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Beyond Proximity: A Review and Framework to Further Understanding of Greenspace Accessibility in the X-Minute City

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Abstract:

1. Urban greenspaces are crucial for public health, climate resilience, and community well-being, yet there are inequalities in accessibility in cities across the world. The 'x-minute city' framework has been proposed as a potential solution, proposing that essential services and amenities—including greenspace—should be accessible within a short commute from every residence. However, current approaches to measuring and implementing this framework often rely on single dimensional metrics that fail to capture the full complexity of how people actually access and use urban greenspaces.
2. This review synthesises methods from three distinct fields to develop a more comprehensive understanding of greenspace accessibility: geographic information science (GIScience), which provides spatial analytical tools; behavioural ecology, which offers frameworks for understanding movement decisions; and human mobility analysis, which reveals movement patterns through the urban environment.
3. While GIScience approaches allow for the identification of spatial inequalities in greenspace distribution, they often overlook the behavioural and social factors that influence actual usage, highlighted in behavioural ecology approaches. Similarly, human mobility models can track movement patterns but may miss environmental and cultural factors.
4. To bridge the gap between these methods, we introduce the Multi-context Inclusive City (MIC) framework, which integrates spatial, behavioural, and mobility perspectives to analyse greenspace accessibility. This framework moves beyond proximity measures to incorporate diverse experiences, movement pathways, and the environmental and social factors that influence greenspace usage.

5. The MIC framework offers practical guidance for selecting appropriate models and methods based on specific research questions or planning objectives. By providing a more nuanced understanding of how people interact with urban greenspaces, this framework can help planners and policymakers develop more effective strategies for creating equitable, accessible, and sustainable cities.

Keywords: x-minute city, greenspace, accessibility, human mobility, foraging, movement, modelling

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1 Introduction

Since the Industrial Revolution, cities around the world have been developed with an emphasis on productivity and economic growth rather than liveability. This focus has often led to sprawling, dense built environments that prioritize industrial and commercial functions over residential comfort, greenspaces, and community well-being (Childe, 1950; Reps, 2021). Greenspaces—encompassing parks, urban forests, and green infrastructure—are crucial for creating healthier, more resilient cities. They provide residents with critical ecosystem services—the benefits that natural environments provide to human wellbeing and functioning of cities—such as air purification, heat reduction, stormwater management, and noise buffering, all of which directly contribute to improved public health (Bolund &

Hunhammar, 1999; Coutts & Hahn, 2015). Research consistently links greenspaces to positive health outcomes, including reduced stress, enhanced mental health, and lower rates of respiratory diseases (Gianfredi et al., 2021). As climate challenges grow, greenspaces also strengthen urban resilience by mitigating the urban heat island effect, improving biodiversity, and managing flood risks. For instance, a recent systematic review highlighted that regions abundant in greenspaces report lower rates of heat-related morbidity and mortality compared to those with sparse greenspace (Nazish et al., 2024). However, disparities in greenspace distribution and accessibility exacerbate health inequalities, particularly in underserved or "left-behind" areas (Houlden et al., 2018). Addressing these disparities is essential for creating sustainable, inclusive, and productive cities that prioritize well-being (Kabisch & van den Bosch, 2017).

These disparities in greenspace accessibility are influenced by income inequality, historical planning practices, and urban development patterns, among other social factors. In the UK, for example, there is a clear need for more equitable greenspace access, with recent statistics indicating that approximately 38% of people in the UK do not have greenspace within a 15-minute walk of their home, reflecting the ongoing accessibility crisis (Department for Environment, Food and Rural Affairs, 2023). The income gap in greenspace accessibility can be clearly seen in European cities such as Brussels, Milan, Prague, and Stockholm; higher income residents typically enjoy greater access to greenspaces. In contrast, Birmingham in the UK shows a reverse pattern, with more greenspace in lower income areas (Buckland & Pojani, 2023). Similar inequities are found globally, as in Denver and Los Angeles, where minority and low-income neighborhoods face limited access to parks (Rigolon et al., 2018; Rigolon & Flohr, 2014; Wolch et al., 2005). However, addressing these disparities in greenspace access requires careful planning as sudden enhancements of greenspace can lead to "green gentrification," where improvements elevate property values and push out lower-income residents, as observed in various U.S. and European cities (Anguelovski et al., 2022; Quinton et al., 2022; Wolch et al., 2014).

