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EVOLVING RESEARCH METHOD IN THREE-DIMENSIONAL AND VOLUMETRIC URBAN MORPHOLOGY OF A HIGHLY DENSE CITY: ASSESSING PUBLIC AND QUASI-PUBLIC SPACE TYPOLOGIES

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Abstract. An appropriate urban density is a vital part of a sustainable urban fabric. However, when it comes to measuring the built urban fabric and how people walk through it and use, a difficulty has been observed in defining applicable measurement tools. With the intention of identifying the variables that will allow the best characterization of this fabric and movement, a multi-variable analysis methodology from the field of artificial intelligence (AI) is proposed. The main objective of this paper is to prove the capacity of AI as an evolving research method in urban morphology and specifically to evaluate the capacity of such a methodology to measure the way in which people travel through defined multi-levels of typologies of public urban space. The research uses the case of Hong Kong as a dense city that is three-dimensionally activated in terms of its public realm, not just at street level, but also via below ground subways and upper-level walkways, public and quasi-public spaces. This includes the three-dimensional volumetric assessment of public and quasi-public space typologies within a highly dense city. For the purpose of the study, a characterization and term definition of these spaces has been further developed: "Junctions", "Landmarks", "Intersections", "Districts", "Passages" and "Lobbies" (both outdoor and indoor) based on Lynch's 5 main key elements (District, landmark, path, edges, node). The results obtained using AI prove to be more robust and rational than those based on a more limited range of tools, evidencing that using AI can offer operational opportunities for better understanding of morphological and typological evolution within the vertical and volumetric built urban fabric.

Keywords: urban shape, built density, urban fabric, artificial intelligence, measurement of urban morphology.

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1. Introduction

1.1. Density, public place usage and the three-dimension city network

Almost since the formation of cities began, city planners and decision makers have been conscious of the impact of building density and the pattern of urban morphology, and sought to contain and control it. In the first century BC, Emperor Augustus of Rome set up in the first definitions that set limits on the building density in Rome. More contemporary examples include the controls on plot density in Barcelona put in place in 1860 by Cerda, the population density targets set by Ebenezer Howard for the Garden City proposals in 1898, and the maximum density of 30 dwellings per hectare set by Unwin in his urban proposals of 1909 (Choi, 2011; Lin, 2018). In Germany in the interwar period, a floor space index was set up to control the density of Berlin, and since the 1950s there have been controls in place for the density of built-up areas in New York (Generalova et al., 2016; Nethercote & Horne, 2016), and in 1997, the American Planning Association promulgated statutes for planning and zoning reform that aimed to preserve or protect open space, agricultural land, and environmentally sensitive areas (Ding et al., 1999).

Contemporary research on the topic includes Rao et al. (2018) explore the morphology of urban retail typologies of, defining the patterns of interior public realm in relation to scale, function and control. Their work was mainly categorizing the types of urban typology with their programs and function using symbolic characters. Lin and Gámez (2018) further argue for how the city can be seen as a multi-layered and multi-dimensioned organism (Lin & Gámez, 2018, p. 11). And their work elaborated this morphological form using complexity and density using three-dimensional modelling, as cities have long been regarded as complex systems (Chettiparamb, 2006). Foth and Sanders (2008) argues that mixed-use residential complexes are arguably one of the most prominent components that exacerbate urban densification and increase urban and social complexity. This is due to the emergence of new social networks characterized by individualism, which presents challenges to conventional understandings of "public places". Ireson and Barley (2000) have also highlighted how the verticality of the city is achieved through a series of stacked horizontal layers, with accessibility and interconnectivity to and between many levels.

In Hong Kong, as with many other cities, public space is an *assemblage*, to use Dovey's term (2010); the outcome of intentional design, historical accretions, combined with a social and economic structure. This assemblage may be viewed as a continually negotiated construct, informed by the social and commercial institutions of the city, overlaid on a dense urban form, which in turn is the consequence of the morphological development of the city over a long period, constrained by the topographical condition of the landscape on which it has been built (Choi et al., 2023). This environment is "negotiated" between public and private interests, becoming an intermediary space that creating a higher density of linkage within a multi-layered public realm. The three-dimensional intermediary space (public, quasi-public spaces) has complexity of spatial networks which exists at various levels thus creating more complicated task for legibility.

1.2. Kevin Lynch's work and its connection with the subject of the research

Considering that, reviewing Lynch's City Image, it is a mental model of the city that approaches urban design mentally and focus on legibility (the apparent clarity of the city). It is a part of a wider geographical movement called "psychogeography" which aimed to understand spaces around us based on how we perceive them, rather than the rigid objective physical description. This model is similar to the serial vision brought up by Cullen (1961) which decoded traversing an urban environment as an emotional and psychological journey, and the cognitive maps used in urban design education to concretize students' mental images of the perceived space (Marshall, 2012; Topcu & Topcu, 2012). Legibility for Lynch means the ease by which its physical parts and components can be recognized and organized into coherent pattern. The city should be easily grasped as related patterns of recognized symbols. Legible city is a place that its pathways, landmarks and districts are easily recognized and can be grouped into a coherent pattern. Lynch's legibility map concept is a result of five years of experiments on how people understand the city's physical structure as they navigate through it. He aimed to collect the mental images of the city which is held by its citizen. He concluded that people understood their surrounding cityscape in predictable ways creating mental maps of five physical elements: District, Edge, Landmark, Node and Path.

These five elements, when properly designed and organized in space, represent an assurance that the design is legible. This map is not scaled and it is not scientifically true and it is not based on an actual geographically correct basemap (Dovey & Pafka, 2015). It is an abstract representation. Obviously, the map elements do not stand alone; they overlap to shape the space. So, a district might have a landmark inside it, and a path can penetrate a district.

The aim behind creating a mental map is not presenting the map itself, but creating a legible urban space: familiar and distinct. Legible space or, as Lynch calls, "Imageable" space can give a sense of emotional security when it reduces the fear of disorientation for users. It can also organize activities, according to Lynch, by giving possibility of choices and starting point for collecting further information about the surrounding environment. Everything is about a clear image of the cityscape. Whether the design is regular square grid or an organic grid, legibility should be guaranteed.

