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A spatial model of cognitive distance in cities

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ABSTRACT
Spatial cognition is fundamental to the behaviour and activity of humans in urban space. Humans perceive their environments with systematic biases and errors, and act upon these perceptions, which in turn form urban patterns of activity. These perceptions are influenced by a multitude of factors, many of them relating to the static urban form. Yet much of geographic analysis ignores the influence of urban form, instead referring most commonly to the Euclidean arrangement of space. In this paper we propose a novel spatial modelling framework for estimating cognitive distance in urban space. This framework is constructed from a wealth of research describing the effect of environmental factors on distance estimation, and produces a quantitative estimate of the effect based on standard GIS data. Unlike other cost measures, the cognitive distance estimate integrates systematically observed distortions and biases in spatial cognition. As a proof-of-concept, the framework is implemented for 26 cities worldwide using open data, producing a novel comparative measure of 'cognitive accessibility'. The paper concludes with a discussion of the potential of this approach in analysing and modelling urban systems, and outlines areas for further research.

KEYWORDS
Spatial Cognition; GIScience; Cognitive Geography; Cognitive Distance; Accessibility.

1. Introduction

Distance is an intrinsic component of all spatial processes and fundamental to all human activity in geographical spaces. People make use of the concept of distance to plan journeys, undertake activities, and interact with their environment (Montello, 1997). However, whereas in most analytical contexts the convention is that distance is measured on a Euclidean plane, human behaviour and social systems are instructed by a notion of distance that involves a subjective or psychological dimension. At a fundamental level, humans perceive the external, phenomenal environment, giving shape to a behavioural environment within which they act (Kirk et al., 1963). In modern-day, geographical analysis we make no such distinction.

The study of human perception of distance has typically taken one of two forms. As a *cognitive* (Canter & Tagg, 1975) (or *subjective* distance (Thompson, 1963)) which is 'the impression of distance formed in the mind' between places that are not visible from each other (Walmsley & Jenkins, 1992, p. 24), or, alternatively, as *perceptual distance* (Baird, 1970) which regards estimation of distance to places directly visible from the observer's position. Even though misrepresented distances had been already reported by Brennan (1948) to describe consumers preferences, a more explicit interest for the notion of cognitive distance arose in behavioural geography between the 1960s and 1970s. The dissatisfaction with simplistic assumptions regarding the human-environment interaction, based on the principles of *homo economicus* and the perception of an objective external world (Golledge & Timmermans, 1990; Portugali, 2011), triggered the development of alternative models to explain spatial behaviour. The reporting of misjudgements in distance assessment amongst shoppers from San Francisco (Thompson, 1963) inaugurated a series of studies which described overestimation of distances under a variety of contexts and circumstances (Canter & Tagg, 1975; Pocock & Hudson, 1978).

This vein of research was further enriched by studies on the 'mental image' of the city, and the relationship between urban form, its elements and cognitive representations (Appleyard, 1970; Horton & Reynolds, 1971; Lynch, 1960). Behavioural geographers investigated how external properties of the environment mould the internal representation and the formulation of spatial relationships, such as cognition of spatial separation (Briggs, 1973). Moreover, by highlighting the role of action as a medium between people and the city, Chapin (see: Chapin, 1968; Chapin & Brail, 1969) introduced the concept of *action space*, the environment wherein an individual engages in most of her activities. Such a space generates stronger and more detailed mental representations, affecting route and destination choices but also magnifying miscomputation of distances and distortions in spatial relations. In a similar manner, Hägerstrand's *Time Geography* approach (Hägerstrand, 1970) stressed the importance of the temporal dimension and other external constraints, like (cognitive) distance, which may affect people's activity trajectories.

At the end of the last century, collaborations with environmental psychologists (Kitchin et al., 1997) and the shift of paradigm in cognitive science have led geographers to partly abandon the study of the *what* and *where* to dedicate more attention to the *how* and *why* (Golledge, 2002). This change of perspective have prompted a more explicit study of cognitive processes and internal representations of space. Cognition of distance has been included in the general domain of spatial distortions research (Montello, 1997; Tversky, 1992) and is seen as part of processes of simplification and organisation of the external world knowledge. Along with Euclidean information, the human mind makes use and assimilates spatial information by means of hierarchical organisation (e.g. Hirtle & Jonides, 1985; McNamara et al., 1989; Stevens & Coupe, 1978), change of perspective (e.g. Tversky, 1981) and environmental cues, as landmarks (e.g. Hommel et al., 2000; Jansen-Osmann & Berendt, 2005). These three principles involve the perceptual and attentive cognitive systems and are behind the general cognitive functioning (Gibson, 1979; Neisser, 1976; Rosch, 1973), and may result in distance distortions (Tversky, 1992).

Even though it has been shown that cognitive distance reflects real distances (e.g.: Jansen-Osmann & Berendt, 2005) and that people are able to store and process metric information about the environment (Ishikawa & Montello, 2006; Montello, 1998), the study of cognitive distance remains valuable. The concept is informative of individual behaviour, as it discloses hints about the cognitive organisation of spatial knowledge (Montello, 1997) and the relationship between internal and external representation (Portugali, 1996); but furthermore, as a behaviour determinant, it provides insights for analysing movement patterns and the human-environment interaction at the macro-level. The cognition of distance is at the basis of spatial decision-making (Hägerstrand, 1970), navigation (Cadwallader, 1976), and wayfinding behaviour (Brunyé et al., 2015). Research in neuroscience and neuropsychology has also shown that distance is explicitly encoded in the human brain and it involves the activation of different areas in the hippocampus formation (Morgan et al., 2011), depending on the spatial task performed (e.g. Chen et al., 2019; Howard et al., 2014) and the familiarity with the environment (Patai et al., 2019).