The “x-minute city” framework has emerged as a potential solution for equitable urban accessibility, promoting the idea that essential services, including greenspaces, should be accessible within a short walk or bike ride (typically 15–20 minutes) of every household (Moreno et al., 2021). Although the x-minute city framework is a recent concept, it builds on a long tradition of urban planning principles that emphasize density, proximity, and diversity—ideas rooted in Jane Jacobs’s, *The Death and Life of Great American Cities*, in the 1960s (Jacobs, 1961)—expanding upon them by including digitalization, the integration of smart technologies to enhance accessibility (Moreno et al., 2021). For a more comprehensive history of these planning principles, see Fuller & Moore (2017) for an early review and LeGates et al. (2020) for a recent synthesis that highlights significant developments in urban planning frameworks.

Given their role in enhancing public health and serving as “ecological guardians” for urban areas, greenspaces are a key amenity that should be within the accessible range of the x-minute city (Wolch et al., 2014). However, greenspace accessibility presents unique challenges that distinguish it from other forms of accessibility, such as transportation or retail access. Greenspace use is influenced not only by physical proximity but also by individual perceptions, environmental quality, landscape patterns, and social factors, which standalone accessibility metrics generally fail to capture (Ha et al., 2022; Jarvis et al., 2020; Robinson et al., 2023).

To fully understand greenspace accessibility, there is a need to move beyond traditional location-based metrics such as proximity and density and incorporate additional individual-based metrics to capture the nuanced, variable factors that influence greenspace use. This review identifies a critical gap in the literature: while geographic information science (GIScience hereafter), human mobility analysis, and behavioural ecology each contribute valuable insights, these fields remain largely siloed, limiting their ability to address greenspace accessibility comprehensively. Methods from GIScience provide essential spatial analysis techniques to map and quantify greenspace distribution, highlighting spatial inequalities, but often neglects the behavioural and contextual elements of accessibility—the *perceived accessibility* (e.g., how crime taking place in a greenspace influences the decision to visit it) (Pot et al., 2021). Human mobility analysis—encompassing fields such as geographic data science and network science—leveraging big data from sources such as mobile phones and social media, has made significant strides in tracking real-world movement patterns, yet it often overlooks the socio-environmental and motivational factors that influence greenspace use (Toole et al., 2015). Behavioral ecology, through the Movement Ecology Paradigm, focuses on adaptive behaviours and movement motivations, adding a qualitative aspect of the perceived accessibility, but this theoretical framework and modelling strategy has been underutilized in urban planning contexts (Joo et al., 2022). By combining spatial analysis, empirical movement data, and behavioural frameworks, we can develop more comprehensive insights into both physical and perceived accessibility to urban greenspace.

While acknowledging the breadth of literature in these fields, this review concentrates on their primary methodological approaches to establish a 'Multi-Context Inclusive City' (MIC) framework. This framework provides a structured approach for combining and integrating methods from GIScience (GIS), human mobility studies (HM), and behavioural ecology (BE).

The MIC framework offers guidance on how existing approaches can be systematically combined to provide more comprehensive insights into greenspace accessibility, rather than presenting entirely new models. The framework identifies four potential integration pathways: combining two approaches (GIS-BE, HM-BE, or GIS-HM) or all three approaches (GIS-HM-BE) to address specific research questions and planning needs.

2 From Minimal to Comprehensive Interactions: Capturing the connections between people and nature in the x-minute city.

2.1 Spatial place-based approaches: Perspectives from GIScience and Urban Analytics

While spatial accessibility analysis has evolved beyond simple proximity measures, proximity-based approaches remain common for mapping and defining the x-minute city across disciplines. These approaches apply a variety of spatial analytical techniques derived from GIScience, ranging from basic distance measures to more sophisticated methods incorporating multiple transport modes and temporal factors (Geurs & van Wee, 2004). For example, Natural England defines a ‘15-minute walk zone’ for greenspace accessibility as any residence that falls within 1km of a natural greenspace, without considering the road network (Natural England, 2023). Another example of this can be seen in a recent study by Balletto et al (2021) that described the ‘service area’ as an area of 1,200m around a building, corresponding to an approximation of a 15-minute walk along the street network. These proximity-based metrics, in this case buffer analysis, provide a simplistic way of defining spatial coverage but lack the ability incorporate real-world travel conditions or temporal variability.

