instagram data and questionnaire. Johnson et al. (2019) studied the perceived benefits from urban greenspace using both Twitter dataset and semi-structured interviews. Wang et al., (2018) studied the perceived attractiveness of the Olympic Forest Park in Beijing using both social media and survey data; the above studies exposed the biases of the virtual world data and they suggested a combined approach. In a recent paper, Fang et al. (2021) constructed a multi-faceted measure of urban vitality using indicators of concentration, accessibility, livability, and diversity. Interestingly, they concluded that vitality associated positively with various street network

metrics such as connectivity and closeness, largely consistent with Alexander’s idea yet without citing him.

2.3. Street network and travel behaviors

The impact of street network on travel behaviors have been studied extensively in transport and health literature. Again, many overlapped with Alexander in inputs (street network) or outcomes (walking trips) without citing him. In general, researchers consider street network characteristics such as connectivity, network density, and patterns, contribute positively to walking, biking, and transit ridership (Marshall and Garrick, 2010). In particular, walking is positively correlated with land use diversity, intersection density, and the numbers of destinations within walking distances, while public transit usage positively associated with the proximity to transit and street network patterns, with land use diversity as a secondary factor (Ewing and Cervero, 2010). A well-connected street network is found to promote walking, while poorly connected ones promote driving (Oakes, Forsyth and Schmitz, 2007; Berrigan, Pickle and Dill, 2010), although a large proportion of observations were made in the British-American context. In a global-scale analysis, Barrington-Leigh and Millard-Ball (2019) cautioned that the associations between street network attributes and travel behaviors may not be universal, and a place-based approach is necessary.

2.4. Empirical testing

Alexander’s premises and constructs have rarely been tested empirically, despite repeated calls for doing so (Marshall, 2012; Gabriel and Quillien, 2019; Mehaffy, 2019). A survey of academic publications yielded a trio of recent publications which tested Alexander partially. de Rijke et al. (2020) studied the graph-network properties of six cities and concluded that old (natural) cities, notably Amsterdam, Rome, and Geneva, contained more “living structure” than new (planned) ones such as Chandigarh, Levittown, and Brasilia. Their study did not, however, measure urban life; nor was their choice of the six cities sufficiently justified to rule out possible selection biases. In another study, Mohajeri, French and Batty (2013) analyzed the evolution of London’s street network over two centuries. They found more “loop-like” structures in historical London boroughs and more “tree-like” structures in new ones, hence partially supported Alexander, although they have not studied urban life either. A third study by Jiang and Ren (2019) measured both

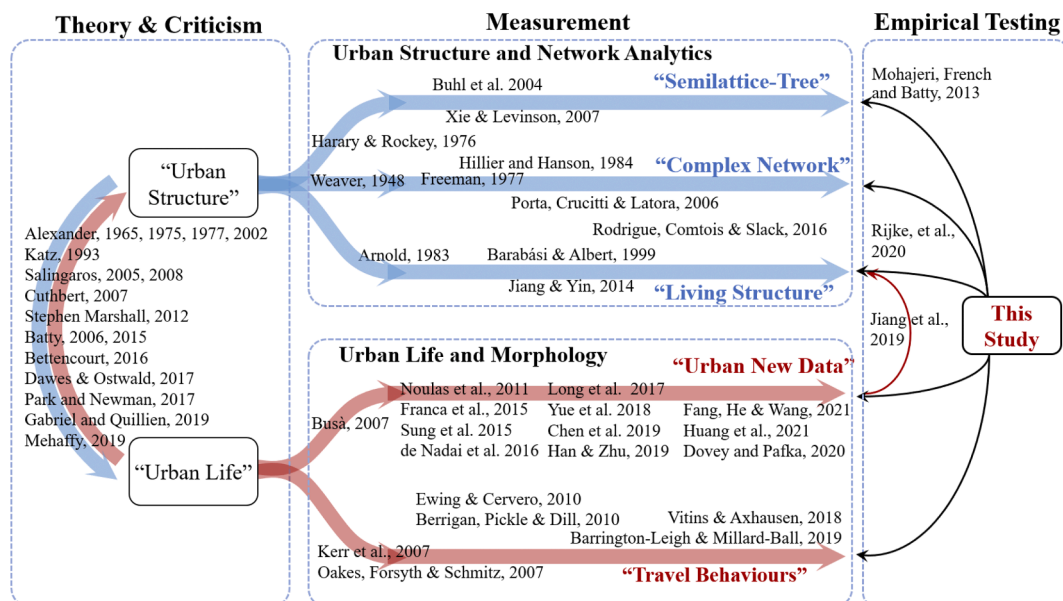


Fig. 1. A summary of literature related to the Alexander’s theoretical constructs, measurement, and empirical testing, relative to the scope of this study.

urban street networks and Twitter activities, a proxy for “urban life”. They found that H_t Index, a mathematical indicator for “living structure”, can predict the location of geo-coded tweets in the UK in support of Alexander, although their analysis failed to statistically control variables such as density, land use, social and demographics, begging the question of whether the H_t Index is independently associated with “urban life” or in interaction with confounders.

3. Research gaps

The following knowledge gaps remained concerning Alexander’s urban structural theory:

First, existing literature failed to distinguish the structural differences between the old and new cities in systematic ways. One can argue that, by common sense, street networks are perhaps more fragmented in newly built suburbs and more inter-connected in historical city centers. But these evidence suffer from the lack of a counterfactual, that is, whether such structural differences can be consistently observed between an old and a new city that are similar in every other aspects.

Second, his asserted structure-life relationships have not tested with statistical rigor. Existing evidence fell short of determining whether the structure-life relationships are independent of or in interaction with urban form and socio-demographic confounders. Each of his construct (i.e., “semilattice”, “complex network”, “living structure”) has been substantiated and operationalized by his followers (Salingeros, 2005; Jiang and Ren, 2019; Mehaffy, 2019), although without consensus over which construct ‘behave’ in consistency with his premise.

Third, the generalizability of Alexander’s theory across cultures and societies remains unclear. His writings drew heavily upon British and American cases, where he spent most of his academic career, while his idea has been tacitly accepted as universal, exemplified by numerous urban planning and design case studies, and by his own built work from Japan to Mexico. We note with caution, however, that it is hard to imagine how any of the above could inform the external validity of Alexander in any meaningful way.

There is a need for a comprehensive, multi-city study to test Alexander’s urban structural theory. Such a study will not only help resolve the ongoing theoretical disputes over a classic text, but also enhance its relevance for contemporary cities and planning practices. Evidence collected from multiple cities can shed light on the external validity of Alexander’s theory across cultures and societies.

4. Methods

We translated Alexander’s theory into a mathematically testable form. His key constructs were measured using a variety of performance and graph-network indicators. We used statistical models to test the life-structure relationships and the structural differences between old and new cities or districts. The above research design was adopted in four cities: London, New York, Hong Kong and Gdansk, where empirical datasets of behaviors and street networks have been compiled and analyzed.

4.1. Empirical translation of Alexander

A testable form of Alexander’s theoretical premise is provided in Eq. (1), in which urban life is expressed as a function of urban structure, urban form and socio-demographic conditions.

$$L = f(S, U, E, D, e) \quad (1)$$

where L stands for the “patina of life”, measured in Twitter activities, POI, and walking trips; S represents urban structural indicators, operationalized following Alexander’s constructs of “Semilattice-Tree”, “Complex Network”, and “Living Structure”; U represents confounding urban form conditions, such as density, land use mixture, block size, and

parks. E & D represent the socio-demographic characteristics; e is the unmodelled error term.

A conceptual framework is then derived according to the above (Fig. 2), with blue arrows specifying the hypothesized relationships between urban life and urban structure.

4.2. Measuring urban life

We used three data sources, namely Twitter, POI, and walking trips, to capture the “patina of life” or the multi-faceted human-built environment interactions.

Twitter is a popular social media platform which allows users to communicate in concise, instant messages about life events (Lau, Collier and Baldwin, 2012). It is also popular among researchers as a data source to capture the intensity of human activities, since Twitter data (tweets) are accessible from the public domain by default. We used Twitter API, a computer program interface (Morstatter et al., 2013) to exhaustively retrieve tweets in each city within a predefined bounding box, marked by the longitudinal and latitudinal coordinates of the lower-left and upper-right corners (see Fig. 4). The retrieved tweets contain text, user ID, time stamp, and, for a proportion of users who enabled the location sharing by default, the location of the mobile device from which the tweet was sent. The range of accuracy for GPS-based smartphone positioning is supposedly <5 m under an open sky, or up to 30 m in a density city (PNT, 2008), sufficient for our study purposes. The original Twitter database were cleaned by removing repetitive tweets and those from fake accounts. Tweets containing GPS coordinates from mobile devices were geo-coded using ArcMap 10.4 software. For each district, the density of geo-coded tweets (T_{den}) can therefore be computed by dividing the number of geo-coded tweets by its area.

Point-Of-Interest (POI) refers to an umbrella category of destinations, from tourist attractions to local community amenities such as restaurants, library, community centers. It is often used as a proxy for human activities, since its presence depend on and generate pedestrian traffic (Zukin, 2010; Yue & Zhu, 2019). We used the density of POI per square kilometer (P_{den}) to measure urban life, computed by dividing the POI count by the area of the district. The POI databases in the four cities were acquired via OpenStreetMap (OSM), an open access digital platform enriched by millions of contributors (OSM, 2019). The database covers a range of destinations from landmarks, e.g., the Empire State Building in Manhattan, New York to corner shops in London’s West End.