Parallel to developments in the understanding of spatial cognition, quantitative geography and GIScience have emerged as established fields of research, underpinned by common principles of spatial representation. Central to spatial analysis is the encoding of geometric features on a Euclidean plane, differentiating objects within this space as points, lines, or polygons. Euclidean space has the benefit of being readily measurable on the Earth's surface and a reasonable proxy for spatial friction and interaction (Wilson, 1971). The ubiquity of the Euclidean approach translates to the all spatial data, models, and maps in common use, yet the ubiquity of adoption does not make it suitable in all applications. Uncertain or fuzzy perceived, semantic, and social constructs in space - such as neighbourhood regions and salient locations - are not adequately represented by the crisp precision of GIS definitions (Burrough & Frank, 1996) and the use of such features may result in misleading analysis (Kwan, 2012). Models of spatial phenomena in health and transportation may integrate metric distance decay with non-Euclidean or non-metric spatial components (e.g. time, cost). It is well understood that translation errors occur in during the reading and cognition of 2D maps and cartography (Lobben, 2004).

In view of these limitations, a range of alternative non-Euclidean models of space have been presented, capturing alternatively time and connectivity. The most established set of methods is found in *time geography*, where Euclidean space is augmented by a third temporal dimension in the form of a path or prism (Kwan, 2004, 2013), along or within which spatio-temporal accessibility measures can be computed. This representation is highly suited for describing the activity of humans and mobile objects, but does not capture perceptual and non-Euclidean distortion of space. Another source of spatial data is derived from topological connectivity between spatial features, where graph adjacency may be spatial and/or non-spatial in nature. Within this context, the computation of regional properties may arise from a variety of topological factors, from flow between features (e.g. goods, people, resources), strength of spatial connectivity (e.g. based on angle or distance) (Hillier & Iida, 2005; Turner, 2007), or infrastructural connection (Derrible & Kennedy, 2010). The properties of connectivity have important implications for describing the characteristics of urban systems. There remains, however, little exploration of how the systematic biases and limitations inherent to human spatial cognition can be integrated into spatial models of distance and connectivity. With such a measure, opportunities would arise to compute 'cognitive' measures of spatial accessibility,

The aim of this paper is to outline a quantitative framework for integrating cognitive distance into computational representations of space. The framework is built on a wealth of research into cognitive distance, developed over the last few decades, and proposes a preliminary set of measures and weights that link environmental features to their systematic impact on cognitive geographic distance. As we will demonstrate in this paper, the production of such a measure allows us to consider how cognitive distances vary in aggregate by spatial context. Through a case study application, we will explore variation in cognitive distance across a subset of cities.

In the next section we will draw together the wealth of prior research into the relationship between humans, environment features, and distance perception. Taking these lessons on, the third section will present the proposed framework for augmenting Euclidean distance according to the exposure to environmental features. In the fourth section, a case study implementation of the framework is described within the context of 'cognitive accessibility', drawing on globally available GIS data sources. The paper will conclude with thoughts on the future directions and potential of this research. The framework we present, at this stage, is intended as only an initial integration of these previously disparate fields. It is hoped that, by highlighting the relationship between human cognition and the representation of geographic space through GIS, further advances in our understanding of how urban space impacts human behaviour can be made. The definitions made within this paper should therefore be read as a starting point for further verification, validation, and development through collaboration across the geography and psychology research communities.

2. Urban form and cognitive distance

In building a framework for encoding cognitive distances within geospatial representations, one can draw upon a wealth of past empirical studies. These studies were, for the most part, conducted with small numbers of participants within controlled settings. As such, it cannot be claimed that any comprehensive study, able to define cognitive distance estimation at all scales and contexts, exists. However, they provide a set of guiding principles for developing a geocomputational framework to cognitive distance. Research around cognitive distance is widely influenced by the conceptualisation of spatial perception offered by Lynch (1960), decomposing the urban environment in five elements - paths, nodes, districts, landmarks and edges. We here embrace this approach, although other semantic representations of the urban environment have been proposed (e.g. Berta et al., 2016; Dibble et al., 2019).

The central relationship between environmental features and cognitive distance can be considered to relate to a few fundamental theories. Milgram (1973) argued that the more information associated with a geographical area, that is the more features contained in a region, the greater the perceived extent of the area. Likewise, a route with a high number of features would be represented as longer, in comparison to routes of equal length but featured by fewer environmental stimuli. The effect is known as the *information storage* hypothesis (Sadalla et al., 1980) or *feature accumulation* effect (Montello & Freundschuh, 1995). Furthermore, the presence of geographical features along a route relates to a tendency to represent knowledge about the external space in a hierarchical manner (Hirtle & Jonides, 1985). According to the *route segmenting* hypothesis (Montello, 1997), environmental features or groups of features induce a representation of space organised in blocks or homogeneous stretches (Jansen-Osmann & Berendt, 2005) that cause distortions in distance knowledge. The influence of different environmental features - including intersections, barriers, landmarks and turns - revolve around these two cognitive processes.

2.1. Intersections and landmarks

Sadalla et al. (1980) demonstrated that estimated distances increased with the number of intersections encountered within both artificial and urban settings. In the same fashion, Kahl et al. (1984) found that children would estimate routes fragmented by several interruptions as longer than continuous routes. The results of these studies are aligned with the route segmentation hypothesis: intersections form one basis for *chunking* a route, a process that consists in organising a complex route into more easily memorable segments or blocks, so as to increase cognitive efficiency (Allen, 1982; Klippel et al., 2003). A similar argument applies to landmarks: relevant buildings belonging to the same group (e.g. proximity, functions, colour, etc.) would be perceived as closer than what they are, whereas elements of different classes are estimated to be more distant than in reality (see: Hirtle & Jonides, 1985; Hommel et al., 2000).