Place-based, proximity metrics can be extended by incorporating transportation costs to calculate travel times or distances, and competition of many people trying to access the same amenity, forming the basis for catchment area analysis. A common example is the Two-Step Floating Catchment Area (2SFCA) method, which incorporates transportation networks, supply (e.g., greenspace area), and demand (e.g., population density) to create catchment areas and identify spatial inequalities (Luo & Qi, 2009; Luo & Wang, 2003). The 2SFCA method is not solely proximity-based, but flexible enough to account for different transportation modes, including walking, cycling, or driving (Liu et al., 2022). An important strength of the 2SFCA method is its ability to account for service provision weighted by demand, while also considering the availability of alternative options for potential users within a given time or distance catchment. This approach mitigates issues related to cross-boundary flows—situations where service areas are not simply confined to administrative boundaries, instead incorporating time and distance into the accessibility measure (Higgs, 2004). However, the 2SFCA method has its limitations. It often relies on generalized parameters with single standardized values, ignoring individual features, and assigns arbitrary values to key characteristics, such as average walking speed (Liu et al., 2022). It also implements a place-based approach instead of an individual-based one, making it less effective for capturing person-specific accessibility dynamics.

Efforts have been made to incorporate qualitative data (such as surveys, walkability indices, and visual reporting) into the traditional quantitative approaches of proximity-based metrics for the x-minute city (Campisi et al., 2021; Ignaccolo et al., 2020; Weng et al., 2019). Studies by Weng et al. (2019), Calafiore et al. (2022), and Liu et al. (2021) demonstrate how combining spatial analysis with survey data and sociodemographic factors can reveal accessibility patterns that place-based measures miss. Similarly, approaches like geographically weighted regression and equity-specific metrics have revealed how accessibility varies across sociodemographic and spatial scales, underscoring the persistent disparities faced by marginalized groups. Yet, these methods often remain static and aggregate, failing to capture the dynamic, individual-level interactions that shape greenspace use.

Recent research has further exposed the inadequacy of relying solely on objective measures of accessibility. For example, analyses of greenspace access have revealed significant disparities in both inter-group and intra-group equity, such as variations between racial/ethnic groups and income-based inequities within those groups (D. Liu et al., 2021). These findings challenge the assumptions underlying aggregate accessibility metrics, emphasizing the need for tools that address not only physical proximity but also the socio-spatial dynamics of equity and inclusion. Moreover, the disconnect between objective accessibility and actual greenspace use highlights the critical role of subjective perceptions—such as attractiveness, safety, and inclusivity—in determining how and whether people engage with greenspaces (D. Liu et al., 2024). These insights suggest that accessibility is as much about perceived opportunities as it is about physical availability. Person-based approaches, including human mobility assessment, provide a promising avenue for addressing this gap (see Section 2.4).

Place-based, proximity approaches provide a critical starting point for understanding greenspace accessibility within the x-minute city. These methods offer straightforward, scalable tools for identifying underserved neighborhoods and spatial disparities. However, their focus on service areas and place-based aggregate accessibility measure limits their ability to address the nuance of greenspace accessibility. To move beyond these limitations, place-based approaches must be integrated into a broader, multi-dimensional framework that incorporates mobility patterns, behavioural insights, and subjective experiences. The Multi-Context Inclusive City (MIC) framework proposed in this review provides a pathway to advance greenspace accessibility analysis, bridging spatial, mobility, and perceptual dimensions.