Walking trip reflects the intensity of people “walking from place to place” in Alexander’s remarks (Alexander, 1965, p.14), and it is another accepted proxy for “urban life” in research literature (Sung, Lee and Cheon, 2015; Yue and Zhu, 2019). We computed the area-weighted density of walking trips (W_{den}) according to Eq. (2) below.

$$W_{den} = Dw_{den} * 100 * W_{perc} * W_n \quad (2)$$

where Dw_{den} is the dwelling density (people / km²); W_{perc} is the percentage of trips carried out on foot, and W_n is the number daily trips per person, all acquired from official travel demand survey databases.

4.3. Measuring urban structure

Following the graph-theoretical approach specified by Steadman (2004), we represented the structure of a real city using a mathematical graph consisted of “nodes”, i.e. a street intersection or a dead-end, and “links”, the street segments. By street, we refer to a public road accessible to both vehicular and pedestrian traffic, therefore excluding private roads, hiking trails, or bicycle tracks, etc. The street network database for each district in the four cities was prepared in the following procedure. First, road network databases were acquired from official sources (Section 3.5); Redundant road segments and traffic islands were removed; fragmented road polylines were joined together. We removed the “pseudo node”, a type of node connected by only two adjacent links;

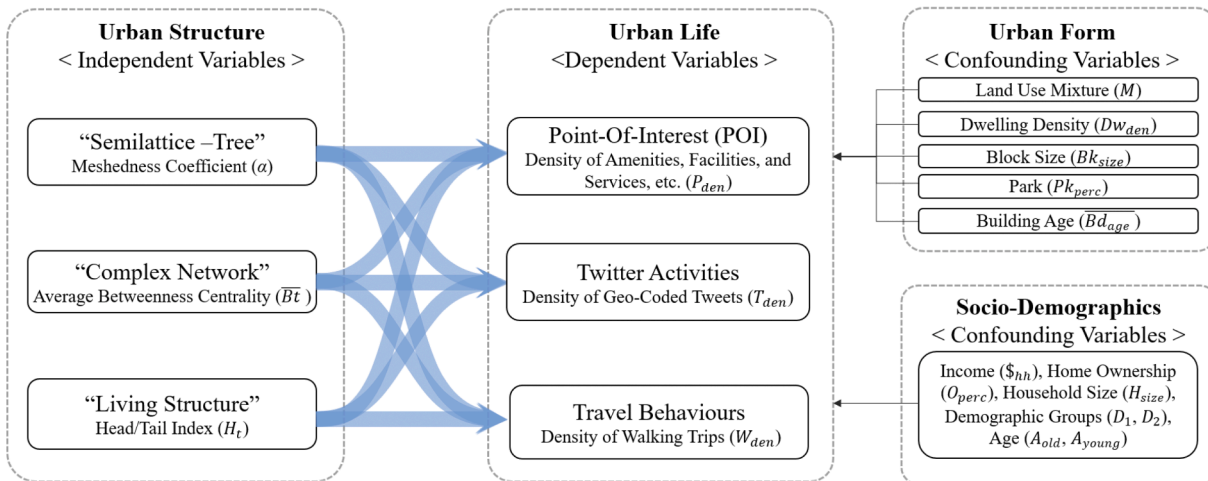


Fig. 2. A conceptual framework for testing Alexander’s theory on urban structure and urban life.

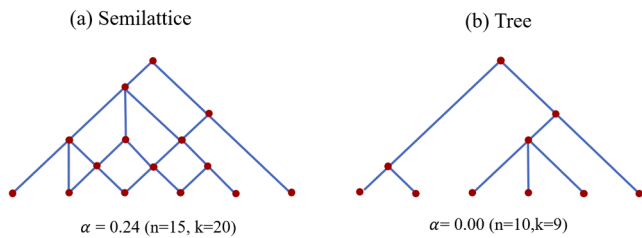


Fig. 3. (a) A “semilattice” network with redundant connections and loops ($\alpha = 0.24$). (b) A “tree” network without loops ($\alpha = 0.00$).

we then re-joined the remaining two links together using the “Unsplit” command in ArcMap 10.4 software. Other loosely connected street segments were also checked and fixed. The above procedure was implemented using the sDNA software (Cooper, 2013) and automated in Python. For quality assurance, the results were independently checked against Google Street Map by two trained researchers. The prepared database was then used to compute network indicators below.

The “semilattice” quality was measured using Meshedness Coefficient (α), a graph indicator to describe the overlaps and redundancy in a network, following the equations developed by Buhl et al. (2004) and later by Rodrigue et al. (2016). α is a normalized value between 0 and 1, with a larger value suggesting a “semilattice”, while a smaller α implies a “tree” (Fig. 3). A mathematical expression of α is provided in Equation (3), where n and k are the number of nodes and links in the network, which were computed using the “Network Dataset Function” in ArcMap 10.4 software; u and v were the current and the maximum possible number of loops in the network, which were expressed using the Euler characteristic (Spanier, 1981) as $k - n + 1$ and $2n - 5$ respectively.

$$\alpha = \frac{u}{v} = \frac{k - n + 1}{2n - 5} \quad (3)$$

The “complex network” quality of a street network was measured using node-based betweenness metrics. We used the Average Betweenness Centrality (\overline{Bt}), defined as the arithmetic mean of Betweenness Centrality (Bt_i) of a total of n nodes across a network, and it is expressed in Eq. (4). \overline{Bt} has been used to measure the interactive relationships within a network (Ding et al., 2015). A high \overline{Bt} value suggests a complex, highly connected network with intense traffic flow, and possibly intense “urban life”. For walking trips, we adopted an analysis radius of 600m in accordance with literature (Calthorpe, 2004). The above computation was implemented using ArcMap 10.4 and sDNA software.

$$\overline{Bt} = \frac{\sum_{i=1}^n Bt_i}{n} = \frac{\sum_{i=1}^n \sum_{x=y \neq z} \frac{6_{ij}(i)}{6_{ij}}}{n} \quad (4)$$

The “living structure” quality were measured based on the presence of fractals across various levels of scale in a street network. We adopted the H_t Index (H_t), a mathematical indicator developed by Jiang and Yin (2014), which classifies the degree of heavy-tailed distribution of node-based betweenness in a street network. H_t was computed following the approach outlined in the same work: all nodes in a given street network were first ranked according to their betweenness values (Bt_i), from large to small; the list was then divided in two using the mean Bt_i value as a threshold. The “head list” contains nodes with above-average values, while the rest belonged to the “tail list”. At each scale, if the length ratio between the head and tail list was smaller than 0.4, this meant there were “far more small things than large ones”, and the head/tail break calculation would repeat using the head list at the next scale, or it would stop otherwise. H_t was the number of times the head/tail break calculation had been repeated. We automated the above workflow using a script written in Python.

4.4. Confounders and statistical analysis

Human activities tend to interact with confounding urban form and socio-demographic variables, as suggested by literature at length (Jacobs, 1961; De Nadai et al., 2016; Ye, Li, & Liu, 2018; Lu, 2019). These confounders have been calculated in the following steps and controlled in statistical analysis.

Land use mixture (M) was computed using Shannon’s entropy (Eq. (5)) based on official land use databases. M is denoted as a function of the area of land use category i as a proportion of the total area of the district (P_i) and the number of land use categories (n). In this study $n = 4$, including residential, commercial, manufacturing, and park land.

$$M = - \sum_{i=1}^n \frac{P_i * \ln P_i}{\ln(n)} \quad (5)$$

Dwelling density (Dw_{den}) was computed using the total population divided by the area of the district. **Block size** was measured using the density of street network intersections (Bk_{size}) in each city district. Bk_{size} was calculated using the number of street intersections divided by the area of the district, the higher its value, the smaller the average block size in the district. **Park** has been associated with urban vitality, especially walking behaviors in a number of studies (Ball et al., 2001; Sung, Lee and Cheon, 2015; De Nadai et al., 2016). Park coverage (Pk_{perc}) was calculated as the percentage of the park land in the district.

Socio-demographic confounders include **Mean Household Size**

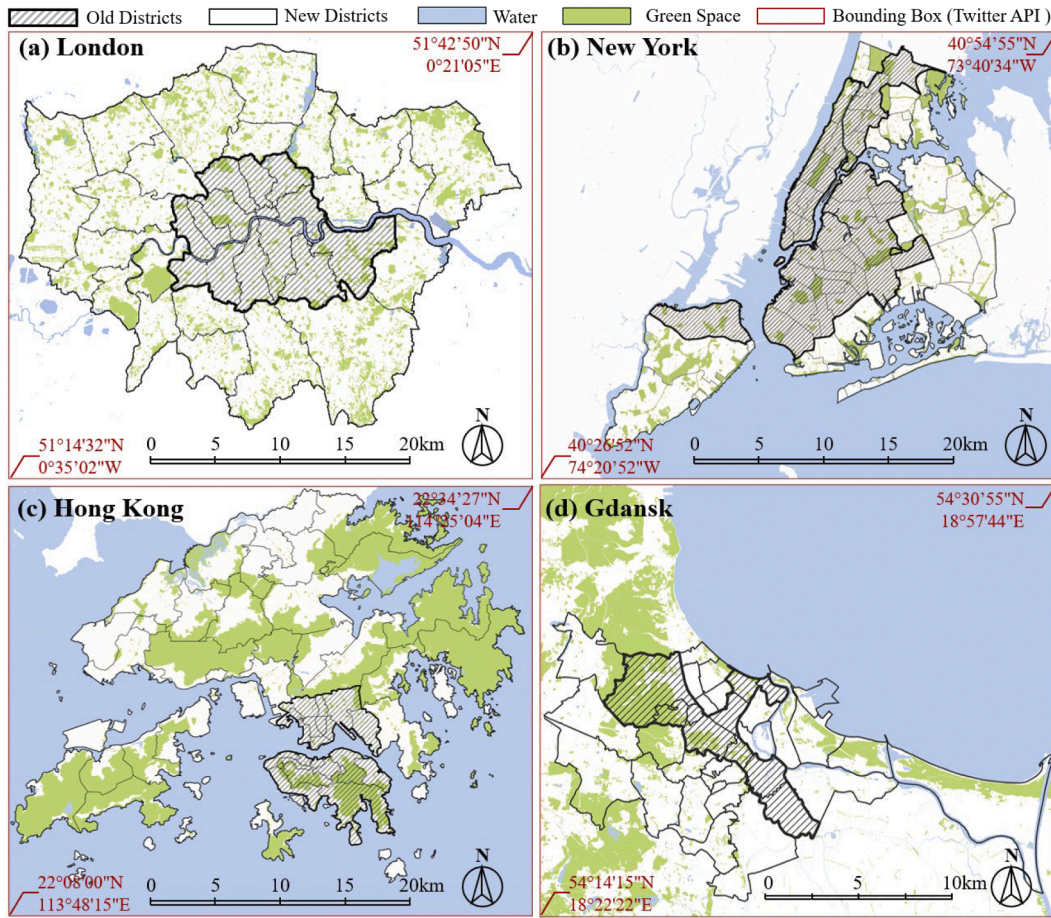


Fig. 4. Map of (a) Greater London, (b) the City of New York, (c) Hong Kong SAR, and (d) the City of Gdansk with the coordinates of the geographical bounding boxes for Twitter data-mining and borders of urban districts. The old districts are differentiated from the new ones according to local planning documents.