Related to the effect of route chunking is that of feature accumulation, which refers to the effect of increasing recalled distance, with higher exposure to spatial features (e.g. landmarks along a route). Briggs (1973) hypothesised a relation between the city structure and the cognition of distances and describes buildings' vividness and variation as possible factors influencing distance knowledge. Jansen-Osmann & Berendt (2005) delved into the interaction between the feature accumulation and the route segmenting effects. In a set of experiments in virtual reality environments (VRE), participants overestimated distances due to accumulation of landmarks or intersections in a route-learning condition, and due to segmenting features in a map-learning condition. The interaction of such effects may depend on how an individual experiences a certain environment (e.g. egocentric versus allocentric frames of reference).

2.2. Turns

The influence of turns has recently received attention in relation to the perception of distances, under the name of the *route-angularity effect* (Jansen-Osmann & Wiedenbauer, 2004). Sadalla & Magel (1980) reported that routes that featured seven right-angle turns were estimated as longer than routes with only two turns in an artificial environment, due to the *scaling hypothesis* (see below). However, Jansen-Osmann & Wiedenbauer (2006) argued that the memory load and uncertainty would determine to what extent people may rely on heuristics such as chunking the route at turns. This idea has been supported by a successive study (Hutcheson & Wedell, 2009), according to which the number of turns is coded and retrieved as a distance heuristics, in particular when 'fine-grained memory for a path distance is disrupted' (Hutcheson & Wedell, 2009, p. 519).

2.3. Barriers and regions

While physical and perceptual boundaries support the hierarchical organisation of the external environment in regions and subjective districts, they may also affect the cognition of distances. In artificial settings, several researchers (Kosslyn et al., 1974; McNamara, 1986; Newcombe & Liben, 1982) observed that objects belonging to different quadrants were perceived as further away by both children and adults, in comparison to objects located in the same region and alike distance. Along the same lines, Cohen et al. (1978) evaluated the effects of natural barriers, as trees and hill, on the perception of 'ease of travel'. When two locations were separated by such barriers the subjected tended to overestimate distances. On the contrary, an absence of edges was associated with underestimated distances.

2.4. Network density and legibility

Kevin Lynch had already discussed the interaction between perceived complexity, urban morphology and mental imagery in The Image of the City (Lynch, 1960), describing several cases where passersby where confused by the poor vividness of certain areas, street-layouts, or the density of similar indistinguishable junctions. In this direction, aimed at discussing possible intrinsic metric properties of urban mental imagery, Canter & Tagg (1975) summarised the results of several experiments on distance estimations in urban environments. Cities with confusing configurations would lead people to overestimate distances. This is, for example, the case of Tokyo (Japan), 'such an intricate city that there is no other overall structure to which reference can be made when representing it schematically' (Canter & Tagg, 1975, p. 76). Conversely, cities featured by rivers, railways, remarkable elements and regular layouts - namely legible cities - would cause distortions in terms of distance underestimation. In this context, little emphasis is given to configurational aspects in terms of network density and complexity. The link between imageability and distortion quantification has not been explored further, perhaps due to the not trivial formalisation of terms such as imageability and legibility.

2.5. Travel time, speed and mode

The relationship between travel time and distance estimation has been widely studied in geography due to its intuitive nature (Montello, 1997). Golledge & Zannaras (1973) argued that the perception of distances is directly influenced by the time that would be necessary to complete the path between the pairs of considered locations. MacEachren (1980) showed that travel time had a stronger relationship with distance estimates, as compared to objective distance combined with environmental factors (number of intersections, turns, traffic lights). However, Montello (1997) questioned these results and the nature of this relationship. Other studies have indeed displayed a negative relationship between time and distance and disregarded the existence of a casual correlation between these variables (e.g.: Crompton & Brown, 2006; Lederman et al., 1987).

No less discussed is the perception of distances of active and passive travellers. Montello (2009) describes two different conceptualisations of active travelling (see also: Chrastil & Warren, 2012). Active travelling entails taking spatial decisions at first hand and refers to *self-guided movement*: a car driver is an active traveller whereas passengers or public transport users are passive travellers. For example, Appleyard (1970) reported better distance estimates in bus and car drivers than in public transport passengers; yet, other studies presented conflicting results regarding distance estimation of drivers and non-drivers (e.g. Lee, 1970; Lowrey, 1973; MacEachren, 1980).

Another perspective discerns active from passive travelling on the basis of the the effort involved in the completion of the trip. An active traveller is someone who is *self-powered*, such as walkers, runners and cyclists, whereas passive travellers exploit motorised vehicles, either as drivers or passengers. The distinction is important when studying human perception of distances but, once again, evidence is not unequivocal (see: Crompton & Brown 2006; Hart 1981, and studies in VR, e.g.: Foreman et al. 2004; Gaunet et al. 2001; Mellet et al. 2010; Ruddle et al. 2011; Sandamas & Foreman 2015).

2.6. Topographic change

To explain Euclidean distance overestimation resulting from the presence of hills, Cohen et al. (1978) resorted to the influence of the physical effort required to the subjects when reaching the destination. Aware of the presence of hill or up-hill sections, individuals would incorporate a fatigue component into the distance judgement and thus magnify the estimate. However, as suggested by Okabe et al. (1986), down-hill routes, trails or section of stairs may require extra-care and therefore induce another kind of effort. Indeed, the authors found out that distances were overestimated in adults and children that walked along uphill, downhill (average slope 8.5°) and flat trails 100 meters long. In their view, errors derived by walking uphill were associated with physical effort, errors caused by walking downhill were associated with cognitive effort. Stefanucci et al. (2005) reached similar conclusions across experiments in real world and virtual environments, for 20° and 25° slopes (target distances were between 8 and 14 meters).

2.7. Route distance

The navigation task at hand is shown to have an additional effect on distance cognition, as the context and distance between origin and destination are relevant. One important finding suggests that people tend to overestimate shorter distances and underestimate longer ones (Lloyd, 1989), (scaling hypothesis). This study, which asked participants to estimate distances between landmarks that they had been asked to memorise, identified significant differences in estimation error between pairs of locations at short and long distances. These results were consistent for both Euclidean and route distance estimates. The study demonstrated as a secondary effect that distance estimates within urban settings were worse than those in rural areas, further validating earlier studies showing that the density of spatial features play a role in distance cognition.