2.2 Approaches from Behavioral Ecology: Incorporating a movement ecology perspective

Broadly, behavioural ecology allows us to explore the 'why' behind human movement. The movement of animals, especially in how they access resources in the environment, has been heavily studied for decades with various models that explore how organisms forage in their environment (Ahearn et al., 2017; Fretwell & Lucas, 1969). These models can be applied to human behavior to understand how humans move through the environment and examine their internal motivation for doing so (Miller et al., 2019). These models assess the cost-benefit relationship associated with movement, and incorporate aspects of learned behavior (assuming that organisms will use their previous knowledge of the environment), past experiences, and social networks to decide where to move (Dolan et al., 2021; Glover, 2009). While these models have yet to be applied to human movement in the x-minute city, they have the potential to assess how people choose their destination based on their individual circumstances.

Optimal foraging theory proposes that while foraging, animals act in a way to maximize their net benefit by obtaining the most resources while minimizing the associated costs such as time, energy, and risk (Pyke, 1984). This can further be broken down into how an individual chooses, handles, and consumes a resource in the environment (King & Marshall, 2022). When applied to humans seeking services (including ecosystem services) and amenities in the x-minute city, this can be viewed as, for example, the behavior of people moving through the environment to access the resource of greenspace, considering the travel time, quality of greenspace, and crowdedness of the space. Extensions of this such as the marginal value theorem (Charnov, 1976) and ideal free distribution (Flaxman & deRoos, 2007) attempt to quantify these aspects of movement by describing the weights of the benefits of staying in one place versus moving to another based on the benefit they gain in a place. For the marginal value theorem, the ideal time to leave a location is variable depending on the quality of the current location and the distance to other potential destinations. For example, people may choose to leave a low-quality, crowded greenspace sooner than a higher-quality greenspace with more space between individuals. The concept of ideal free distribution handles the aspects of competition and cooperation between individuals to determine the optimal ratio of resources and people (e.g., how community members share and coordinate park usage times to maximize greenspace accessibility for everyone) (Flaxman & deRoos, 2007). In this way, the marginal value theorem and ideal free distribution can consider both social group dynamics and the quality of a greenspace as components that contribute to an individual's motivation to move throughout the city when seeking greenspace, or simply when trying to find the most optimal route to get to work (Barton et al., 2009; Cantor et al., 2020; Davis et al., 2022; R. A. Fuller et al., 2007).

While not a direct method for modelling the x-minute city, behavioural aspects of these models could be considered when taking a quantitative approach as they can refine the movement dynamics of people in the urban environment. For example, urban greenspace usage would be influenced by factors such as the size of the greenspace, its facilities, the crime present in the area, and the number of access points. These behavioural ecology models could be applied to a wide range of human behaviours, modelling how people interact with resources such as urban amenities, transportation, and the local economy, providing a general framework for understanding resource use, decision making, and the process of when and how to move around the city (Kennedy & Gray, 1993).

The movement ecology paradigm (MEP), elaborated by Nathan et al. (2008), incorporates a more complex approach to studying the movement of organisms in relation to benefits. It proposes that movement trajectories result from four interconnected components: motion capacity, navigation capacity, the internal state of the individual, and the external factors of the environment. The motion capacity of an individual incorporates the factors that enable an individual to move (i.e., transportation accessibility, walking speed, movement disabilities). Navigation capacity similarly details the factors that contribute to an individual's ability to navigate in the environment (i.e., spatial awareness, map reading skills, sensory perception). The internal state encompasses the psychological reasons for moving, addressing why the individual is moving, and the external factors detail the environmental layout of a city, such as the transportation and technological infrastructure. This framework is able to address multiple mechanisms that drive movement: why move, how to move, when and in what direction to move, and how external factors influence movement (Nathan et al., 2008).

The MEP's value in x-minute city planning lies not in replacing existing transport modelling methods, but rather in providing decision-makers with a structured framework to conceptualize and analyse human movement behavior holistically (Demšar et al., 2021). Rather than jumping directly to technical metrics like transport availability measures, the MEP framework encourages first considering the basic drivers of movement behavior. The structured consideration of internal motivations (why move?), navigation capabilities (where to move?), and motion capacities (how to move?) helps identify which aspects of mobility truly need to be measured and modelled in each context (Demšar et al., 2021; Nathan et al., 2008). When applied to the x-minute city concept, the MEP's components can be meaningfully adapted to incorporate the behavioural components of movement.