Regarding the urban morphology of multi-levels of three-dimensional spatial city network, like Hong Kong, publications by Cummer and DiStefano (2021), Marshall (2004) and Shelton et al. (2011) identified an urban system whereby streets, plots and their aggregation into street-blocks, and patterns of land use with multiple layers of usage and access that are vertically stacked and connected. Densely built-up neighborhoods and human activity in Hong Kong include recognizable patterns and order in the arrangement of buildings, spaces and functions (themes). These urban studies challenge the common perception that there is an unplanned, chaotic or vaguely organic character to this urban development, and highlight three complexes of plan elements traditionally associated with urban morphology: streets and their interconnectedness and configuration into a system, plots (or lots) and their aggregation into street-blocks, and patterns of land use (Conzen, 1960, p. 69; Rauber & Krafta, 2018).

A particular and more contemporary condition of Hong Kong's spatial and population density is the variety of vertically stacked and connected layers of usage that occurs, influencing the spatial perception by users in forming a city image and in relation to the five elements of urban design defined by Kevin Lynch in his book Image of the City (Choi et al., 2023). It is in fact possible to re-define these terms Lynch (1960) theorized, once they are projected onto and into this three-dimensional urban rhizome in form and spatial layout. In order to understand this complex urban system and fabric, together with its usage, AI systems can integrate and penetrate models to a greater degree than more longstanding automated and manual technologies. The implications of this are considered in more details in the following sections below.

1.3. AI and its usage in urban morphological (density and place usage) studies

Although research in multiple literature streams has considered the characteristics of the physical network and sought to formalize and clarify these, Boeing (2018) has noted that since the relationship between design and urban form is often considered in a more subjective sense, this can make the drawing of concrete, objective outcomes more complicated. Recent contributions to this area of research have included the synchronous study of variables such as floor area ratio (FSI) (Lin & Gámez, 2018), the Ground Space Index (GSI) (Shelton et al., 2011), network density (N) (Bruyns et al., 2021), with the most recent research also including depth of building in plan and cut-off angles that show the length of separation between buildings.

Research discourse regarding computational urban research tools for organic form making processes at both micro and macro scales has informed urban technology (Kim et al., 2018; Makki et al., 2019; Oliveira & Medeiros, 2016; Ye et al., 2017; Yigitcanlar & Cugurullo, 2020). However, the potential for AI methodologies in the in-between neighborhood scale, including within the morphology of urban block development and evolving typologies, is less well understood. From the good scholar search engine, when we use key words "urban morphology" and "AI research methods", there are only four articles we can find. Comparing that, "computational research methods" in Environmental Sciences, there are 11,187 articles up to 2022 for last two decades, Medicine, Health and Life Sciences has over 7, 078, as well as computer and information science, there are more than 2,335 research projects and articles appeared.

The situation of AI in the observation area, for instance in Hong Kong, is mainly in real-time crowd measurement in the airport and shopping malls during the coronavirus disease 2019 (COVID-19) public health management period, and for certain autonomous vehicles. With AI models of sufficient detail, the social, physical and economic variables within particular urban morphologies can be both measured and predicted in an iterative manner alongside the processes of built forms (Floridi et al., 2018, 2020).

Despite the relevance of the concept of built density, when it comes to evaluating or measuring built density, there are research gaps, which include (1) some limitations in methods of statistical analysis such as the lack of big data (Batty, 2013), and (2) a limitation in the variables used in the analysis; and (3) the lack of integrating multi-dimensional levels, with these elements yet to be combined in one clustering analysis. With a focus on addressing such knowledge gaps, the main aim of this research is to evaluate the capacity of a methodology based on AI techniques to analyze, measure and visualize usage and activity within the multi-dimensional, multi-ownership, indoor and outdoor spatial networks and volumetric morphology of Hong Kong. To this end, this paper will provide evidencing data sets using AI research method that can offer operational opportunities for better understanding of morphological and typological evolution within the vertical and volumetric built urban fabric, based on triangulation between spatial design network analysis (sDNA) and multiscale geographically weighted regression (MGWR) algorithms.

2. Research methodology

2.1. MGWR and its relations with Lynch's 5 physical elements

While many scholars (Boeing, 2018; Ferrara et al., 2019; Sanchez et al., 2022; Yigitcanlar & Cugurullo, 2020) have been exploiting these computational advantages to study cities, which has included how AI as a predictive, open ended tool can drive design processes and how AI can engage with the urban planning process, both in terms of the measurement of management of public resources, such as parking meters and street lighting, and how infrastructure and public space is laid out, there are not as yet proven research methods and tool using AI being applied to the design of the public realm within vertical and volumetric typologies. Most applications to date support the provision of utilities and services, but with increasing computational power and advancing computational technologies, AI can provide new opportunities to tackle city issues more strategically (Batty, 2018). Two schools dominate the prevailing planning and design decision support systems that facilitate the design process. The planning support systems (PSS) school, which is defined as loosely coupled technique assemblages to aid planning decision-making (Batty, 2003), and the generative design systems school that produce novel and efficient spatial designs through computing (Shea et al., 2005). Both of them have advantages and limitations in supporting complex urban sustainable design issues with design, science, and computation (Goodchild, 2010; Hopkins, 1999).

2.2. Usability of MGWR

Geographically weighted regression (GWR) incorporates geography context and allows parameter estimation for i of interest position (u_i, v_i), thereby correcting for differences in the distribution of spatial scales (Fotheringham et al., 2017). However, it remains a challenge for GWR to determine the optimal bandwidth under high process spatial dependency and variability (Fotheringham et al., 2022). MGWR, on the other hand, builds on GWR by extended to a generalized additive line model as a way to deal with the bandwidth parameters of multiple variables in the modeled process (Fotheringham et al., 2017; Oshan et al., 2020). Specifically, MGWR is used to explore the spatial relationships between response variable and explanatory variables. Traditional or global regression assumes that the relationships examined through the model parameters are spatially constant, which implies that variables on the spatial distribution share a global bandwidth and tend to lose details of scale observations. In particular, unlike traditional or global regression, additional options for the neighborhood selection method from MGWR, including "golden search", "gradient search", "manual intervals" and "user defined", allows for estimating the optimal spatial scale for each of the explanatory variables by using bandwidths that vary across parameter surfaces (Fotheringham et al., 2017). Therefore, the MGWR model addresses spatial heterogeneity and complexity better.