(H_{size}) measured by the number of persons in each household, **Median Household Income** ($\$_{hh}$) per annum (converted to US dollars), **Home Ownership Percentage** (O_{perc}), the percentage of households owning homes, **Demographic Groups**, the percentage of population in the top-two demographic groups (D_1, D_2), depicted by ethnicity in London and New York, or linguistically in Hong Kong and Gdansk, and **Age Groups** measured by the percentages of the elderly (A_{old}) and the young (A_{young}) population. The relationships between urban structure and urban life were tested using a multivariate Ordinary Least Squares (OLS) regression model shown in Eq. (6).

$$L = \beta_0 + \beta_1 S + \beta_2 M + \beta_3 Dw_{den} + \beta_4 Bk_{size} + \beta_5 \overline{Bd}_{age} + \beta_6 \overline{Bd}_{stdv} + \beta_7 Pk_{perc} + \beta_8 H_{size} + \beta_9 \$_{hh} + \beta_{10} O_{perc} + \beta_{11} D_1 + \beta_{12} D_2 + \beta_{13} A_{old} + \beta_{14} A_{young} + \mu \quad (6)$$

where the dependent variable L represented urban life indicators ($T_{den}, P_{den}, W_{den}$); S was the street network indicators ($\alpha, \overline{Bt}, H_t$); $M, Dw_{den}, Bk_{size}, \overline{Bd}_{age}, \overline{Bd}_{stdv}, Pk_{perc}$, were confounding urban form conditions; $H_{size}, \$_{hh}, O_{perc}, D_1, D_2, A_{old}$ and A_{young} were the socio-demographic confounders; $\beta_0 - \beta_{14}$ were the intercept and regression coefficients; μ was the unmodelled error term. Assumptions of the OLS regression were checked robustly. The data distribution of each variable above was checked against a normal distribution curve. Multicollinearity diagnosis for each independent variable was performed using the Variance Inflation Factor (VIF) (Thompson et al., 2017). We also checked the spatial autocorrelation of the OLS regression using Moran's I (Moran, 1950), implemented using the spatial regression package `sgl62` (Pisati, 2001) and STATA MP/16.1 software.

The above OLS regression was performed for each city and all four

together. The structural distinctions between old and new districts were tested on “semilattice” (α), “complex network” (\overline{Bt}) and “living structure” (H_t), using t -test.

4.5. Study locations, data and sources

Our research design was implemented in New York, London, Hong Kong, and Gdansk, four metropolises with relatively developed street network, data accessibility, and digital infrastructure. All ranked high in smartphone penetration and social media usage (Go-Globe, 2015). The choice of the four cities allows us to test the generalizability of Alexander: London and New York frequently appear in Alexander's writings and both are typical of what German geographer Burkhard Hofmeister (1970) referred to as “Anglo-American” cities. Hong Kong and Gdansk were never mentioned by Alexander, although Hong Kong can be marginally related to the Anglosphere due to its colonial history.

The unit of analysis was the urban district, although named differently in each city. We divide the total of 168 urban districts in four cities (excluded two sparsely inhabited ones in Hong Kong) into the “old” and “new” by local plans (Fig. 4)

Greater London (London) ($51^{\circ}30'N$ $0^{\circ}5'W$), the largest metropolitan area in the UK, covered an area of $1,596 \text{ km}^2$ and accommodated a population of 8.2 million. London consisted of 33 Local Authority Districts (LAD) designated by the UK Parliament (1963), each measuring some 50 km^2 in land area and 220,000 residents on average. The “natural” and “planned” cities in London were distinguished according to the 1944 Greater London Plan (ACO, 1946), which had transformed London into “. a large number of communities, each sharply separated from all adjacent communities... The structure is a tree” (Alexander, 1965, p.6).

Road centerlines and travel mode choice data were obtained from Transport for London (TfL, 2019); land use and open space databases were obtained from the Office of National Statistics (ONS, 2010); demographic and economic information, including population density, household income, home ownership, ethnicity, etc., were acquired through the Greater London Authority (GLA, 2018).

The City of New York (New York) (40°42'N 74°00'W) was the largest city in the USA. It covered an area of 777 km² and it was home to a population of 8.4 million. New York consisted of 59 Community Districts, each measuring 13 km² in land area and hosting 140,000 people on average. New York's historical districts, designated by the Regional Plan of New York and Its Environs in 1929 (CRPNYIE, 1929), were located mostly in Manhattan and Brooklyn, while newer districts were in Bronx, Queens, and Staten Island (Fig. 4 (a)). Road centerline data were obtained from official sources (NYC OpenData, 2017). Travel data were collected from the city's 2019 report of Citywide Mobility Survey (DOT, 2019). Land use, and open space information were acquired from the Primary Land Use Tax Lot Output (PLUTO™) data (DCP, 2020). Household income data were acquired from the 2018 American Community Survey (US Census Bureau, 2020); demographic data were acquired from New York City Government Department of City Planning (DCP, 2018).

Hong Kong Special Administrative Region (Hong Kong) (22°18'N 114°12'E) was a vibrant metropolis in Southern China, covering a land area of 1,106 km² and home to 7.1 million residents (HKCSD, 2017). Hong Kong consisted of 44 Secondary Planning Unit (SPU) (HKPD, 2017), each accomodates some 170,000 people and covers 22 km² of land on average. The two sparsely inhabited SPUs (# 81 & 91 of remote islands) were excluded from analysis. The "old" districts are located mainly on the Hong Kong Island and Kowloon Peninsula (Loo and Chow, 2008), while newer districts consist of new towns in the New Territories. The two sparsely inhabited SPUs, #81 and #91, were atypical of Hong Kong's urban conditions and they were dropped from analysis.

The City of Gdansk (Gdansk) (54°22'N 18°38'E) was a large city in Northern Poland, covering an area of 263 km² and home to a population of 470,800 (COGD, 2020). The city consisted of 34 administrative neighborhoods, each measuring 6.7 km² in land area and 12,800 in population on average. Gdansk's historical urban core dated back to the Middle Ages (Lorens, Kamrowska-Zaluska & Kostrzewska, 2014), while the new growth started after the WWII. The "old" districts were

demarcated using the Protected Historical Neighborhoods designated by the municipality (GDA, 2018). Databases of road centerlines, demographics, land use, parks, and walking behaviors were obtained from official sources (NCGCD, 2020; GDA, 2016).

5. Results & discussion

We analyzed datasets from the four cities. Results are discussed relative to Alexander's theoretical premises, constructs, generalizability and practical implications.

5.1. Data characteristics

The indicators for urban life, structure, urban form and socio-demographic confounders are summarized in Table 1. We acquired 151 million tweets within the bounding boxes covering the four cities between May 2016 and December 2018. Some 20 million tweets contained mobile GPS coordinates. After extensive cleaning, 2.5 million can be geo-coded within the boundaries of the 168 districts. We retrieved 227,805 geo-coded POIs from OSM in the 168 districts.

New York had the highest Twitter, POI, and walking trip densities, whilst Gdansk's were the lowest. Structure-wise, New York had the highest α at 0.38 and London had the lowest α of 0.16. London and Gdansk had the highest and lowest values in \overline{Bt} and H_t . Hong Kong had the highest dwelling density of 21,000/km², contrary to the lowest of 3,790/km² in Gdansk. Income was the highest in New York and lowest in Gdansk. Percentage-wise, Gdansk had the most elderly population (16% >65), while New York had the largest share of young people (22% <18). Home ownership was higher in Hong Kong and Gdansk (>=50%) and lower elsewhere.

5.2. Distinguishing old districts from new ones

We found more "semilattice" and "complex network" qualities in old urban districts than in new ones. Fig. 5 summarizes α , \overline{Bt} , and H_t by old and new districts in four cities. The mean α and \overline{Bt} were consistently higher in old districts than in new ones (Fig. 5 (a) and (b)). A *t*-test of the two rejected the null hypotheses at 95% confidence level, suggesting both "semilattice" and "complex network" are viable constructs, and α

Table 1

The mean value and the range of indicators for urban life, urban structure, urban form, and socio-demographic confounders for the 168 urban districts in four cities.