Behavioral and movement ecology frameworks provide essential insights into how people navigate and utilize urban greenspaces, moving beyond simple distance-based accessibility measures to consider the complex motivations and decision-making processes that influence movement patterns. While traditional accessibility metrics remain valuable, the MEP framework demonstrates the importance of considering multiple contexts simultaneously—from internal motivations and individual capabilities to environmental conditions and social factors. This multi-dimensional perspective reveals why conventional planning approaches may fall short: they fail to capture the dynamic interplay between spatial accessibility, behavioural patterns, and contextual factors that shape how people access and use greenspaces. By highlighting these interconnections, the MEP framework helps justify the need for more comprehensive, integrated approaches to understanding greenspace accessibility. Such holistic frameworks must be capable of bridging between technical measurements and behavioural realities while accounting for the diverse contexts that influence how different communities experience and access urban greenspaces.

2.3 Understanding Urban Dynamics: Population mobility models.

Both population-level and individual-level mobility models offer critical insights into understanding the movement of people in the urban environment. Population-level models, including proximity-based approaches like the 2SFCA method (Luo & Qi, 2009), are grounded in the gravity model framework. The gravity model is the foundation of population level human mobility models and has been used to analyse spatial relationships and movement dynamics in a variety of areas including economics, international trade, transportation analysis, and human migration (Lewer & Van den Berg, 2008; Ramos, 2016; Rodrigue et al., 2013; Schläpfer et al., 2021). Fundamentally, the gravity model suggests that two locations have distinct levels of attraction based on their population and the distance between them (Zipf, 1946).

Approaching population-level mobility from a different perspective, Stouffer's law of intervening opportunities was proposed in 1940 to address the relationship between proximity and migration (Stouffer, 1940). It suggests that as an individual moves towards their destination, they are likely to choose the closest area with sufficient 'opportunities' relative to where they started, halting their migration once a suitable location is encountered (Stouffer, 1940). This concept has been incorporated into several human mobility models as a way of explaining an individual's decision-making process in choosing a location to stop at while in route to their destination.

Choosing an appropriate model depends on the context, research goals, and data availability. Comparative studies have shown mixed performance outcomes for the intervening opportunities model relative to the gravity model. For example, Akwawua & Pooler (2001) found that the intervening opportunities model performs about the same as the gravity model when modelling US interstate migration patterns; while Wilmot et al. (2006) reported that it outperforms the gravity model in certain contexts, suggesting that when intermediate opportunities are accurately represented and data quality is high, the intervening opportunities model can capture spatial flows more effectively. However, Elffers et al. (2008) and Kotsubo & Nakaya (2021) observed that the gravity model sometimes performs better than the intervening opportunities model, which may occur when travel patterns are strongly influenced by population size and distance. The varying performance of these models can be attributed to the context and specific factors of the migration flows being studied, such as the scale, the characteristics of origin and destination locations, and the availability of data.

Both the intervening opportunities and gravity models are constrained by their assumptions. Neither model can perfectly predict flows under all conditions, with the gravity model relying on aggregate measures of population and distance, and the intervening opportunities model being influenced if the attractiveness of intermediate destinations is only moderately influential (Anderson, 2011). In other words, each model encounters an “upper bound” on predictive power: conditions under which its assumptions no longer provide reliable predictions. The fluctuations in performance are not solely due to data availability or scale, but also to the theoretical constraints embedded within each framework.

The radiation model is a modern application of the intervening opportunities model that captures more movement characteristics than Stouffer’s model. The model is based on the idea that when an individual decides on their destination, they go through a dual-step procedure, accounting for the internal motivation of the individual and the proximity of opportunities (Nathan et al., 2008; Simini et al., 2012). First, an individual looks for opportunities at a coarse scale, expanding their seeking range to cover a large geographic area. Second, the ideal location is chosen based on the proximity of the opportunity to the individual’s home, and the weight of the benefits in comparison to other opportunities closer to the individual’s home. A closer location with sufficient opportunities is more likely to be chosen over a farther location with better opportunities (i.e., travel distance has more weight over the opportunity value). For example, someone in an urban area who wants to enjoy a hike may first identify (or have existing knowledge of) all the greenspaces that are within an hour's drive from their home. Within this area there may be several small greenspaces, a few large greenspaces, and one long corridor of greenspace. While the small greenspaces may be very close to the person's home, they do not offer much in terms of hiking. The large greenspaces may have a few short trails and are a short drive from home. The corridor of greenspace may be an hour drive from their home but provides a scenic hiking trail. In theory, based on the radiation model, the individual would likely choose one of the nearby large greenspaces with sufficient hiking opportunities, over the farther location with better opportunity. However, this would depend on the exact distances and the exact value of the opportunities at each location.