2.3. How sDNA works and how it is used

In order to better understand the interaction between pedestrians and the environment in detail, this study combines sDNA (Cooper & Chiaradia, 2020) and MGWR (Fotheringham, 2019) algorithm to simultaneously measure and compare urban fabric. On the basis of the collection of spatial feature data in the Taikoo Place area, MGWR is used to automatically classify and recognize the spatial distribution of the five elements. In this way we will also seek to evaluate the effectiveness of MGWR as a new tool for data analysis algorithms in urban morphology.

sDNA is used in the study since, like the common Space Syntax model, spatial analysis software sDNA as a tool aims to systematically describe the interaction between individuals and their society and environment. The heterogeneity of space and daily life is described by quantifying the structural characteristics and scale of urban space based on social network theory (Freeman, 1978; Hillier, 2008). Considering that, AI methodologies in the in-between neighborhood scale, including within the morphology of urban block, sDNA in ArcGIS was used to quantify the capacity to simulate vertical movement along paths via stairs, escalators and elevators (Cooper & Chiaradia, 2020) in public and quasi-public spaces within the buildings and through the pedestrian roads.

The analysis uses the 3D pedestrian network provided by HKSAR Land Department (2020). The measured value of centrality of the network was chosen as "Betweenness". In betweenness analysis, the pedestrian network is assumed to be populated with entities that go from everywhere to everywhere else, subject to a maximum trip distance determined by a radius (Cooper, 2021). Therefore, betweenness was chosen, as it represents the path's potential to be used as pedestrians' primary traversal channels. Moreover, in order to evaluate the spatial-temporal data distribution in different key elements in neighborhood scale, within the agglomerated buildings of a block in Taikoo Place, the spatial statistical method this paper used is MGWR (Fotheringham, 2019). It was used to identify the cognitive effect of pedestrians on regional imagination and to obtain its distribution position and scale based on the evaluation of the space where the walking position is located.

2.4. What are the sources of data

Each bandwidth in MGWR represents a unique scale for each process, as a way to achieve multiscale distribution form estimation of multiple variables based on spatial position.

Its formula is as follows:

$$y_i = \beta_0\left(u_i, v_i\right) + \sum_{j=0}^{m} \beta_{bwj}\left(u_i, v_i\right) x_{ij} + \varepsilon_i,$$

where x_{ij} is the j th (j = 0,1,2..., m) predictor variable, $\beta_{bwj}\left(u_i, v_i\right)$ is the j th coefficient, bwj in β_{bwj} indicates the bandwidth used for calibration of the j th conditional relationship, ε_i is the error term, and y_i is the response variable (Fotheringham et al., 2017; Oshan et al., 2019). If $\left(\beta(u_i, v_i\right) = \left(\beta_0\left(u_i, v_i\right), \beta_1\left(u_i, v_i\right), \ldots, \beta_m\left(u_i, v_i\right)\right)^T$, the Ordinary least squares of $\left(\beta(u_i, v_i\right)$ at position $\left(u_i, v_i\right)$ is:

$$\hat{\beta}\left(u_i, v_i\right) = \left[X^T W\left(u_i, v_i\right) X\right]^{-1} X^T W\left(u_i, v_i\right) y,$$

where $X = (X_0, X_1, \ldots, X_m)$, $X_j = (x_{0j}, x_{1j}, \ldots, x_{ij})$, $W\left(u_i, v_i\right)$ is the spatial weighting matrix for location that weights each observation based on its distance from location $\left(u_i, v_i\right)$. $\hat{\beta}\left(u_i, v_i\right)$ is a j by 1 vector of coefficients, and y is a j by 1 vector of observations of the dependent variable (Fotheringham et al., 2017; Oshan et al., 2019).

This is because MGWR can simultaneously explore the scale of action of different variables and show the characteristics of different variables in the form of clustering (Fotheringham et al., 2017). In this study, pedestrian cognition as a response variable and the five elements of Lynch as explanatory variables are used in MGWR to explore their distribution forms and explicate them to explore the interpretation of the detailed features of spatial patterns (Figure 1). That is, the j in the formula is district, edge, landmark, node, and path is very much in line with $\beta_0\left(u_i, v_i\right)$ in the formula because it is a combination of the above five elements and varies with spatial position. This analysis uses the beta coefficient as an indicator that formulates the co-relationship between specific spatial structure and spatial cognition. Based on this since this study elaborates the relationship between the five elements and cognition, the grading of the beta coefficient has more meaning than the value itself, so this study classifies the beta coefficient into five grades: strong positive correlation, positive correlation, neutral, negative correlation, and strong negative correlation, to qualitatively determine the correlation between spatial cognition and the elements. This helps to identify the scale of the distribution from the data itself and allows information to be obtained about the overall impact of Lynch's five elements on cognition and scale.

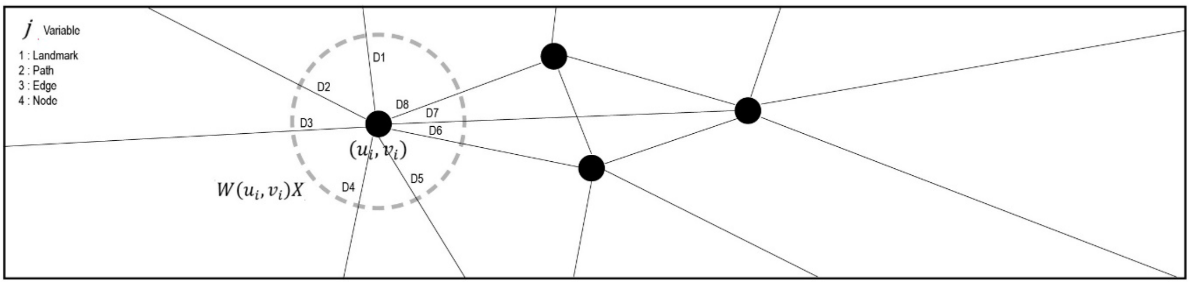

Figure 1. Illustration of the clustering pattern of variable types and their spatial distribution (source: authors)

3. Case study: Taikoo Place, Quarry Bay

Taikoo Place is a business district on the eastern side of Hong Kong Island, privately owned and managed by Swire Properties, a large developer and landholder. The district includes three-dimensional public space and realms that support a network of public and private functions (Choi et al., 2023). As such it can serve as a useful instance for study of the spatial cognition and urban patterns of morphology and building typology based on Lynch's five key elements.