3. Towards a spatial model for cognitive distance

The review has highlighted the variety of environmental and contextual factors that influence distance perception. Next we address how these findings can be integrated within a quantitative framework for estimating cognitive distance. The framework proposes, first, a set of spatial data and, second, a set of weightings that can be used in calculating cognitive distance.

3.1. Spatial data selection

In order to align with the findings in spatial cognition outlined above, we must first establish the nature and availability of spatial data by which such distortions are influenced. Below the features impacting cognitive distance are discussed in terms of their representation in spatial data.

- *Intersections* are typically defined as point features in spatial data, located at the intersection of two or more streets, and may be associated with a road network hierarchy. While the literature recognises the prominent role of hierarchy in spatial cognition, it does not draw a clear distinction between different types of intersection. However, the locations described appear to relate to 'decision points' where the individual faces a form of decision or distraction. As such, where defining a set of intersections that might influence distance perception, one should limit the effect of minor road junctions and dead ends.
- *Landmarks* are less clearly defined both in GIS and in their description in prior studies. They are typically thought of as 'well known' or remembered locations (Presson & Montello, 1988; Winter et al., 2008), and physically or visually set

apart from other buildings (Filomena et al., 2019), which suggests their spatial definition integrates structural, visual, and semantic meaning. Some have advanced quantitative definitions of landmarks based on GIS data (Raubal & Winter, 2002; Winter et al., 2008) that capture aspects of prominence, position, and salience (Röser et al., 2012), yet given the subjective nature of landmark recognition, the limitations of these representations are noted by the authors.

- Similar to landmarks, the definition of *features* is relatively vague, but can generally be attributed to locations that increase visual heterogeneity in urban space. In terms of spatial data, we can potentially identify features from their land use function (e.g. building class, function). The selection of specific feature types, with generally greater visual salience, may be one approach for identifying heterogeneity in land use, another may be to calculate entropy values for features relative to surrounding areas (Frank et al., 2005).
- *Turns* exposure may be captured through route selection through a road network. In GIS, such a metric may be derived through accessibility measures, where a shortest path (measured in distance, cost, time, etc.) is constructed between two locations to indicate interaction and access. Turn-based paths have been developed elsewhere (Turner, 2007), and are generally defined as angular deviations between road segments of greater than 60°.
- *Network density and order* may be defined according to the regularity or clarity of organisation of the local network and the proximity of intersections. In terms of its computational representation, the network may be abstracted from the standard polyline and node-based road network data. Building on this model, a measure for local legibility is found in the form of the InterConnection Density (ICD) metric proposed by O'Neill (1991). While others have linked legibility to the space syntax form of the road network, and its associated measures (Long et al., 2007). Nevertheless, a simple measure of node density (e.g. number of intersections within a given radius) may equally encode the scale of potential interactions and decisions required from an individual within a certain space.
- Definitions of *barriers, edges and regions* are readily available within GIS data sets, however, their applicability to human cognition is less clear. Administrative boundaries, while commonplace in GIS, do not necessarily align with cognitively salient boundaries. Instead, boundaries relating to geographic features and function are more likely to capture the 'boundary effect'. In this case, the simple selection of edges at changes in land use (e.g. parks, building morphology) or in terms of natural barriers (e.g. rivers, major roads, rail) provide some of these locations. It has been shown how community detection methods can be used on street networks to define realistic urban neighbourhood boundaries (Filomena et al., 2019; Manley, 2014).
- *Travel speed and transport mode* can be incorporated within any path-based measure as a product of route distance. In this respect, one may wish to differentiate the impact of pedestrian distance perception relative to vehicular or public transport travel modes. In these cases, estimates of travel speed can be extracted using speed limit data, road width data, or service timetables.
- *Topographic* data is very readily available within GIS, with numerous global models of elevation available at highly granular scales. With this data in place, changes in topography may be assigned to roads based on direction of travel. Alternative approaches have been recently proposed to better integrate physical effort into pedestrian movement models (Greenberg et al., 2020).
- The Euclidean *route distance* can be easily extracted and functions in varying

distance perception assigned accordingly. Although, it is often the case that humans do not necessarily use the shortest path in urban areas (Manley et al., 2015), it allows us to extract a probable route connecting an OD pair, and evaluate its features accordingly.

As can be surmised from this review, there is variation in the availability of spatial data sources to adequately capture the features influencing cognitive distance. Further work is required, and is ongoing, around improving how we extract spatial features in line with their perception (Filomena et al., 2019).

3.2. Estimating feature effects on cognitive distance

There have been no previous studies defining the compound effect of spatial feature exposure on cognitive distance, and as such, here we present an approach for drawing together these effects within an integrated model of cognitive distance. The factors and their weighting relative to conventional spatial data are shown in Table 1.

There are important points to be considered in the practical application of this framework. The first is that these estimates have been derived in a variety of geographic contexts. The absence of systematic experimentation on cognitive distance means that some estimates are drawn from controlled experiments (both physical settings and virtual reality), some from real-world environments, and some from non-urban contexts. This limitation points to a need for further work in this area, but also cautions our application of the framework. To clarify the extent of existing evidence, we have indicated where evidence is 'direct' (presence of ecological evidence), 'indirect' (where evidence exists within virtual reality settings), or 'indicative' (when no quantitative evidence is available but established hypotheses indicate an important role). The varying strength of these findings impact on our final definition of weights. In cases of direct or indirect evidence existing, we have extracted weights directly from the studies listed in Table 1. Nevertheless, one should be aware that even in the cases of there being direct evidence available, these experiments are conducted in specific geographic contexts (often in the United States), and we have noted some of these biases. Despite these biases in the evidence base, it is important to recognise that all experimental and indicative findings are based on established cognitive processes relating to human spatial cognition, as described earlier.