	London	New York	Hong Kong	Gdansk
Observations	33	59	42	34
Urban Life Indicators				
Density of Geo-Coded Tweets, #/km ²	2,363(63–30,961)	3,260(29–61,415)	2,435(1–39,220)	86(1–1,380)
POI Density, #/km ²	160(23–960)	1,393(235–4,214)	125(1–786)	90(6–353)
Density of Walking Trips, 10 ⁶ #/d.km ²	0.68(0.11–1.83)	3.32(0.05–9.23)	0.87(0.00–5.19)	0.36(0.01–1.42)
Urban Structure Indicators				
Meshedness Coefficient (α)	0.16(0.10–0.23)	0.38(0.23–0.56)	0.17(0.07–0.28)	0.19(0.12–0.30)
Average Betweenness (\overline{Bt})	1,678(885–3,685)	700(404–1,473)	1,014(11–4190)	521(91–1,619)
Head/Tail Index (H_t)	8.00 (5–11)	7.20(5–9)	6.11(3–8)	5.56(4–8)
Urban Form Confounders				
Land Use Mixture (<i>M</i>), ratio	0.84(0.53–0.96)	0.52(0.19–0.84)	0.62(0.03–0.88)	0.62(0.30–0.85)
Dwelling Density, 10 ³ / km ²	7.38(2.21–16.10)	17.38(2.39–42.49)	21.07(0.05–106.05)	3.79(0.09–17.95)
Street Intersection Density, #/km ²	128(59–250)	112(63–226)	107(1–538)	42(5–127)
Park Coverage, %	32(5–60)	7(1–30)	30(1–83)	61(12–88)
Socio-Demographic Confounders				
Average Household Size, ppl./hh.	2.4(1.6–3.0)	2.7(1.7–3.4)	3.0(2.3–4.2)	n.a.
Median HH. Income, 10 ³ US\$/yr.	55.90(40.58–89.70)	66.58(25.73–148.15)	57.26(20.23–201.67)	16.79(14.65–18.15)
Home Ownership Percentage, %	22(7–38)	27(4–71)	53(28–81)	50(26–64)
Primary Demographic Group ¹ , %	59(27–83)	32(1–85)	79(41–92)	58(1–100)
Secondary Demographic Group ² , %	9(2–25)	30(6–75)	9(1–48)	28(0–98)
Perc. of Old (>65), %	12(6–18)	12(6–22)	16(9–28)	22(8–35)
Perc. of Young ³ , %	20(11–27)	22(7–34)	11(7–18)	16(11–26)

¹ White for New York and London, Cantonese-speaking group for Hong Kong, and English-language Twitter users for Gdansk.

² Hispanic and Asian for New York and London, English-speaking group for Hong Kong, Polish language Twitter users for Gdansk.

³ <18 for New York and Gdansk, <15 for London, and <14 for Hong Kong.

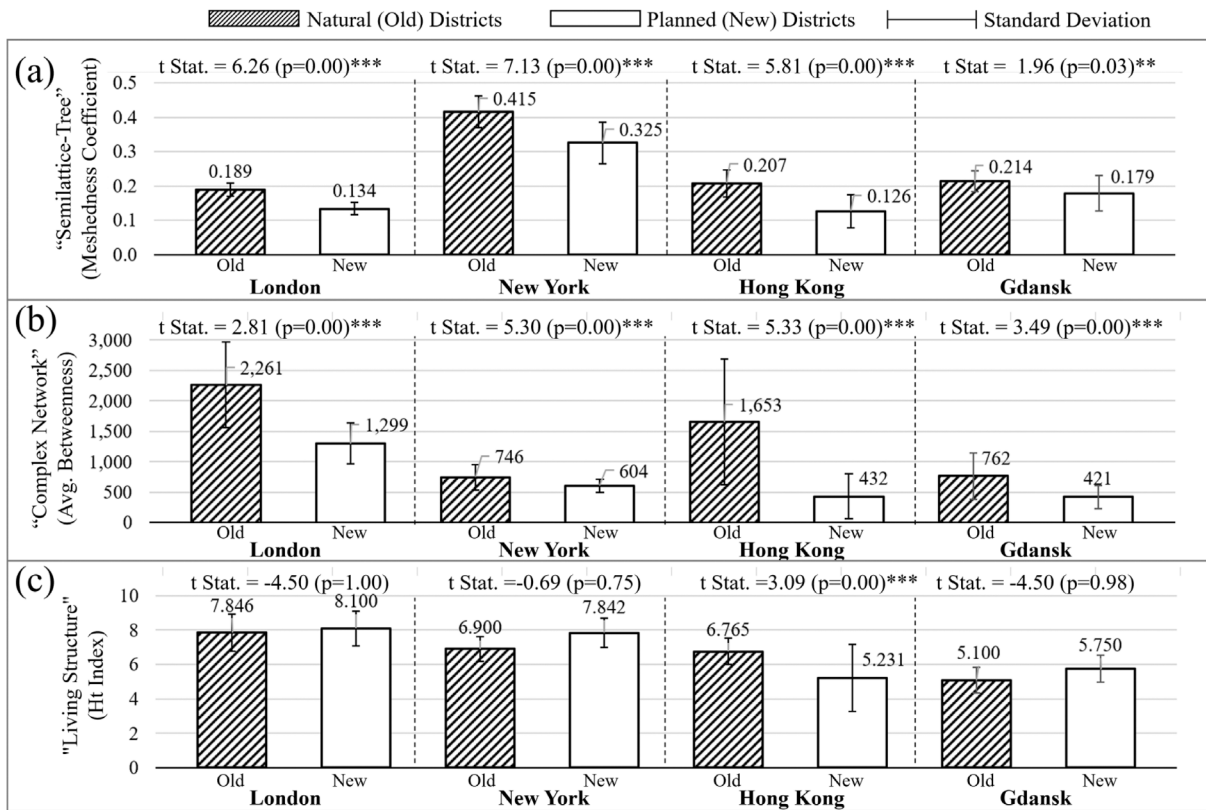


Fig. 5. Testing the structural differences between old and new districts, measured by (a) Meshedness Coefficient, (b) Average Betweenness, and (c) H_t Index in the 168 urban districts in four cities.

and \bar{B}_t are viable indicators to capture the structural differences between the old and new. The same cannot be observed on the “living structure” qualities. The differences between the old and new districts measured in H_t were inconsistent (Fig. 5 (c)). Old districts in Gdansk, London, New York had lower H_t than new ones, contrary to literature, although such differences in London and New York were statistically insignificant. Hong Kong was the only normality, where H_t was higher in its old districts than in new ones ($p = 0.00$). Our findings contradicted de Rijke et al. (2020) who reported higher H_t in old cities (Amsterdam, Rome, Geneva) than in new ones (Chandigarh, Levittown, and Brasilia), although our observation was at the district level (intra-city) vs. de Rijke’s at the city level (inter-city). Nevertheless, this inconsistency raises questions on either the construct of “living structure” or the effectiveness of H_t in capturing the structural differences between old and new cities.

A possible explanation of why old districts contained more “semilattice” lies in the road geometric standards, which were adopted in the UK and the US concurrently with Alexander’s observations. An example

is illustrated in Fig. 6, in which α was computed for each of the four-stage evolution of the predominant street patterns outlined by Stephen Marshall (2005). α was high in the pre-industrial “Altstadt” ($\alpha = 0.26$) and the “Bilateral” of the 1920s ($\alpha = 0.35$). It reduced in the later stage of “Conjoint” ($\alpha = 0.22$) and further in “Distributory” ($\alpha = 0.01$). The transition took place around the 1950s, when “A City is Not a Tree” was conceived. The transition was driven, in Marshall’s view, largely by the road geometric standards in the UK, the US, and later elsewhere (ITE, 1984; HA, 1999; AASHTO, 2018). These standards purportedly played a role in reducing the “semilattice” qualities in newly planned districts by rejecting the traditional, well-connected street network as “dysfunctional” and “unplanned”, while promoting the cul-de-sacs and three-way intersections (Marshall, 2005).

5.3. Urban structure and urban life

The predictive powers of street network indicators on urban life were tested using correlational statistics. Table 2 shows nine bivariate

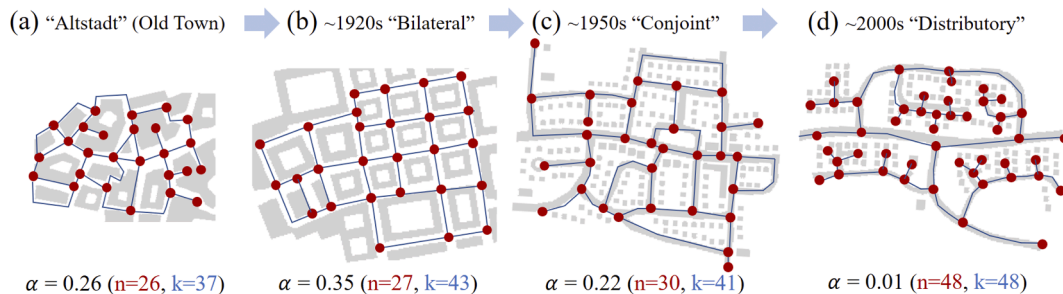


Fig. 6. The evolution trajectory of street network outlined by Stephen Marshall (2005) with declining α , suggesting a shift from “semilattice” towards “tree” over time.

Table 2

Regressing Twitter and POI density (logarithmic) on “Semilattice”, “Complex Network” and “Living Structure” indicators for the 168 urban districts in four cities.

Regression Coefficient (p-value) R ²	Urban Life in Virtual World	Urban Life in Physical world	
	Twitter Density (Logarithmic)	POI Density (Logarithmic)	Walking Trip Density
“Semilattice-Tree” (α)	Model 18.593 (0.000) *** R ² = 0.184	Model 212.833 (0.000) *** R ² = 0.712	Model 313.081 (0.000) *** R ² = 0.570
	“Complex Network” (\overline{Bt})	Model 41.932 (0.000) *** R ² = 0.364	Model 55.738 (0.002) ** R ² = 0.055
“Living Structure” (H_t)	Model 70.667 (0.000) *** R ² = 0.139	Model 80.437 (0.000) *** R ² = 0.104	Model 9 0.157 (0.190) R ² = 0.010

* p < 0.05 **p < 0.01 ***p < 0.001.

regression models, each regressing an urban life indicator (Twitter, POI, walking trips) on a street network indicator (α , \overline{Bt} , H_t).