3.1. Site information

Taikoo Place is linked by an elevated pedestrian bridge to Quarry Bay MTR urban underground railway station on its western side and Tai Koo station to the east. As shown in Figure 2, nine office buildings and a range of ground and podium level functions combine to provide a commercial and business district with a horizontally and vertically linked spatial layout and structure both from horizontal and vertical levels. Additional elevated walkways and landscaped quasi-public gardens are under construction and due to complete at the end of 2023. At ground level, the Tong Chong Street provides street level access from the MTR stations to the office buildings and new public spaces. It is a semi-pedestrianized and closed to vehicles on the weekend for a contemporary street market with food trucks; an attempt to break the pattern and character of the district being an exclusively weekday, workplace venue. A response to Hong Kong's often hot and wet climate, the elevated walkway system provides an alternative cool and dry interior public realm and access route from the MTR station to a network of elevated building lobbies, together with a series of amenities and facilities.

Figure 2. Taikoo Place, Quarry Bay in Hong Kong (source: authors)[1]

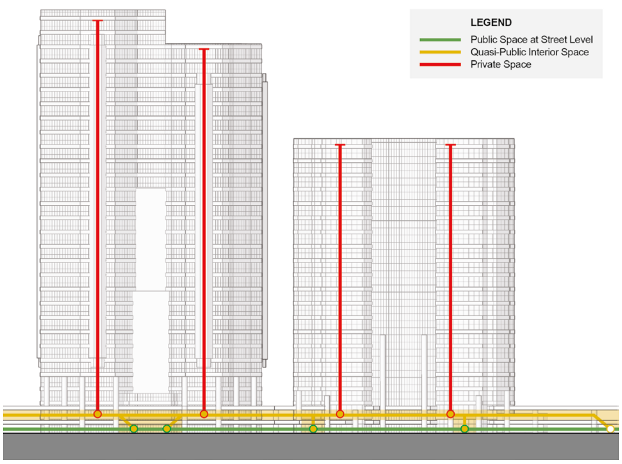

Figure 3. Three-dimensional public/quasi-public spaces and connectivity (source: authors)

Hong Kong is a city of uneven terrain that is also highly dense in character. The outcome is a public space network that often extends beyond the street and the street level, rising up and through elevated floors, pathways and quasi-public interior realms, as illustrated in Figure 3. As such the morphological character of these cities, and how they are analyzed, becomes a three-dimensional exercise not limited to a masterplan.

3.2. Data collection

Choi and Yang (2022) argued how in a highly dense built-up area, pedestrians' route considerations are based primarily on the presence of landmarks (tall buildings, buildings with design, including service facilities) and their visibility. At a smaller scale for wayfinding from street to street, pedestrians consider the guiding role of map/digital map/path guidance more to judge nodes in different environmental conditions (Li et al., 2020; Stevens, 2006). Subsequently, a path with more connections is selected as the travel choice rather than a dead-end path. Obstacles or physical separations act as edges to make pedestrians realize the possibility of moving (Hospers, 2010). At a district scale, landmarks, nodes, paths and edges constitute its heterogeneity (Stevens, 2006). These are also the variables selected for this study in the Taikoo Place area (Table 1).

To summarize the characteristics of user cognition of the environment, Figure 4 (Hospers, 2010; Li et al., 2020; Stevens, 2006) depicts the relationship between users' cognition and spatial cognition within spatial complexities. AI methods such as sDNA, discern and quantify the characteristics of the environment by analyzing numerical and geometric properties of all possible routes connecting random origin-destination pairs within a given network. Measurements of accessibility and flow prediction are common outcomes of these machine cognition methods (Cooper & Chiaradia, 2020). For users, on a larger scale, pedestrians' route considerations are mainly based on the presence of landmarks as points of attraction when moving from one location to another, which is expressed in the presence of the landmark buildings (tall buildings, buildings with distinctive design) on the travel route, the visibility of the landmarks, and the well-known convenience services (Li et al., 2020). As a result, the pedestrian routes

[1] *Publisher's note:* AccScience Publishing remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Table 1. Data collection and interpretation of variable selection (source: authors)

Elements	Data	Explanation
Landmark	Landmark buildings	Whether there are landmarks in the observation position
	Visibility	Can the landmark be seen from this observation position
	Amenities	Whether there are convenient facilities or commercial services in the observation position
Path	Connectivity	Whether the road is closed at the observation position
Edge	Edge	Whether the observation position is physically separated or explicitly off-limits
Node	Directory with map	Whether there are road signs or maps at the observation position
	Digital direction	Whether the observation position can be navigated from the electronic map
District	Not available	Obtain distribution pattern based on the combined evaluation of landmark/path/edge/node

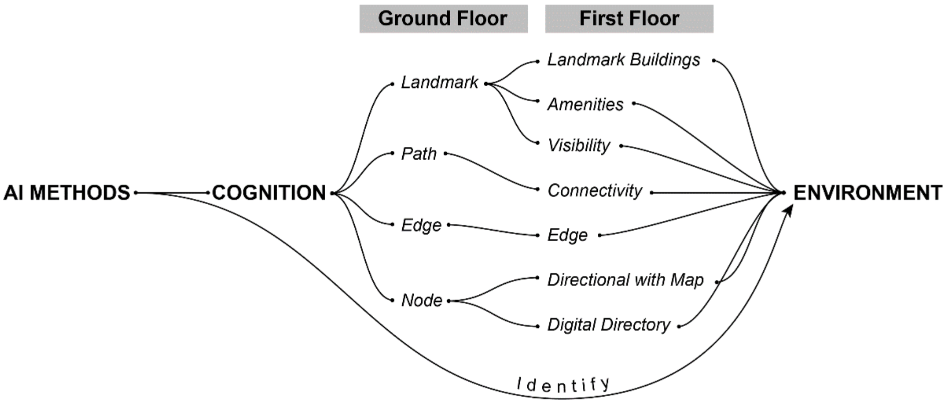

Figure 4. Data collection of urban spatial element configuration in Taikoo Place area and variable composition of five elements of urban imagery (district, edge, landmark, node, path) (source: authors)