A secondary important point to consider in the application of the framework is the nature of exposure to each type of spatial feature. We can define exposure as being either *behavioural* or *spatial*. Behavioural exposures relate to factors that occur due to specific actions being taken during the traversal of space, with the increase in cognitive distance a product of the choices made or actions being taken. Spatial exposure refers to the visual interaction with features residing in the urban realm that leads to a change in distance perception, and as a secondary outcome of a task being executed. Those effects experienced through behavioural exposure can only be captured for a specific routing task (and varied on a route-by-route basis), whereas locations of spatial exposure can be applied to the static GIS representation. This differentiation sets cognitive distances aside from conventional GIS-based distance measures, such as accessibility, and may result in asymmetric distortions in distances across space. This differentiation is provided for each factor in Table 1.

Given the absence of literature on the relative importance of each factor in influencing distance estimation, all factors are weighted equally within our model. However, the execution of weights should account for prior or joint exposure to other features, and thus be computed to account for a cumulative effect. As such, the order of execution of weight calculations plays a role in determining the composite measure. This order is determined here by the scale at which each feature imposes an effect - therefore road segment features (e.g. salient buildings, slope, local network order) are executed first, then come intersections and turns, followed by major features (e.g. barriers), through to finally executing route-level factors, such as total route distance and speed.

Within this proposed framework we have outlined the complete landscape of evidence, related them to spatial data sources, and uniformly combined them. An alternative formulation would be to incorporate only factors that have direct previous evidence. In particular, given the behavioural nature of some factors (e.g. intersections, slope changes, route distance), their inclusion in route choice decision models could represent a useful implementation of cognitive distance. Nevertheless, the accumulation of evidence suggests that a variety of features play a role in cognitive distance in cities, and as such, warrant inclusion in a comprehensive framework.

Factor	Hypothesis	Evidence	Indications	Weight	Exposure
Intersections	Segmentation	*Direct*: Sadalla et al. (1980)	25% increase in estimated distance with 4 additional major intersection (US setting)	Increase path distance by 6.25% for each major intersection encountered, reduced effect (4.5% increase) for medium intersections	Behavioural
Salient Features	Accumulation	*Indirect*: Jansen-Osmann & Berendt (2005)	50% increase in estimated distance between routes empty of features and those filled with visually diverse features (in virtual reality setting)	Increase segment length by 50% where more than 10 salient features (non-residential, named features) occur on a single segment	Spatial
Landmarks	Accumulation	*Indicative*: Hirtle & Jonides (1985)	Landmarks play a role in organising the cognitive map	Increase route length by 5% where landmark is adjacent	Spatial
Travel Speed	Effort	*Indicative*: Montello (2009)	Reduced self-powered effort leads to lower distance estimates (contended finding)	When travelling by vehicle 0.9% of sum distance after accounting for other factors	Behavioural
Network Order	Segmentation	*Indirect*: Canter & Tagg (1975)	'Confusing' urban structures leads to higher distance estimation, but no formal measure of structure provided	Areas of high network density (upper quartile) increases segment distance by 5%	Spatial
Slope Change	Effort	*Direct*: Okabe et al. (1986)	Found 7% increase in estimated distance uphill and 15% increase downhill (non-urban setting)	Increase segment lengths by 7% and 15% where elevation change exceeds 5° uphill or downhill respectively	Spatial
Turns	Segmentation	*Direct*: Sadalla et al. (1980)	Turns added 15.06 feet or 9.57% to distance estimates (US setting)	Increase sum distance by 9.5% for each turn over 60°	Behavioural

Route Distance	Scaling	*Indirect*: Lloyd (1989)	Distance overestimated on short routes (0.8 inches, approx. 960 feet) and underestimated long routes (-1.5 inches, approx. -1800 feet) in urban settings (route categories not provided)	Increase length of short routes by 10%, reduce length on long routes by 10%	Behavioural
Barriers	Segmentation	*Indirect*: Cohen et al. (1978)	Found underestimation and overestimation of distances where barriers absent or present	Reduce total distance by 10% where barriers absent; increase total distance by 8% where barriers are present	Spatial

Table 1.: Sources of evidence used in factor weighting

4. Case study: cognitive accessibility at the city scale

As a demonstration of the concepts that integrate the effects described in section 3 to conventional GIS data, a case study on the development of an objective measure of 'cognitive accessibility' is calculated. This measure aims to capture the 'cognitive cost' of traversing urban space, influenced by interaction with environmental features. In this study, we aim to produce a measure of relative accessibility, with comparability across a range of global cities. The measure will be based on the discrepancy between our cognitive distance estimates and metric distances (Euclidean and route lengths).

4.1. Implementation

For the purposes of this study, we are interested in investigating how our measure of cognitive accessibility varies across global cities. In the absence of a measure of validation, we require a set of cities with clear differences in urban design and structure, and variation in the occurrence of features described earlier. A set of cities were identified for this initial study, providing global coverage, structural variation (from planned and grid-like to organic structure), topographic variation, and general familiarity due to their size and prominence. The final list can be found in Table 2. For each city, a set of routes will be constructed that capture variation in cognitive distance. These will be compared against Euclidean and network distances, as indicators of the effect of the aforementioned factors on cognitive distance.

4.1.1. Data selection and workflow

The construction of a global measure of cognitive accessibility requires a collection of data with near global coverage and able to reproduce the factors documented in Section 3. For this purpose, we make use of OpenStreetMap GIS data, which provides fine-grained representation of road networks, buildings, and land use at near universal coverage. We further supplement this data source using SRTM topography data accessed via Elevation API[*], which again provides global coverage at 5 to 30 metre resolution.