- A semilattice-shaped street network is a strong predictor for urban life in the physical world. In model 1–3, α contributed positively and statistically significantly to Twitter density, walking trip density and POI density (p = 0.000). Particularly, model 2 and 3 had high R² at 0.712 and 0.570, suggesting that α was more predictive for POI and walking, and both are proxies for life in the physical world. In contrary, the R² in model 1 was much lower at 0.184, suggesting that α was less predictive of Twitter activities.
- The “complex network” quality is a strong predictor for urban life of the virtual world. \overline{Bt} contributed positively to Twitter density (p = 0.000) and the regression model explained 36% of the variations in Twitter activities, which was a proxy of urban life in the virtual world. In comparison, the R² values for model 5 & 6 were lower (0.055 & 0.019), suggesting that “complex network” quality were less effective in explaining life in the physical world.

Table 3

Regressing urban life indicators on α , controlling for urban form and socio-demographic confounders.

Dependent Variable	Model 1 Twitter Density		Model 2 POI Density		Model 3 Walking Trip Density	
	Coef.	(p-value)	Coef.	(p-value)	Coef.	(p-value)
Meshedness Coefficient (α)	5.514	(0.001)***	10.593	(0.000)***	7.778	(0.000)***
Urban Form Confounders						
Land Use Mixture, ratio	3.698	(0.000)***	1.923	(0.000)***	0.482	(0.327)
Dwelling Density, 10 ⁶ /km ²	-2.684	(0.781)	10.342	(0.047)*	60.219	(0.000)***
Street Intersection Density, #/km ²	0.006	(0.002)**	0.004	(0.000)***	-0.002	(0.147)
Percentage of Park, %	-0.007	(0.284)	-0.005	(0.170)	-0.006	(0.305)
New District (New = 1, Old = 0)	-0.839	(0.003)**	-0.031	(0.832)	-0.325	(0.152)
Economic Attributes						
Median Household Income, 10 ⁶ US\$/yr.	10.883	(0.016)*	5.885	(0.015)*	8.0857	(0.030)*
1st Demographic group, % ¹	-0.023	(0.003)**	-0.008	(0.048)*	-0.001	(0.859)
2nd Demographic group, % ²	-0.024	(0.001)**	-0.002	(0.955)	0.009	(0.126)
Perc. of Old (>65), %	-0.097	(0.000)***	0.002	(0.903)	0.0052	(0.815)
Perc. of Young, % ³	-0.111	(0.000)***	0.038	(0.016)*	0.022	(0.368)
Intercept	6.370	(0.000)***	0.460	(0.492)	-1.976	(0.056)
Number of obs.	168		168		168	
R-squared	0.714		0.857		0.741	

* p < 0.05 **p < 0.01 ***p < 0.001.

¹ White for New York and London, Cantonese-speaking group for Hong Kong, and Polish-speaking group for Gdansk.

² Black and Asian for New York and London, English-speaking group for Hong Kong, and English-speaking group for Gdansk.

³ <18 for New York and Gdansk, <15 for London, <14 for Hong Kong.

- The “living structure” quality is an inconsistent predictor for urban life. H_t correlated positively with Twitter and POI density (p = 0.000) in model 7 and 8. The result in Model 7 agree with Jiang and Yin (2019) that H_t can predict the location of tweets. However, the R² values for model 7 and 8 were much lower than those of Model 2, 3, and 4, suggesting that H_t was perhaps a weaker predictor for urban life than α and \overline{Bt} . Also, we found no correlations between H_t and walking trips in model 9 (p = 0.157).

The semilattice indicator α contributed independently to urban life, which is a strong support for Alexander. Table 3 summarized the results of three multivariate models of regressing urban life indicators (i.e., Twitter, POI, walking trips) on α , while holding urban form and socio-demographic confounders constant. α was found to have associated positively with Twitter density (p = 0.001), POI density (p = 0.000), and walking trip (p = 0.000) in all three models with controls. α “out-competed” the dwelling density in Model 1 and it also “out-competed” mixed use and street intersection density in Model 3, so that these urban form confounders became insignificant with α in the models. We found no spatial autocorrelation in the above regression models in four cities (Moran’s I = -0.424, p = 1.329), which justified the use of OLS regression. A multi-collinearity check yielded high VIF values (>10) for variables of building age, household size and home ownership (\overline{Bd}_{age} , \overline{Bd}_{stdv} , H_{size} , O_{perc}), hence they were dropped from analysis to ensure the stability of regression results.

We found that a new (planned) district, on average, is less active on twitter compared with old ones, as it is shown in the negative coefficient of the New District dummy variable in Model 1 of Table 3 (p = 0.003). There is more in a new (planned) district that is punitive to Twitter users, aside from the street network, mixed use, density, and block size already in control, that our model did not capture. This is an important finding since the lack of vitality is a common pitfall for new town development, and placed-based social media activities is increasingly viewed as a planning success. The “semilattice” structure contributed positively to urban life in both old and new districts, with or without controlling the New District dummy, suggesting that such structure-life relationship is consistent.

Additional tests were conducted on the predictive power of \overline{Bt} and H_t on urban life, after controlling the same confounders (Table 4). \overline{Bt} associated positively with Twitter activities (p = 0.000), but not with

Table 4

Regressing urban life indicators on “complex network” and “living structure” indicator for the 168 urban districts in four cities, controlling urban form and socio-economic confounders.

Independent Variable	Dependent Variable (Urban Life Indicators)		
	Twitter Density (Logarithmic)	POI Density (Logarithmic)	Walking Trip Density
“Semilattice” (α)	Model 1 5.514(p = 0.001)*** R ² = 0.714	Model 2 10.593(p = 0.000)*** R ² = 0.857	Model 3 7.778(p = 0.000)*** R ² = 0.741
	Model 4 1.398(0.000)*** R ² = 0.753	Model 5 0.288(0.112) R ² = 0.737	Model 6 60.307(0.165) R ² = 0.670
	Model 7 70.149(0.153) R ² = 0.661	Model 8 80.082(0.256) R ² = 0.735	Model 9 -0.151(0.087) R ² = 0.695

* p < 0.05 **p < 0.01 ***p < 0.001.

POI (p = 0.112) nor walking (p = 0.165), suggesting it can predict life in the virtual world but not in the real world. We found no statistically significant associations between H_t and all three urban life indicators (Model 7–9), contrary to earlier results in Table 2 where H_t associated positively with Twitter and POI density without controls. Our findings suggest that such association is not robust, the H_t effect may disappear after controlling for urban form and socio-economic confounders. The inconsistency raised doubt on the reliability of “living structure” and its mathematical expression (H_t) in explaining urban life.

5.4. Generalizability

Alexander’s theory can better explain observations in London and New York, less so in Hong Kong, a former British colony, and much less so in Gdansk. The results of city-by-city multivariate regressions, including the regression coefficient for α and R² values, are summarized in Table 5. α contributed positively (p-values within the range of 0.000 – 0.034) to Twitter, POI, and walking trips in London and New York (Model 1–6), suggesting observations from the two cities strongly support Alexander. In Hong Kong, α correlated positively with Twitter (p = 0.000) and POI (p = 0.001), but not with walking trips (Model 7–9). In Gdansk (Model 10–12), α was predictive of only walking trips (p = 0.008), not Twitter (p = 0.54) nor POI (p = 0.133), suggesting evidence from the Polish city did not fit Alexander’s theory well.

Table 5

Regressing urban life indicators on α for the 168 urban districts in four cities, controlling for urban form and socio-demographic confounders.

Independent Variable	Dependent Variables		
	Twitter Density (Logarithmic)	POI Density (Logarithmic)	Walking Trip Density
α in London	Model 1 119.028(0.002) ** R ² = 0.941	Model 2 29.909(0.004) ** R ² = 0.948	Model 3 37.604(0.001) *** R ² = 0.941
	Model 4 46.498(0.034) ** R ² = 0.758	Model 5 54.044(0.000) *** R ² = 0.869	Model 6 62.368(0.007) ** R ² = 0.990
α in Hong Kong	Model 7 728.276(0.000) *** R ² = 0.858	Model 8 812.852(0.001) *** R ² = 0.896	Model 9 96.428(0.067) ** R ² = 0.854
	Model 10 103.310(0.542) R ² = 0.501	Model 11 113.731(0.133) R ² = 0.762	Model 12 121.069(0.008) ** R ² = 0.967

* p < 0.05 ** p < 0.01 *** p < 0.001.

5.5. Discussion

This study marked a first attempt to test Alexander’s urban structural theory under a comprehensive framework. Overall, our results supported his early works outlined in “A City Is Not A Tree” (Alexander, 1965) and “Notes on the Synthesis of Form” (Alexander, 1966). An old urban district contains overlapping structures in resemblance to a “semilattice” and “complex network”, more so than new districts. This structural difference can explain variations in urban life, independent of other well-known confounders such as mixed use, density, and block size, etc. A well-connected, complex city encourages human movement, and a by-product to this is increased social interactions, captured in both Twitter and POI datasets. In this sense, Alexander is a pioneer in observing, documenting, and theorizing the fragmentation of street network and its socio-behavioral consequences.