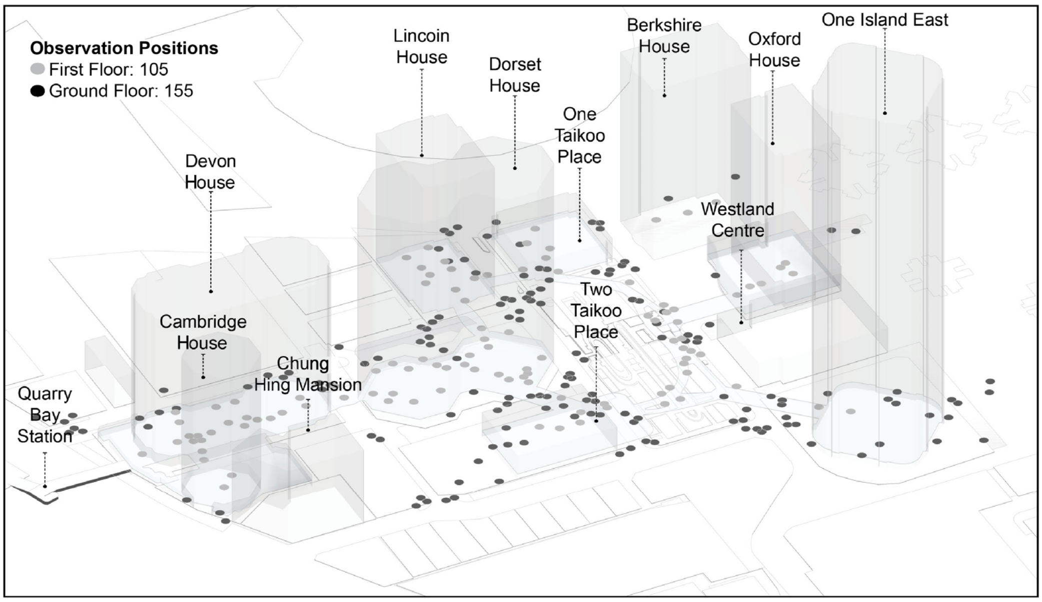

Figure 5. A total of 260 observation positions in the Taikoo Place area, Quarry Bay (source: authors)

around these landmarks can also take on a certain primacy and distinction as a special spatial cognitive public space.

This research seeks to assess how the multi-dimensional urban fabric at vertical and volumetric levels has accumulated the specific images from users and provides perceptions, organization, and spatial structures of the city, followed by districts, edges, landmarks, nodes, and paths.

The site observations from Quarry Bay MTR station and the neighboring Taikoo Shing MTR station included a count of 11,000 people per hour arriving at Taikoo Place in the morning, before the start of the working day via both stations on foot. Each of the nine Taikoo Place office buildings have an entrance at ground floor, with all but one being also accessible via the first-floor internal walkway system. There is an entrance to the elevated and internal quasi-public realm via an escalator adjacent to Quarry Bay MTR station, and an entrance through the One Island East lobby, which is a five-minute walk from Taikoo MTR station. From these two arrival points, the pedestrian traffic is split, with a proportion of visitors choosing the elevated internal walkway system to reach their destination, and a proportion remaining at street level.

The data was collected at each building entrance point and where the pedestrian traffic can be split and where the users changed their destination between public and interior quasi-public realm. Twelve different points, at junctions and intersections where the pedestrian traffic can split to different destinations were selected. These covered:

(1) Cambridge House entrance, (2) Devon House entrance, (3) the junction between Taikoo Place Apartments and Dorset House, (4) between Lincoln House and PCCW Tower entrances, (5) elevated walkway from Quarry Bay MTR towards PCCW Tower, (6) the intersection between One Taikoo Place and Berkshire House, (7) the elevated walkaway between One Taikoo Place and One Island East, (8) the interior of the quasi-public realm between Dorset House and PCCW Tower, (9) the interior of the quasi-public realm between Lincoln House and PCCW Tower, (10) Oxford House entrance, (11) One Island East Main entrance and side entrance, (12) Taikoo Shing MTR entrance/exit (Choi et al., 2023).

Except the figures for pedestrian flow, the research has set up a total of 260 observation locations in and around Taikoo Place to collect data on the urban environment (Figure 5), including 155 observation positions on the ground floor street level and 105 observation positions on the first floor.

The data representing each element was averaged and weighted to obtain a comparative score for each element. From Figure 6, we can see that the scores of landmark, path and edge are higher in the ground floor. This indicates that the building density of Taikoo Place is high and the building height is high, and at the same time, the road traffic in the area is well connected and convenient. The large difference in node scores between ground and first floor by spatial cognition indicates that the high-density area is still subdivided in the human design or organization to highlight the key areas.

The highest average values for path and node (see Figure 6 for the highest point with red color) in the first floor indicate that the interior (first floor) of the building in the Taikoo Place area is well organized in terms of traffic, while the interior is more subdivided by human design or organization compared to the exterior. This is very much in line with the function of the Quarry Bay area as a commercial and office center. Again, the difference in scores between landmark and edge is greater due to the influence of human guidance and physical separation.

In this study, to investigate the correlation between pedestrian spatial cognition and the five urban elements,

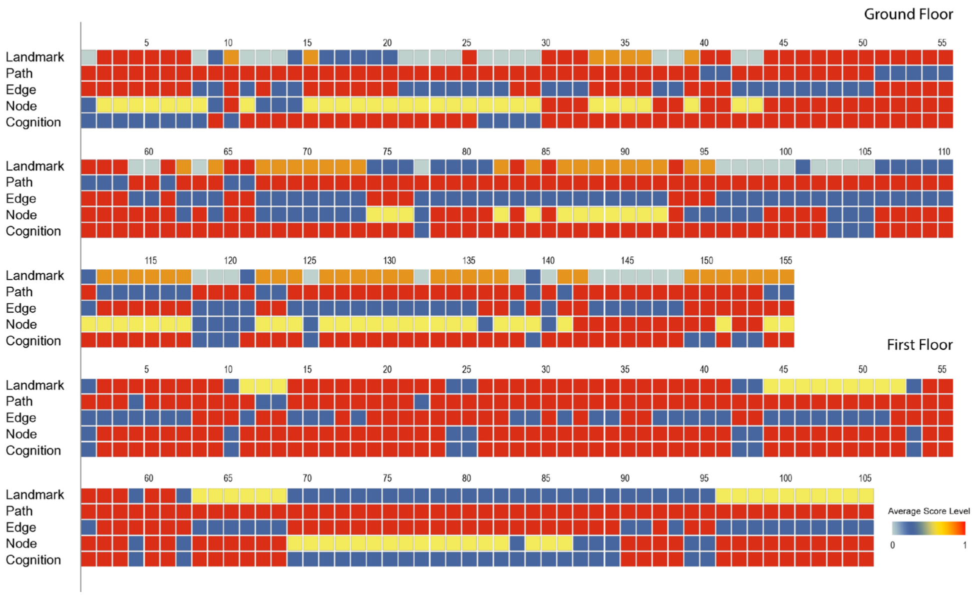

Figure 6. Edge, landmark, node, path, and scores obtained through data collection and average processing, users' cognition in relation to identity, image, memory (source: authors)

together with its usage and program details such as facilities, amenities, directories in Taikoo Place, we first tested using a global regression model. Subsequently, the MGWR model was used for multi-scale analysis and the best bandwidth was obtained. The response and explanatory variables were normalized to have a mean of **zero** and a variance of **one**, so that the bandwidth of MGWR was independent of the scale and variability of the explanatory variables, facilitating relative comparisons of bandwidths. Following the literature (Oshan et al., 2019), we prepared digital maps to visualize the parameter estimates and their uncertainty, and we showed them on the maps despite the presence of statistically indistinguishable estimates from zero because the current study focused on heterogeneity of individual cognition at small scales, so their comparative relevance is still more important. Finally, obtain the influence and scale of landmark, node, distinct, path, and edge on pedestrian cognition.