Access to data on each city was made through use of the OSMNx Python package (Boeing, 2017), which enabled extraction of both road network and building data from OpenStreetMap for each city. Furthermore, OSMNx enables the construction of a topological graph of the road network, and exploitation of the network analysis tools available in another Python package, NetworkX. Using NetworkX and the network graph created in OSMNx, shortest paths can be calculated between any locations within the network. A set of methods for calculating the geometries of routes (i.e. turns, elevation change, distances) and proximity to spatial features, implementing the GeoPandas, Fiona, and Shapely Python packages, were written to supplement these tools. References to intersection and road hierarchies were extracted from 'Highway' attribute[†] within OpenStreetMap road network data. Salient features were defined as any building object with a defined 'Amenity' attribute[‡] excluding 'Residential' classifications. These classifications are current standards within OpenStreetMap data, and though may lack completeness, allow exploration and comparison of global trends for the purposes of this study. The extraction of landmarks follows the methods defined

[*] Described at `https://elevation-api.io`

[†] Further details on classification: `https://wiki.openstreetmap.org/wiki/Key:highway`

[‡] Further details on classification: `https://wiki.openstreetmap.org/wiki/Key:amenity`

Figure 1. Plots of cognitive distance against network (1a) and Euclidean (1b) distance, with routes in Delhi and London highlighted in red and blue respectively

in Filomena et al. (2019), which proposes measures for the physical, cultural and pragmatic salience of a building. In this study, we classify landmarks as only the top ten percentile of buildings by this measure.

For each city, we select data within a 1000 metre radius study area around a coordinate at the centre of the city. Within each city study area, 500 random origin-destination pairs are selected, and Euclidean distance (ed), road network distance (nd)[§], and cognitive distances (pd) will be extracted for each pair. The proportional differences between network and Euclidean, $ned = nd/ed$, cognitive distance and Euclidean, $ped = pd/ed$, and cognitive distance and network distance, $pnd = pd/nd$, will be calculated. By capturing the degree of cognitive distraction relative to the shortest possible distance and shortest possible path, the ped and pnd measure will be indicative of the accessibility of the selected region, and used as a basis for evaluation. Lower values of ped and pnd mean greater alignment between perceived and Euclidean distance and therefore higher accessibility. Summary mean distance scores will be taken for each city, for each of the distance metrics.

4.2. Results

As we can see from Table 2, the ped and pnd metrics successfully differentiate between cities with strong urban planning features and those with an 'organic' or historic urban form. Cities with higher scores, such as Jakarta, Paris, Tokyo, and London, exhibit a mix of planned and unplanned spatial regions, having developed over hundreds (or even thousands) of years without uniform or consistent planning oversight. These regions exhibit high intersection density consistently over space, meaning walkers are faced with many options when navigating and encounter more major junctions. Cities with lower ped and pnd scores, such as Casablanca and Delhi, reflect measures taken in areas of heavily planned regions (see Figure 2, described below), low street network density (reducing barrier and location effects), and lack of variance in street type (reducing intersection effect) within the study space. A more detailed breakdown of how each factor influences cognitive distance estimates in each city can be found in Appendix A. In Figure 1, we can see the results for all generated routes, with two cities highlighted. The figures show how cognitive distance scales exponentially with Euclidean and network distance. It is noticeable that variance in cognitive distance increases at higher Euclidean and network distances. We can also note relatively little difference between ped and pnd in ranking or distribution, indicating that network distance has only a limited role within this measure.

There are, however, noticeable exceptions to these general rules, which highlight important aspects of methodology. New York City could be thought to have some of the most easily accessible environments, yet have relatively high ped and pnd scores. An important reason for this is that the metric is calculated for only a limited region of each city, which may not reflect its wider structure or common perception. In the case of New York, the metric is calculated for a region around the Tribeca neighbourhood, which has a skewed grid street design influenced by the geography of Manhattan Island. When the metric is calculated for Midtown, where the grid design is much

[§]Calculated according to the shortest metric distance path.

Figure 2. Plots of indicative cognitive distance (red points) and Euclidean (blue points) distances from a single origin point, in Delhi (2a) and Berlin (2b).

more regular, New York achieves a very low *ped* score (2.24), ranking it third lowest within this set of cities. We can also assess variation between areas of the city. Taking London, we observe higher cognitive distances in areas around Soho relative to the Bank area. On assessing the cause of these differences (see Appendix A), we see the difference relates to a higher interaction with major junctions in Soho relative to Bank. These differences demonstrate how these measures vary within a city, but also how the values defined for these spaces may not be fully representative of the entire city. We expect that development and refinement of the approaches discussed in this paper will result in more robust and useful measures of cognitive accessibility.

Another important facet of these measures relate to the spatial heterogeneity in cognitive distance estimates, which is masked by the averaged scores for *ped* and *pnd*. The nature of cognitive distance and the heterogeneity of urban space mean that estimates can vary widely by direction, given the variable configuration of spaces and location of features. This is best reflected in Figure 2, where we map differences between Euclidean and cognitive distances of 18 destination points located 1000m from a single origin centroid for two cities (note that the early analysis used random origin-destination pairs). The maps demonstrate the difference between quite uniform cognitive distance estimates (e.g. Delhi) and others where we observe some quite large differences between adjacent points. These figures also demonstrate how cognitive distance can fall below Euclidean in some instances, given that these routes are impacted by the route distance rule, but particularly where the cost of turns and intersection encounters are low.

4.3. Limitations

Although this measure of cognitive accessibility is offered only as a proof-of-concept, it is important to address some of the limitations of the approaches described here. First, as we note above, the selection and parameterisation of feature effects on cognitive distance is only *guided* by the literature and currently lacks validation. As such, the findings presented are only indicative of a 'cognitive' accessibility measure, but hopefully something that may provoke further thought and discussion. Secondly, there are certainly reliability issues associated in the use of OpenStreetMap data, which has some consistency flaws between cities in terms of feature mapping, attribute detail, and classification. These limitations have implications for our measures, given the nature of its definition. Finally, as noted above, the selection of 'survey' points for this analysis provides only an indicative measure for each city, which can vary considerably in their urban structure and design. The inclusion of additional bias effects, mentioned in the literature review but not implemented here, remain opportunities for further work.