Our findings diverged from his later work (Alexander, 2002) and follow up literature. We found no supporting evidence for H_t as an effective measure of “living structure”. H_t in historical urban cores were not higher than those of new districts, contrary to de Rijke et al., (2020). We found the relationships between H_t and the location geo-coded tweet were not robust, which disappeared after controlling urban form and socio-economic confounders. More evidence is needed on H_t and Alexander’s construct of “living structure”.

We uncovered a possible British-American predilection of Alexander’s theory, which is well-supported by observations from London and New York, less so in Hong Kong and Gdansk. We speculate that Alexander’s observations weighed heavily upon British and American cities in the 1950s and 60s. Hong Kong’s new towns, however, began late after the 1970s, when the city resisted car-oriented suburban sprawl and embraced high-density, transit-oriented development (Cervero and Murakami, 2009). Gdansk adhered to the gridiron street pattern throughout its post-war development, its suburbanization began only after Poland’s transition to the market economy in the 1990s (Mazurkiewicz and Zupančič, 2015). Evidence from both Hong Kong and Gdansk might not have reached Alexander in time, if at all, for him to adjust the theory. A locally-sensitive approach is therefore needed to anchor case study research and planning practices, while Alexander’s theory should be interpreted with caution outside of the British-American context.

The analytical tools developed can be of value for urban planning. α and $\bar{B}t$, as exemplified in this study, can serve as performance indicators concerning urban life as a goal. Fig. 7 and Fig. 8 provide two examples, in which α and $\bar{B}t$ are plotted against POI and Twitter density. α is a strong predictor for POI density, and $\bar{B}t$ for geo-coded tweets. Urban districts with the highest α and $\bar{B}t$, such as the Midtown Business District in Manhattan, the Srodmieście (Main Town) in Gdansk, Mong Kok and Central in Hong Kong, are also among the most lively in both the real and virtual world.

Lessons can be drawn on street network planning. Apparently, our evidence suggest that a compact, well-connected street network promotes urban life in both old and new districts, and it should therefore be encouraged in practice. Cul-de-streets, three-way intersections are to be discouraged since they reduce the link-to-node ratio and α . Further, our findings suggest that perhaps a semilattice structure can be planned, exemplified by some of the liveliest districts in Fig. 9. The gridiron street patterns in Midtown Business District in Manhattan was a ‘planned’ outcome from the 19th century (Bridges, 1811), which rivaled the even older districts such as the Battery Park City and Greenwich Village in both α and life. This may serve as a counter example to Alexander’s view that a lively city can never be planned; it can and had been done before, although not in the manner of the modernist urban planning against which he rebelled.

The research framework we adopted is reductionist in nature, which is an important limitation. It would be infeasible, nor to our intention, to capture the richness of Alexander’s theory in its entirety. The indicators

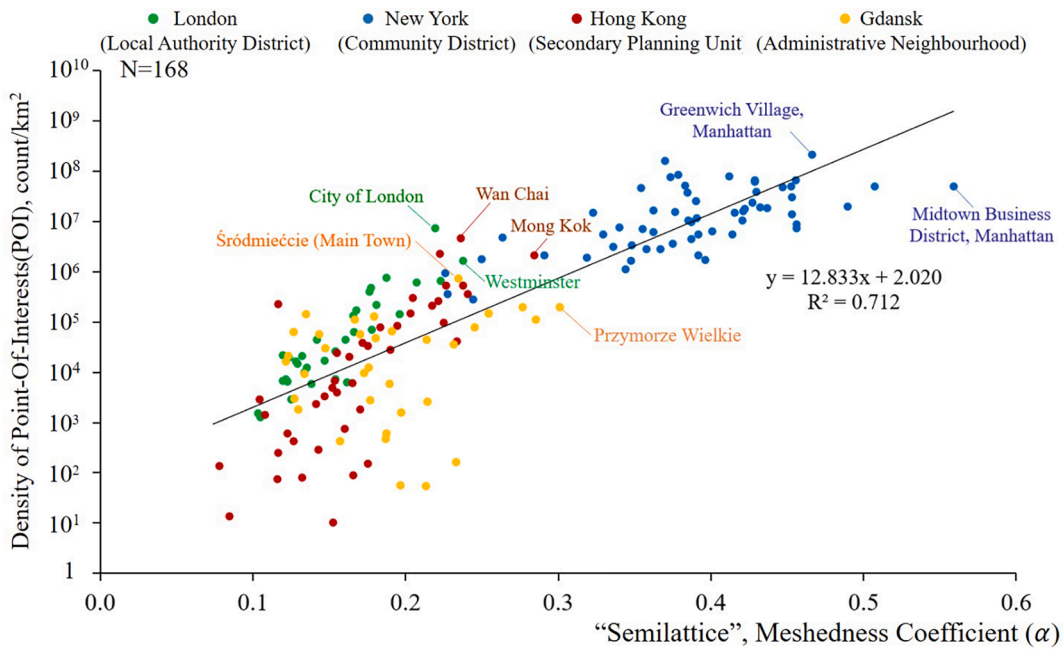


Fig. 7. Scatterplot of urban life in the physical world (POI density) and α for the 168 urban districts in four cities.

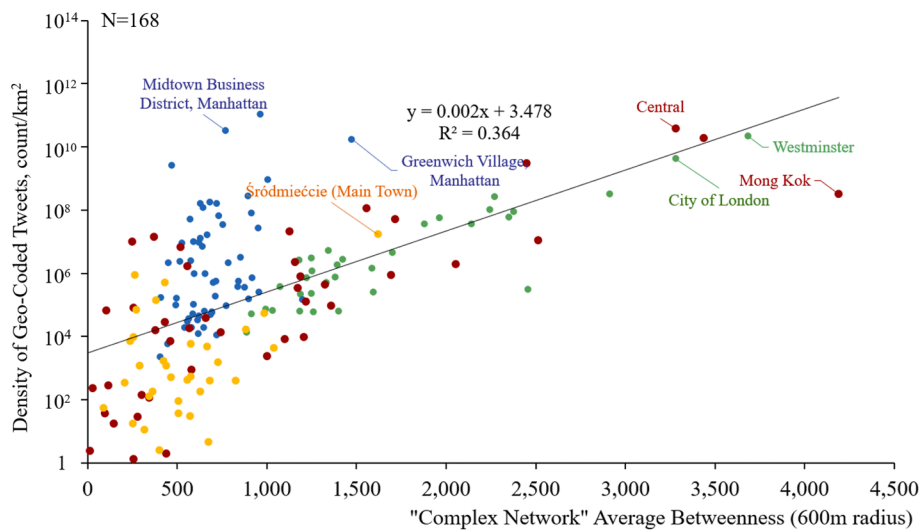


Fig. 8. Scatterplot of urban life in the virtual world (Twitter density) and $\bar{B}t$ for the 168 urban districts in four cities.

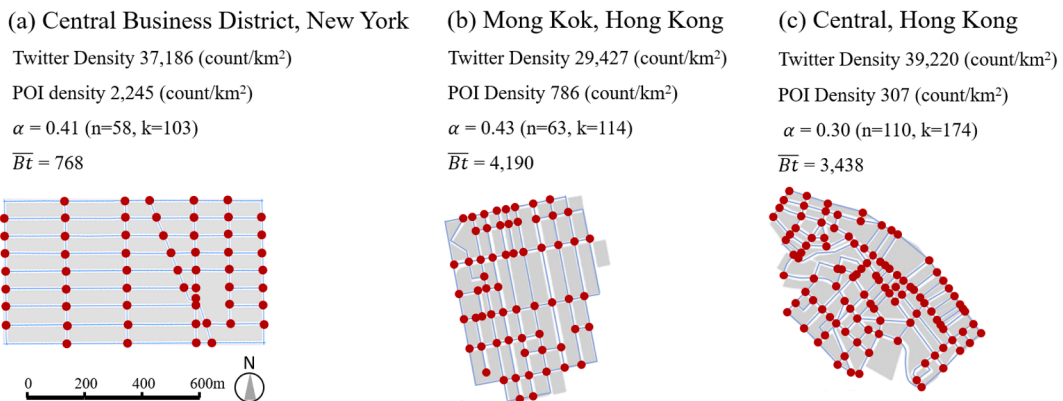


Fig. 9. Examples of urban neighborhoods resembling “semilattice” and high levels of urban life.

of “urban life” were intermediate measures, and can only be so, since the “patina of life” is an unmeasurable outcome. We have also left out other important concepts such as “beauty”. The two-dimensional graph-representation of urban structure might be flawed, which cannot gauge the social, economic, and cultural connectivity among various urban elements and their contributions to life.

Our study is also limited in several technical aspects. The Twitter database is vulnerable to sampling biases, i.e., over-sampling the young, technology-savvy, and male, while under-representing the elderly, low-incomers, or minorities as reported by literature (Rost et al., 2013; Wang et al., 2016). Similarly, POI and travel demand survey data may also suffer from the missing data bias. These drawbacks may be compensated, to a certain extent, by combining multiple data sources and cross-checking the results with each other, as demonstrated in our analysis.

As a postscript, we do not expect our findings to be used to validate or falsify Alexander’s ideas; those are based on his observations made six decades ago. Our societies have since been profoundly transformed, so is the way people live, work and socialize with each other. Alexander might not have guessed that digital technologies lend powerful meanings to monitor, analyse, and understand cities and people today with precision and granularity. The observations presented in this study are and should be of relevance at present, not in retrospect. Going forward, Alexander’s work should continue to inspire, except that the field has now converged with multiple burgeoning domains of scientific research (Oakes, Forsyth, & Schmitz, 2007; Berrigan, Pickle, & Dill, 2010; Ewing & Certero, 2010; Fang, He & Wang, 2021). The research landscape has been immersed in new theories, new data and new tools of growing sophistications. To strengthen the scientific rigor of our discipline, one might as well do what we did in this paper, to bring powerfully-narrated yet rarely-tested texts into a system of well-supported hypotheses. We, the community of researchers and professionals, bear responsibility to continuously refine and rebuild urban planning theory, using the best data and analytical tools now at our disposal.