As stated in the previous brief description of the MGWR approach, we first need to determine the spatial relationships of the model parameters. Therefore, before data processing it is first necessary to assume whether the relationships examined through the model parameters are spatially constant using traditional or global regression.

From Table 2, we can see that although the first-floor model identified as better response variable with regression R2 = 0.909, the ground floor model had a poor fit with a response variable regression model of only R2 = 0.139. That means the global fit does not reflect the effect of the five elements on pedestrian cognition. Therefore, it is appropriate to use MGWR for in-depth analysis.

Table 2. Exploring the global regression model fit between the variables and the response variable applies (source: authors). AICc stands for Akaike information criterion, and R2 stands for the coefficient of determination

Location	Number of observation positions	AICc	R2
Ground floor	155	429.27	0.139
First floor	105	58.921	0.909

To solve for the weight matrix in MGWR, the kernel function is first applied to the distance between the observation and calibration points (Fotheringham et al., 2017; Shabrina et al., 2021). In this study a double square kernel function with a nearest neighbor measure is used. More commonly used is the Gaussian kernel function, which considers all data points where the weights decrease gradually from the center of the kernel. In this case, the weights are never assigned a zero value (Oshan et al., 2019). In contrast, the double square kernel function is interpreted as the bandwidth being the number of nearest neighbors that the data are weighted to exactly, and further observations have no effect on each local regression (Oshan et al., 2020). Second, the proximity defined by the nearest neighbor is more robust to irregular spatial sampling.

After specifying these elements, we can use an iterative optimization process to find an optimal bandwidth that minimizes the modified Akaike information criterion (AICc). The AICc optimization measures information distance by capturing the divergence between predicted and observed value (Fotheringham et al., 2017; Oshan et al., 2019; Shabrina et al., 2021). The final beta coefficient is obtained by iterating over the AICc values of the model, and the multiple testing of the MGWR model helps us to obtain the 95% confidence t-values and the effective number of parameters due to its setup.

Table 3. Optimization of the fitting results of the multiscale model of the correlation between pedestrian cognition and five factors calculated by MGWR (source: authors). AICc stands for Akaike information criterion, and R2 stands for the coefficient of determination

Location	Number of observation positions	AICc	R2
Ground floor	155	349.781	0.652
First floor	105	–153.748	0.991

As can be seen from Table 3, the results obtained from the MGWR analysis have a better fit (ground floor R = 0.652 and first floor R = 0.991). In other words, the data collected in this time present a smaller scale in the analyzed area, and the reliability of the analysis results is higher.

4. Results and findings

4.1. Assessment of pedestrian cognition in Taikoo Place area by sDNA

The sDNA analysis of Taikoo Place area was performed to obtain information on the locational advantages across the accessible pedestrian network. The radius was adopted as 0.1 mile/528 feet to restrict the scope of analysis within the neighborhood as illustrated in Figure 7. Accessibility in the analysis is determined by the betweenness of a particular path, which indicates its potential usage intensity. As Taikoo Place is a business district, pedestrians are assumed to travel via the shortest path within the network. Euclidean metrics were used to define physical distance.

From the analysis results shown in Figure 7, it can be seen that the areas with high accessibility are located near Lincoln House, Dorset House, and One Taikoo Place, from which the center gradually diminishes outward. Combined with the distribution of pedestrian cognition obtained from the verbal research, the pedestrian cognition is mainly distributed on the first floor of highly accessible routes. Such an interpretation is slightly ambiguous. The reason for this is that the analysis scale of the road is much larger than the distribution scale of the observation points thus blurring the details.

Figure 7. Results of spatial configuration analysis of Taikoo Place by sDNA (source: Choi et al., 2023)

4.2. Assessment of pedestrian cognition in Taikoo Place area by MGWR

MGWR analysis obtains the scale of the distribution from the data itself, rather than analyzing the data from a finite scale, thus allowing more detail to be obtained. From Figure 8 we can see the impact of landmark, node, district, path and node with scale.

The first is the landmark element. The ground floor analysis shows that the correlation between landmark and cognition is most positive in the neighborhood of Dorset House and one island east. At the same time, these two buildings have the highest design and height in the area. In the first-floor analysis, we can see that landmark has a negative correlation with cognition when the observation is indoors, but it has a positive effect on cognition when they are out of the room. On the composite graph, we can see that the correlation between landmark and cognition on both ground floor and first floor show a gentle transition when outside, and a sharp decline when moving indoors. This is more in line with common sense.

Next is district. In the analysis of the ground floor the site is roughly divided into three areas, Devon House – Cambridge House – Chung Hing Mansion, Two Taikoo Place – Lincoln House – One Taikoo Place, Berkshire House – One Island East – Dorset House – One Taikoo Place, Berkshire House – Oxford House – Westland Center – One Island East. In the first-floor analysis it can be seen that Devon House and Dorset House are in the same group and Lincoln House and One Taikoo Place are in the same group. In reality, these buildings happen to be connected to each other, which shows that the scales and effects obtained from the analysis can be trusted. We can see a smooth transition between district and cognition correlations in the combined results. At the same time its role is similar to the results of the sDNA analysis, as Professor Hillier argues that the results of the sDNA/Spatial Syntax analysis based on social network theory are not only the accessibility of distances but also the importance of constituting social positions (Hillier, 2008), for example, the common locational advantage. On this basis, MGWR is able to identify not only the scale of district, but also to interpret the spatial importance as well as the development potential.