5. Discussion and conclusions

Spatial cognition has a fundamental role in how humans navigate and use cities. In shaping how we move and experience the city, spatial cognition may impact the emergence of a swathe of social phenomena in space. Yet, as we have shown in this paper,

City	**Euclidean**	**Network**	**Cognitive**	*ned*	*ped*	*pnd*
Jakarta	1066.99	1601.25	4211.77	3.95	1.50	2.63
London (Soho)	1003.97	1228.80	3946.91	3.93	1.22	3.21
Glasgow	1024.39	1416.06	3619.36	3.53	1.38	2.56
Paris	1018.03	1310.38	3483.30	3.42	1.29	2.66
Tokyo	951.88	1203.99	3209.91	3.37	1.26	2.67
Singapore	989.53	1267.50	3219.48	3.25	1.28	2.54
Berlin	995.63	1237.13	3151.45	3.17	1.24	2.55
Cairo	1101.04	1434.24	3428.48	3.11	1.30	2.39
Athens	1026.70	1219.67	3111.51	3.03	1.19	2.55
Brasilia	1056.73	1473.54	3135.08	2.97	1.39	2.13
Sydney	989.52	1281.41	2838.64	2.87	1.29	2.22
Bucharest	1014.84	1267.57	2899.11	2.86	1.25	2.29
Lisbon	1021.29	1305.46	2874.77	2.81	1.28	2.20
Mexico City	1031.98	1292.25	2877.48	2.79	1.25	2.23
Cape Town	937.46	1220.92	2593.30	2.77	1.30	2.12
Madrid	1095.48	1315.47	2993.62	2.73	1.20	2.28
Nairobi	951.88	1261.14	2557.17	2.69	1.32	2.03
New York City (Tribeca)	1032.54	1253.03	2746.97	2.66	1.21	2.19
Chicago	991.60	1294.33	2608.43	2.63	1.31	2.02
Rome	935.88	1144.71	2383.34	2.55	1.22	2.08
Buenos Aires	1058.66	1262.00	2673.88	2.53	1.19	2.12
Beijing	1070.86	1580.91	2691.43	2.51	1.48	1.70
La Paz	1025.56	1352.39	2480.43	2.42	1.32	1.83
San Francisco	1014.08	1213.47	2372.24	2.34	1.20	1.95
Lima	993.02	1276.85	2301.51	2.32	1.29	1.80
Casablanca	934.46	1166.85	2055.55	2.20	1.25	1.76
Delhi	1029.13	1348.57	2090.25	2.03	1.31	1.55

Table 2. Global variation in Euclidean, network, and cognitive distance, ordered by proportional difference between cognitive and Euclidean distance *ped*

the concept is difficult to measure and define, with different studies offering different and non-intersecting views. However, it is important that the GIS community addresses the different ways in which we measure and model space, particularly where human behaviour is concerned. The proposals and models outlined in this paper represent only an initial exploration of this topic, and the intention of this discussion is to highlight the challenges and raise prospects for extension and further exploration.

The perception of distance potentially mitigates in a number of spatial phenomena, commonly analysed through Euclidean distance. The detection of clusters and agglomerations of activity are captured through spatial proximity or network distance, yet the presence of spatial features (e.g. attractive landmarks) or barriers (e.g. major roads) may encourage or restrict continuous interaction, leading to non-uniformity in interactions over space. This is particularly important where activity density is strongly associated by local spatial perception, such as in the case of criminal activity. Higher cognitive costs imposed by increased intersection density or the presence of barriers may limit the continuity of crime hot spots, by increasing cognitive distances from 'safe' areas. While the configurational analysis of urban spaces in relation to social phenomena has a rich history (Hillier & Hanson, 1984), there remain opportunities for a broader quantitative analysis of urban form, its relation to spatial cognition, and role in social processes.

Second, we can also consider how the presence of different features affect individual behaviours too, where our interest lies in modelling human behaviour. Within most spatial agent-based models individual decisions in relation to space integrate either Euclidean or network distance as a central cost (with few exceptions, e.g. Manley & Cheng (2018)). Gärling & Loukopoulos (2007) have shown that choice of transport mode - walking or driving to a destination - is compounded by the cognitive cost and not the actual distance. Therefore, by incorporating cognitive distance within our models of behaviour, we can explore how spatial features might impact on behaviour and accessibility (Neutens, 2015), and as a result adjust our simulated predictions of activity or flow across space. Within all cases of distance-based costs, there are opportunities to address the role of spatial features in promoting or limiting interaction. In addition, with better understanding of how spatial features expand and contract cognitive distance, there is room to accommodate this into efforts of behavioural changes at the societal level, for example reducing car dependency and increasing active/public transport use, as well as informing urban planning processes about the impact of urban design and zoning on distance perception and thus behaviour.

A third role for cognitive distance is to assist in designing maps for human navigation. While most cartography is mapped to a consistent plane, these maps are not necessarily useful in aiding human activity. Instead, isometric, 'heads up', and augmented reality mapping have all been shown to more quickly convey spatial proximity and association. Likewise, topological maps, such as the London Underground map, play with the Euclidean plane to better reflect connectivity. In these ways, there is an opportunity for integrating cognitive distance within cartography and navigation aids, by contracting and expanding space according to how they might be experienced. This presents a quantitative basis to visually emphasise (i.e. expand in scale) areas of high urban density and heterogeneity, where greater guidance might be required. For this experimental cartographic approaches may be required. These opportunities may expand beyond cartography. For example, by enabling a machine to better interpret human perception of spaces, we may improve the provision of advice and information to humans about their location (e.g. through navigation aids such as sat-navs).