6. Conclusion

This study marks a first attempt to test Alexander’s urban structural theory under a comprehensive research framework. Our evidence corroborates Alexander’s early work that a semilattice-shaped street network is conducive to life. The intra-city structural distinctions between old and new districts can be found in consistency across all four cities. In contrast, we found inconsistent correlations between urban life and the H_i Index, suggesting a need to further investigate Alexander’s “living structure” construct and the use of H_i Index as its performance indicator. Alexander’s theory can better explain evidence in London and New York than in Hong Kong and Gdansk. A locally-sensitive approach is therefore needed to anchor case study research and planning practices. Our study contributes new evidence to research literature on street network, travel behaviors and subsequent socio-behavioral impact. The analytical protocols are of value for urban planners and researchers in the four cities and elsewhere. The practical message is that the Meshedness Coefficient and the Node-Based Average Betweenness can serve as performance indicators in both new town and urban renewal developments, concerning urban life as a goal.

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References

- AASHTO (2018) *A Policy on Geometric Design of Highways and Streets*. 6th edn, American Association of State Highway and Transportation Officials. 6th edn. Washington DC: AASHTO. Available at: www.transportation.org.
- ACO. (1946). Reviewed work: Greater London Plan, 1944 by Patrick Abercrombie. *The Geographical Journal*, 108(1/3), 93–94. <https://doi.org/10.2307/1789338>
- Alexander, C. (1965). A city is not a tree. *Architectural Forum*, 122(1), 58–62.
- Alexander, C. (1966). *Notes on synthesis of form* (second pri). Cambridge, MA, USA: Harvard University Press.
- Alexander, C. (1987). *A new theory of urban design*. New York: Oxford University Press.
- Alexander, C. (2002). *The nature of order: An essay on the art of building and the nature of the universe, Book I – The phenomenon of life* (1st ed.). Center for Environmental Structure.
- Alexander, C. (1977). *A Pattern Language: Towns, Buildings, Construction*. New York: Oxford University Press.
- Ball, K., et al. (2001). Perceived environmental aesthetics and convenience and company are associated with walking for exercise among Australian adults. *Preventive Medicine*, 33(5), 434–440. <https://doi.org/10.1006/pmed.2001.0912>
- Barrington-Leigh, C., & Millard-Ball, A. (2019). A global assessment of street-network sprawl. *PLoS ONE*, 14(11). <https://doi.org/10.1371/journal.pone.0223078>
- Batty, M. (2006). Hierarchy in cities and city systems, in *Hierarchy in Natural and Social Sciences*. doi: 10.1007/1-4020-4127-6_7.
- Batty, M. (2015). ‘Alexander’s challenge: Beyond hierarchy in city systems and systems of cities. *A City Is Not a Tree* (50th Anniversary ed.). Portland, OR, USA: Sustasis Press.
- Berrigan, D., Pickle, L. W., & Dill, J. (2010). Associations between street connectivity and active transportation. *International Journal of Health Geographics*, 9, 20. <https://doi.org/10.1186/1476-072X-9-20>
- Bettencourt, L. (2016). The complexity of cities and the problem of urban design. In M. W. Mehaffy (Ed.), *A city is not a tree* (50th Anniversary ed., pp. 47–61). Portland, OR, USA: Sustasis Press.
- Bridges, W. (1811) Map of the city of new york and island of manhattan with explanatory remarks and references. New York, USA.
- Brush, J. E. (1966) ‘Walter Christaller. Central Places in Southern Germany. Translated by Carlisle W. Baskin. Pp. 230. Englewood Cliffs, N.J.: Prentice-Hall, 1966. \$9.95’, *The ANNALS of the American Academy of Political and Social Science*, 368(1), pp. 187–187. doi: 10.1177/000271626636800132.
- Buhl, J., et al. (2004). Efficiency and robustness in ant networks of galleries. *European Physical Journal B*, 42(1), 123–129. <https://doi.org/10.1140/epjb/e2004-00364-9>
- Calthorpe, P. (2004). The next American metropolis, *The sustainable urban development reader*, p. 73.
- Cervero, R. and Murakami, J. (2009). Rail and property development in Hong Kong: Experiences and extensions, *Urban Studies*, 46(10), pp. 2019–2043. doi: 10.1177/0042098009339431.
- Chen, T., et al. (2019). Identifying urban spatial structure and urban vibrancy in highly dense cities using georeferenced social media data. *Habitat International*, 89, Article 102005. <https://doi.org/10.1016/j.habitatint.2019.102005>
- Cogd. (2020). *Database of census records by department of population register*. Gdansk, Poland: City Office of Gdansk. Available at: <https://gdansk.stat.gov.pl/en/publications/population/demographic-situation-of-pomorskie-voivodship-in-2020.2.4.html>.
- Cooper, C. (2013). *Detailed measure descriptions of sDNA*. UK: Cardiff.
- CRPNYIE (1929). *Regional Plan of New York and Its Environs Volume I: The Graphic Regional Plan*, Regional Plan Association. Philadelphia: Regional Plan of New York and Its Environs. Available at: <https://rpa.org/work/reports/regional-plan-of-new-york-and-its-environs> (Accessed: 1 January 2021).
- Cuthbert, A. R. (2007). Urban design: Requiem for an era – Review and critique of the last 50 years. *Urban Design International*, 12(4), 177–223. <https://doi.org/10.1057/palgrave.udi.9000200>
- Davis, H. (2021). *Christopher Alexander and Bill Hillier: Overlaps and Divergences*. United Kingdom: UCL. Available at: <https://vimeo.com/506091135>.
- DCP (2018). *Census Demographics at the NYC City Council district (CNCLD) level*. Available at: <https://data.cityofnewyork.us/City-Government/Census-Demographics-at-the-NYC-City-Council-distri/ye4r-qpmp> (Accessed: 1 May 2020).
- DCP (2020). *PLUTO and MapPLUTO*. Available at: <https://www1.nyc.gov/site/planning/data-maps/open-data/dwn-pluto-mappluto.page> (Accessed: 30 May 2020).
- Ding, R., et al. (2015). Complex network theory applied to the growth of Kuala Lumpur’s public urban rail transit network. *PLoS ONE*, 10(10). <https://doi.org/10.1371/journal.pone.0139961>
- DOT (2019) *2019 Citywide Mobility Survey Results*. New York. Available at: <https://www1.nyc.gov/html/dot/downloads/pdf/nycdot-citywide-mobility-survey-report-2019.pdf>.
- Dovey, K., & Pafka, E. (2016). The science of urban design? *Urban Design International*, 21(1), 1–10. <https://doi.org/10.1057/udi.2015.28>
- Ewing, R., & Certero, R. (2010). Travel and the built environment: A meta-analysis. *Journal of the American Planning Association*, 76(3), 265–294.
- Fang, C., He, S., & Wang, L. (2021). Spatial characterization of urban vitality and the association with various street network metrics from the multi-scalar perspective. *Frontiers in Public Health*, 9, Article 677910. <https://doi.org/10.3389/fpubh.2021.677910>
- Franca, U., et al. (2015). Visualizing the “heartbeat” of a city with tweets. *Complexity*, 21(6), 280–287. <https://doi.org/10.1002/cplx>
- Freeman, Linton (1977). A Set of Measures of Centrality Based on Betweenness. *Sociometry*, 40(1), 35–41. <https://doi.org/10.2307/3033543>