The overall analysis trends for edge and node are similar. As mentioned earlier, the edge represents physical separation while the node represents a local intervention achieved through design or organization, both of which show a higher impact of the first floor indoors than it does outdoors and on the ground floor. This suggests that in a high-density residential environment such as Hong Kong, design or management is more concerned with guiding pedestrian cognition in functional spaces, with outdoor areas being reduced to in-between spaces and their functions and roles diminishing.

In contrast to node and edge, path shows an overall positive effect on the ground floor and a graded effect on the first floor. Obviously, this is also related to the properties of high-density cities. In a high-density urban environment, the accessibility to each destination is high, while indoors, due to the limited space and the economic factors involved, there are primary and secondary paths, which also influence people's cognition in the design, management and organization process.

Finally, with MGWR we also obtained information on the overall impact of the five elements on cognition, the scale, and statistical tests. From Table 4 we can see that the R2 of the first floor is much larger than that of the ground floor, and the effective number of parameters of the first floor is also smaller than that of the ground floor. This indicates that the variables of the first-floor model fit better than those of the ground floor. That is, there are more elements outdoors that interfere with pedestrian cognition. Estimates analysis shows that node as a key factor

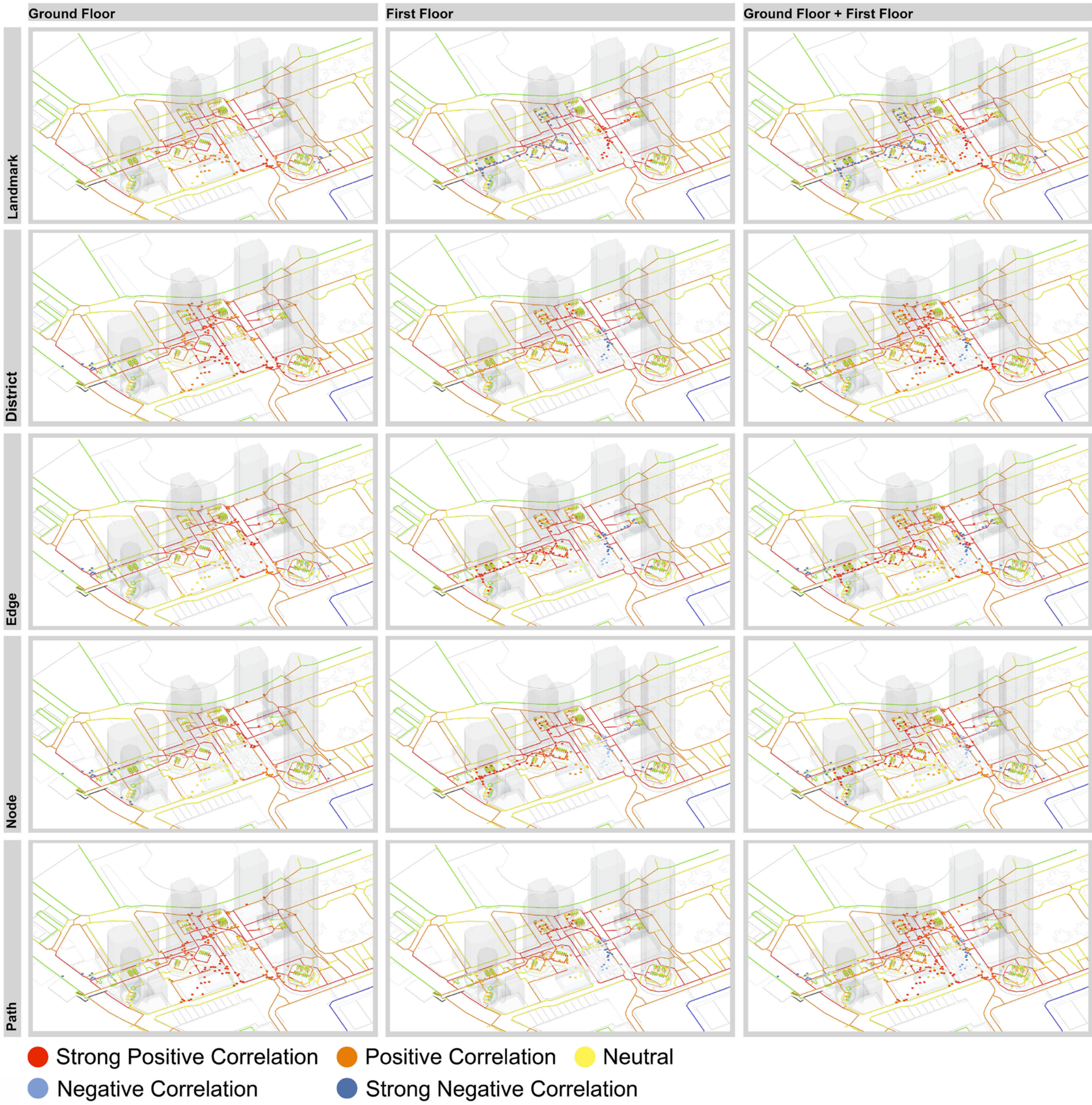

Figure 8. The impact and scale of the five elements by spatial cognition at ground and first level (source: authors)

Table 4. Statistical diagnostic information and the impact and scale of the five elements on cognition (source: authors)

Diagnostic information	Ground floor	First floor
Number of observation positions	155	105
AICc	349.781	–153.748
R2	0.652	0.991
Effective number of parameters (trace(s))	28.503	18.137
Landmark bandwidth	46	44
District bandwidth	44	44
Path bandwidth	96	43
Edge bandwidth	44	44
Node bandwidth	44	43
Landmark estimates	0.073	0.236
District estimates	0.143	0.094
Path estimates	0.028	–0.11
Edge estimates	–0.027	–0.143
Node estimates	0.118	0.601

influences pedestrian cognition, which also indicates that human design, management and organization have an important influence on interfering with human flow. Edge has an overall negative effect on pedestrian cognition.

4.3. Distribution results

Understanding and analyzing the three-dimensional morphological character of Hong Kong, beyond the street level, rising up and through elevated floors, pathways and quasi-public interior realms, the sDNA and MGWR algorithms simultaneously measured and formulated the co-relationship between spatial structure and spatial cognition. MGWR data has allowed a classification in spatial distribution of the five elements as noted below.

"District" defined as territories and forms, and it shows different forms to define its terms between ground and first floor.

- Ground floor: geographical size of district.
- First floor: agglomeration of buildings through accessible indoor public realm.

"Landmark" can be defined by scale.