The opportunities for a new model of urban space are naturally faced with a range of challenges, both conceptual and technical, as highlighted during this paper. A wide variety of spatial factors may influence distance perception, some of which may be more easily captured through spatial data than others. This paper draws together some of these sources, but we readily recognise the limitations of these existing sources - variously not based in real-world settings, employing small samples sizes, or not adequately controlling for confounding factors. We also must recognise a wider array of influencing factors on distance perception. Prior studies have shown, perception may also be associated with demographic factors (McCormack et al., 2008) and prior experience of space (Golledge, 1999; Ishikawa & Montello, 2006), which are much harder to capture through static GIS measures. More recent studies (Ralph et al., 2020) identify contextual factors relating to fear of crime or fear of getting lost as impacting distance estimation too. More work is therefore required on both how we capture the systematic effect of all spatial features on cognitive distance, as well as the representation of population-based variation. This will mean collecting more data on distance perception, at large scale and with adequate spatial and demographic variety, with a view to building more comprehensive models of perceived spatial distance. It also requires a deeper consideration of how we represent cognitively salient spatial features within GIS. Quantitative estimates of concepts such as visual salience and landmark importance are of growing interest (Filomena et al., 2019), but consistent and agreed definitions of how these characteristics are captured and defined are yet to be determined. In guiding these efforts, opportunities are presented in extending existing classifications of urban morphology, that may allow us to circumvent issues of inconsistent definition (Berta et al., 2016).

As our understanding of human cognition and behaviour improves, the need for greater unity between our human and computer-based representations of space will only increase. While Euclidean and network distance measures provide a proxy for what drives human behaviour, cognitive distances are at the heart of these actions. As we have demonstrated in this paper, there are pathways for integrating these concepts within quantitative models of space, as well as global-scale open data and tool kits, but there are also significant challenges and research opportunities. It is imperative on the GIS community to consider how we take on this challenge, and advance our understanding and representation of human behaviour in urban spaces.

Data and code availability statement

The code supporting the findings of this study are available on Figshare at the link `https://doi.org/10.5522/04/11777736`. The data used in this study is freely available from OpenStreetMap, and can be accessed via methods described at `https://wiki.openstreetmap.org/wiki/Downloading_data` or through using the code accompanying this paper.

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Appendix A

Table showing influence of each spatial feature type on cognitive distance estimates, by city.

City	Euclidean	Network	Cognitive	Segment	Landmarks	I/sections	Turns	Distance	Barriers
Athens	1026.70	1219.67	3111.51	2.95	144.24	574.51	1171.50	-248.60	247.25
Beijing	1070.86	1580.91	2691.43	-265.73	81.05	21.68	1253.21	-190.30	210.61
Berlin	995.63	1237.13	3151.45	-13.03	74.00	428.28	1413.03	-237.80	249.85
Brasilia	1056.73	1473.54	3135.08	-80.02	12.59	436.27	1296.78	-252.31	248.23
Bucharest	1014.84	1267.57	2899.11	-19.04	74.50	318.62	1250.43	-222.91	229.94
Buenos Aires	1058.66	1262.00	2673.88	-30.62	221.47	277.78	954.44	-222.84	211.64
Cairo	1101.04	1434.24	3428.48	-21.11	15.19	244.64	1767.55	-284.99	272.97
Cape Town	937.46	1220.92	2593.30	-45.14	37.63	47.16	1305.49	-175.68	202.92
Casablanca	934.46	1166.85	2055.55	-12.86	21.71	147.24	701.44	-128.40	159.57
Chicago	991.60	1294.33	2608.43	-50.98	32.36	292.05	1025.73	-190.27	205.21
Delhi	1029.13	1348.57	2090.25	-48.65	16.74	0.00	767.57	-157.34	163.36
Glasgow	1024.39	1416.06	3619.36	-46.88	108.18	437.04	1695.00	-275.54	285.51
Jakarta	1066.99	1601.25	4211.77	-24.78	111.68	877.52	1642.11	-329.87	333.87
La Paz	1025.56	1352.39	2480.43	-45.43	25.88	100.97	1032.84	-180.29	194.06
Lima	993.02	1276.85	2301.51	-29.63	85.11	103.53	847.17	-160.63	179.12
Lisbon	1021.29	1305.46	2874.77	-11.59	67.66	237.53	1261.74	-213.35	227.32

London (Bank)	907.85	1140.92	3310.50	-24.23	28.50	491.12	1645.96	-233.34	261.57
London (Seven Dials)	1003.97	1228.80	3946.91	-3.93	51.17	898.68	1769.90	-312.44	314.73
Madrid	1095.48	1315.47	2993.62	-49.50	145.64	143.37	1451.43	-251.06	238.27
Mexico City	1031.98	1292.25	2877.48	6.62	105.00	486.02	992.82	-231.67	226.43
Nairobi	951.88	1261.14	2557.17	4.74	13.85	259.03	991.70	-172.54	199.27
New York City (Midtown)	1012.16	1283.48	2270.69	-0.64	59.81	92.25	823.48	-164.43	176.75
New York City (Soho)	1036.20	1242.54	2923.96	-1.25	91.40	480.82	1122.50	-245.09	233.04
New York City (Tribeca)	1032.54	1253.03	2746.97	-10.74	128.43	215.00	1156.83	-214.03	218.45
Paris	1018.03	1310.38	3483.30	-9.96	131.26	508.15	1541.63	-274.80	276.64
Rome	935.88	1144.71	2383.34	-13.29	56.00	105.04	1064.46	-160.54	186.96
San Francisco	1014.08	1213.47	2372.24	-51.29	164.25	116.47	925.63	-183.87	187.58
Singapore	989.53	1267.50	3219.48	-75.93	26.20	589.51	1406.78	-249.99	255.41
Sydney	989.52	1281.41	2838.64	-19.47	88.78	92.00	1388.11	-216.98	224.79
Tokyo	951.88	1203.99	3209.91	-22.85	71.21	234.82	1690.35	-221.24	253.63