- Gabriel, R., & Quillien, J. (2019). A search for beauty/A struggle with complexity: Christopher Alexander. *Urban Science*. <https://doi.org/10.3390/urbansci3020064>
- GDA (2016). *Gdańsk Research on mobility 2016 (Gdańskie Badanie Ruchu)*. Gdańsk, Poland. Available at: <https://www.brg.gda.pl/attachments/article/282/Raport-III.pdf>.
- GDA (2018). Study of conditions and directions of spatial development in the City of Gdańsk adopted by the City Council on 23 April 2018 (Studium uwarunkowań i kierunków rozwoju przestrzennego miasta Gdańska). Gdańsk, Poland. Available at: <https://www.brg.gda.pl/planowanie-przestrzenne/studium-uwarunkowan-i-kierunkow-zagospodarowania-przestrzennego>.
- GLA (2018). *London Borough Profiles*. Available at: <https://londondatastore-upload.s3.amazonaws.com/instant-atlas/borough-profiles/atlas.html> (Accessed: 18 June 2020).
- Go-Globe (2015). *Social Media Use in Hong Kong - Statics and Trends, Go-Globe*. Available at: <http://www.go-globe.hk/blog/social-media-hong-kong/> (Accessed: 10 September 2016).
- HA (1999). *Design Manual for Roads and Bridges, Standardsforhighways.Co.Uk*. Birmingham.
- Harary, F., & Rockey, J. (1976). A city is not a semilattice either. *Environment and Planning A*, 8(4), 375–384.
- Hillier, B. (1989). The architecture of the urban object. *Ekistics*, 56(334–335), 5–21.
- HKCS (2017). *The 2016 Hong Kong Population By-census*. Available at: <https://www.bycensus2016.gov.hk/en/bc-dp.html> (Accessed: 1 September 2020).
- HKPD (2017). *Tertiary Planning Units*. Available at: <http://www.census2011.gov.hk/en/tertiary-planning-units.html> (Accessed: 28 December 2017).
- Hofmeister, B. (1970). Anglo-America's great cities: Major characteristics, recent trends, regional variations. *Geoforum*, 1(3), 17–29.
- Huang, J. et al. (2021). The image of the City on social media: A comparative study using "Big Data" and "Small Data" methods in the Tri-City Region in Poland. *Landscape and Urban Planning*, 206, p. 103977. doi: 10.1016/j.landurbplan.2020.103977.
- ITE. (1984). *Recommended guidelines for subdivision streets: A recommended practice of the Institute of Transportation Engineers*. Washington DC: Institute of Transportation Engineers.
- Jacobs, J. (1961). *The death and life of great American Cities*. New York: Random House.
- Jiang, B., & Ren, Z. (2019). Geographic space as a living structure for predicting human activities using big data. *International Journal of Geographical Information Science*, 4(33), 764–779. <https://doi.org/10.1080/13658816.2018.1427754>
- Jiang, B., & Yin, J. (2014). Ht-index for quantifying the fractal or scaling structure of geographic features. *Annals of the Association of American Geographers*, 104(3), 530–540. <https://doi.org/10.1080/00045608.2013.834239>
- Johnson, M. L., et al. (2019). Mapping urban park cultural ecosystem services: A comparison of twitter and semi-structured interview methods. *Sustainability (Switzerland)*, 11(21), 6137. <https://doi.org/10.3390/su11216137>
- Katz, P. (1993). *The new urbanism: Toward an architecture of community*. New York: McGraw-Hill Education.
- Kerr, J., et al. (2007). Urban form correlates of pedestrian travel in youth: Differences by gender, race-ethnicity and household attributes. *Transportation Research Part D: Transport and Environment*, 12(3), 177–182. <https://doi.org/10.1016/j.trd.2007.01.006>
- Lau, J., Collier, N., & Baldwin, T. (2012). On-line trend analysis with topic models: #Twitter trends detection topic model online. Available at: *International Conference on Computational Linguistics (COLING)*, 1519–1534 <https://www.aclweb.org/anthology/C/C12/C12-1093.pdf>.
- Long, Y. and Huang, C. (2017). 'oes block size matter? The impact of urban design on economic vitality for Chinese cities, *Environment and Planning B: Urban Analytics and City Science*. doi: <https://doi.org/10.1177/2399808317715640>.
- Loo, B. P. Y., & Chow, A. S. Y. (2008). Changing urban form in Hong Kong: What are the challenges on sustainable transportation? *International Journal of Sustainable Transportation Taylor & Francis*, 2(3), 177–193. <https://doi.org/10.1080/15568310701517331>
- Lorens, P., Kamrowska-Zaluska, D., & Kostrzewska, M. (2014). Urban transformations of gdańsk bay metropolitan area. *Urban Design*, 130, 30–33.
- Lu, Y. (2019). Using Google Street View to investigate the association between street greenery and physical activity. *Landscape and Urban Planning*. <https://doi.org/10.1016/j.landurbplan.2018.08.029>
- Marshall, S. (2005). *Streets and patterns* (1st ed.). New York: Spon Press.
- Marshall, S. (2012). Science, pseudo-science and urban design. *Urban Design International. Nature Publishing Group*, 17(4), 257–271. <https://doi.org/10.1057/udi.2012.22>
- Marshall, W. E., & Garrick, N. W. (2010). Effect of street network design on walking and biking. *Transportation Research Record*, 2198, 103–115. <https://doi.org/10.3141/2198-12>
- Mazurkiewicz, W. M., & Zupančić, T. (2015). Sensitivity of public places in Gdańsk Osowa district. *Journal AR Architecture*, 16–23.
- Mehaffy, M. W. (2019). Assessing Alexander's later contributions to a science of cities. *Urban Science*, 3(2), 59. <https://doi.org/10.3390/urbansci3020059>
- Mohajeri, N., French, J. R., & Batty, M. (2013). Evolution and entropy in the organization of urban street patterns. *Annals of GIS*, 19(1), 1–16.
- Moran, P. A. (1950). Notes on continuous stochastic phenomena. *Biometrika*, 37(1–2), 17–23. <https://doi.org/10.1093/biomet/37.1-2.17>
- Morstatter, F., et al. (2013). Is the sample good enough? Comparing Data from twitter's streaming API with twitter's firehose. In *International Conference on WEblogs and Social Media* (pp. 400–408). AAAI, 10.1007/978-3-319-05579-4_10.
- De Nadai, M., et al. (2016). The death and life of great Italian cities: A mobile phone data perspective. *Proceedings of 26th International ACM Conference on World Wide Web (WWW)*, 10.1145/2872427.2883084.
- NCGCD (2020). *Database of topographic objects (Baza Danych Obiektów Topograficznych BDOT10k)*. Available at: <https://www.geoportal.gov.pl/dane/baza-danych-obiektow-topograficznych-bdot> (Accessed: 27 July 2021).
- NYC OpenData (2017). *NYC Street Centerline (CSCL)*. Available at: <https://data.cityofnewyork.us/City-Government/NYC-Street-Centerline-CSCL/-/exjm-f27b> (Accessed: 1 May 2021).
- Oakes, J. M., Forsyth, A., & Schmitz, K. H. (2007). The effects of neighborhood density and street connectivity on walking behavior: The Twin Cities walking study. *Epidemiologic Perspectives & Innovations*, 4(1), 16. <https://doi.org/10.1186/1742-5573-4-16>
- ONS (2010) *Land use statistics (Generalised Land Use Database), Office for National Statistics*. Available at: <https://data.gov.uk/dataset/4413c03c-762a-47ad-a865-6c1ee77fe6c/land-use-statistics-generalised-land-use-database> (Accessed: 18 June 2020).
- OpenStreetMap (2019).
- Park, Y., & Newman, G. D. (2017). A framework for place-making using Alexander's patterns. *Urban Design International*, 22(4), 349–362. <https://doi.org/10.1057/s41289-017-0040-1>
- Pisati, M. (2001). sg162: Tools for spatial data analysis. *Stata Technical Bulletin*, 60, 21–37.
- PNT (2008) *Global positioning system standard positioning service performance standard*. Washington DC. Available at: <https://www.gps.gov/technical/ps/2008-SPS-performance-standard.pdf>.
- Porta, S., Crucitti, P., & Latora, V. (2006). The network analysis of urban streets: A primal approach. *Environment and Planning B: Planning and Design*. <https://doi.org/10.1068/b32045>
- de Rijke, C. A., et al. (2020). Living structure as an empirical measurement of city morphology. *ISPRS International Journal of Geo-Information*, 9(11), 677. <https://doi.org/10.3390/ijgi9110677>
- Rodrigue, J. P., Comtois, C. and Slack, B. (2016) *The geography of transport systems, The Geography of Transport Systems*. London: Taylor & Francis Ltd. doi: 10.4324/9781315618159.
- Rost, M. et al. (2013). Representation and Communication: Challenges in Interpreting Large Social Media Datasets. In *Proceedings of the 2013 Conference on Computer Supported Cooperative Work*. San Antonio, TX, pp. 357–362. doi: 10.1145/2441776.2441817.
- Salingaros, N. (2018). Fractals and Christopher Alexander's "Fifteen Fundamental Properties". *Conscious Cities Anthology*, 2018(1). <https://doi.org/10.33797/cca18.04>
- Salingaros, N. A. (2005). *Principles of urban structure*. Amsterdam, Netherlands: Techné Press.
- Spanier, E. H. (1981) *Algebraic topology, The Mathematical Gazette*. New York: Springer. doi: <https://doi.org/10.1007/978-1-4684-9322-1>.
- Steadman, P. (2004). Editorial: Developments in space syntax. *Environment and Planning B: Planning and Design*, 31(4), 483–486.
- Sung, H., Lee, S., & Cheon, S. (2015). Operationalizing Jane Jacobs's urban design theory: Empirical verification from the great city of Seoul, Korea. *Journal of Planning Education and Research*, 35(2), 117–130. <https://doi.org/10.1177/0739456X14568021>
- TfL (2019) *Transport of London Road Network Dataset*. Available at: <https://data.gov.uk/dataset/101434ec-c34d-486e-89dc-8d0714629e5b/tfl-road-network%0A> (Accessed: 1 May 2021).
- Thompson, C. G., et al. (2017). Extracting the variance inflation factor and other multicollinearity diagnostics from typical regression results. *Basic and Applied Social Psychology*, 39(2), 81–90. <https://doi.org/10.1080/01973533.2016.1277529>
- UK Parliament (1963) *London Government Act 1963*. United Kingdom. Available at: <https://www.legislation.gov.uk/ukpga/1963/33/contents>.
- US Census Bureau (2020) *American Community Survey 1-Year Estimates, Table S1903 (2005-2018)*. Available at: <https://data.census.gov/> (Accessed: 1 May 2020).
- Wang, G. et al. (2016) "Will check-in for badges": Understanding bias and misbehavior on location-based social networks", in *Proceedings of the 10th International Conference on Web and Social Media, ICWSM 2016*.
- Wang, Z., et al. (2018). Comparing social media data and survey data in assessing the attractiveness of Beijing Olympic Forest Park. *Sustainability (Switzerland)*, 10(2), 382. <https://doi.org/10.3390/su10020382>
- Xie, F., & Levinson, D. (2007). Measuring the structure of road networks. *Geographical Analysis*, 39, 336–356. <https://doi.org/10.1111/j.1538-4632.2007.00707.x>
- Ye, Y., Li, D., & Liu, X. (2018). How block density and typology affect urban vitality: An exploratory analysis in Shenzhen, China. *Urban Geography*, 39(4), 631–652. <https://doi.org/10.1080/02723638.2017.1381536>
- Yue, H., & Zhu, X. (2019). Exploring the relationship between urban vitality and street centrality based on social network review data in Wuhan, China. *Sustainability (Switzerland)*. <https://doi.org/10.3390/su11164356>
- Zukin, S. (2010) *Naked city: The death and life of authentic urban places*. New York: Oxford University Press. doi: 10.17323/1726-3247-2018-1-62-91.