- Ground floor: singular buildings on the street level.
- First floor: amenities and facilities from users' perceptions and experience to remember.

"Paths" can be defined as multiple ways for connectivity.

- Ground floor: all the pathways at street level.
- First floor: lines of movements through elevated walkways, corridors, indoor pathways, including stairs and escalators.

"Edges" can be defined as physical boundaries.

- Ground floor: physical boundaries between buildings, plots, districts, and *cul-de-sac*.
- First floor: physical boundaries in the end of the corridors/buildings.

"Nodes" can be defined as physical junctions to cross paths, and pause for the decision-making points (choices) to change the directions.

- Ground floor: street junctions.
- First floor: between spaces to split the directions and levels (upper level to lower levels, vice versa).

Lastly, Table 5 cross compares the spatial distribution patterns of the five elements on the ground and first floors.

5. Discussion and conclusions

5.1. Limitation from Lynch's five key elements and our findings

With the findings, this research is able to elaborate the capacity of a methodology focusing the capability of AI research technology, using sDNA and MGWR techniques which has been set up the assessment criteria of indoor and outdoor spatial networks and volumetric space in three-dimensional space. The result showed a spatial morphological configuration and pattern of urban space focus on five key elements (Districts, Edges, Landmarks, Nodes and Paths) in relation to spatial cognition.

As mentioned earlier, the limitation from Lynch's five key elements that mainly defined by users' cognition with the result of a two-way interaction between the environment and the person observing it (Lynch, 1960), this result, depicts the relationship between users' cognition and spatial cognition within spatial complexities. Specifically, as listed in Table 5, the perception of the five elements varies depending on the location of the observer within the 3D volumetric public and quasi-public space. It demonstrates a clear difference from the application of Lynch's principles in complex multidimensional spatial systems.

Conventionally, districts have been differentiated by their urban fabric at ground level, while on the first floor, they are distinguished by the accessible indoor public realm. Landmarks are typically recognized by singular buildings, but from the first floor, they are recognized by amentities/facilities based on user experience, which can be related to the concentration and diversity of commercial activities and limited spatial visibility within quasi-public indoor spaces. This is because the perceivable volume of the space does not change much, unlike in ground floor outdoor public spaces. While traditionally, edge and node have been distinguished as relating to parking lots and landmarks, they are also related to in-between spaces and

Table 5. Distribution results (source: authors) (need to further explain how the research – and AI methodology – has been able to develop and redefine Lynch's principles in a complex multi-level system

Elements	Ground floor	First floor	Ground and first floor's common spatial distribution
District	Recognition by urban fabric	Distinguished by accessible indoor public realm	Territories and forms
Landmark	Singular buildings based on user perception	Amenities/facilities based on user perceptions and experience	Relatively strong central position
Edge	Around the parking lot and landmarks	The emergence of edge, in-between corners and edges	The places with strong edges have high accessibility
Node	Around the parking lot and landmarks	The emergence of edge, in-between spaces and corners	The distribution trend of nodes are similar to that of edges
Path	All the pathways	Lines of movements, including stairs and escalators	The analysis result of path is similar to the centrality of sDNA and the distribution mode is similar

corners from the first floor, which correspond to interior spatial settings dominated by corridors. Additionally, path refers to pathways on the ground floor, and all vertical connections from the first floor up, including escalators and elevators. In areas where path is not distinguishable spatially, lines of human movement are recognized as paths.

5.2. Triangulation between sDNA and MGWR algorithms

The research used the case of Hong Kong as a dense city that is three-dimensionally activated in terms of public access not just at street level, but also via upper-level walkways, public and quasi-public spaces and access, including three-dimensional volumetric assessment of public and quasi-publics.

Applying AI methodologies at the in-between neighborhood scale, including within the morphology of urban block development, the sDNA and MGWR algorithms have been utilized as a triangulation method to evaluate and measure built density. The data analysis has revealed (1) some limitations in variations between the ground and first level of public/quasi-public spaces in methods of statistical analysis, and (2) great potential tool, using sDNA and MGWR analysis to integrate multi-dimensional levels of taxonomy typologies, combining the fabric in one clustering analysis.

Comparing two-dimension and three-dimension public/quasi-public space, one of the variation input, "visibility" for "passage and lobby" at street level, couldn't be measured at first level due to the fact that there are no "lobbies" in the quasi-public realm owned by this private developer. For this reason, a new variable selection "bypass" was used in place of "lobby" or the variation of "visibility", In addition, at first level, another cluster selection needed to be adjusted to obtain the metrics the "edge", considering the physical *cul-de-sac* condition from each building. More interestingly, the "node" can be considered as a multi-layered transitional point at first level, where a series of elevators and escalators serve different levels. As such, and as previously noted by Shelton et al. (2011), when you are considering a volumetrically intense city such as Hong Kong.

Addressing those key findings, this research was able to elaborate the evaluation capacity of a methodology based on AI techniques in terms of analysis, measurement and visualization of indoor and outdoor spatial networks and three-dimensional volumetric morphology of Hong Kong. It has re-defined the terms of the five key elements from the rhizome that Lynch theorized to the three-dimensional density and complex spatial layout. Secondly, this research highlights how the application of AI in statistical assessment of the defined urban space typologies helps to obtain specific metrics that can inform a taxonomy of typologies for public realm and vertical and volumetric urbanism.

Urban morphology and typology within highly-dense cities such as Hong Kong, Mumbai, Dhaka, New York, London, are continually evolving and intrinsically linked to metabolic processes of the city by addressing resource generation through hybrid and organic patterns of infrastructure that is integrated within the urban fabric. Taking this into consideration, the results of the research obtained using AI can capture the process of metabolism and inform the contemporary characterization of the definitions Lynch made for "district", "edge", "landmark", "node" and "path", that can integrate and penetrate urban models and provide new opportunities to tackle emerging city issues.

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Author contributions

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Availability of data

The final 3D pedestrian network of Taikoo Place for sDNA analysis is available at https://doi.org/10.1186/s40410-023-00194-5, a related paper by the authors. Other data that support the findings of this study is available from the corresponding author upon reasonable request.

Further disclosure

AI sits within a technological area where skepticism is growing (Gilby, 2022) about the extent and usage of data collection as a means of surveillance and influence of private lives and activities (Vinuesa et al., 2020). With search engines and social media platforms "smart" enough to monitor and seek to influence thoughts and actions, there is a growing realization and concern about the Orwellian nature of these powers built into the city infrastructure.

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