The radiation model resolves some of the major limitations of the gravity model, having strictly defined parameters, accounting for variable population density in between the origin and destination, and resulting in a flow output that predicts both the average flow and its variance (Simini et al., 2012). However, one of the major limitations of the radiation model is the issue of scalability. There have been multiple studies in which the radiation model has overestimated the flows terminating at short-distances, and underestimated long-distance flows at the city level, due to the underlying assumption that an individual will terminate their search process once they encounter the closest suitable opportunity (Kotsubo & Nakaya, 2021; Liang et al., 2013; E. Liu & Yan, 2019). As a response to this shortcoming, the model has been adjusted with different parameters to address different areas depending on the scale of the study (Kotsubo & Nakaya, 2021; Simini et al., 2012; Yang et al., 2014).

These population-level human mobility models offer key aspects to consider for incorporating the proximity, density, and diversity aspects of the x-minute city. The concept of intervening opportunities and distance-decay are both critical in understanding how people navigate the urban environment and make decisions on where to go based on what amenities and opportunities are available within their vicinity.

2.4 A Close-up on Citizens: Exploring individual mobility models.

Individual-level mobility models account for personal preferences and constraints and can help in understanding the variability in people's mobility patterns (Barbosa et al., 2018). These models can simulate diverse mobility behaviours, aiding in the assessment of how different population groups access greenspaces in the city. For instance, some individuals might prioritize proximity, preferring to use the closest amenities, while others might prioritize quality or variety and be willing to travel further for better options.

Random walks serve as a foundational concept, providing a null model of individual movement. However, their randomly generated movement trajectories do not mirror actual human movement (Barbosa et al., 2018; Song, Koren, et al., 2010). In a random walk model, each step in the trajectory is independent, uninfluenced by previous locations visited. Due to the random nature of these models, they are not the best fit for realistic human movement, which often exhibits more predictable properties. As a result, various versions of the random walk model, such as Brownian motion (Wang & Uhlenbeck, 1945) and continuous time random walks (Montroll & Weiss, 1965), have been developed.

A particularly successful variant is the Lévy flight model, which has been shown to accurately capture many aspects of human and animal movement. Lévy flights are characterized by a pattern of many small steps interspersed with occasional long jumps, creating a power law distribution for the jump length (Chechkin et al., 2008). This mirrors common human mobility patterns, such as daily commuting interspersed with occasional long-distance travel (González et al., 2008). While Lévy flights can describe routine behavior of human mobility, this model may not capture the nuances of urban travel and the decision of where to travel to. For example, Lévy flights do not consider the external factors present in the city, such as the crowdedness of a destination or the amount of traffic on the street, only creating a network of travel along the edges and nodes of the graph (Barbosa et al., 2018).

The Exploration and Preferential Return (EPR) model (Song et al., 2010a), incorporates an additional component of human behavior, the propensity to visit previous locations at a higher frequency than new locations. The EPR model works on a principle of balance between two significant behavioural actions: exploring new locations and returning to previously visited ones. The evolution of this model over time has seen several adaptations aimed at increasing its realism and representativeness of actual human mobility. For instance, the density-EPR model combines the gravity model and cumulative knowledge of an individual to guide the decision of which location to visit next (Pappalardo et al., 2016). Additionally, incorporating recency bias into the model accounts for another layer of human behavior prioritising the tendency of an individual to re-visit a recent location rather than a frequently visited location (Barbosa et al., 2015).

The recency model breaks down the EPR model, deriving two separate ranks—frequency and recency (i.e. ranking the most frequently/recently visited locations) (Barbosa et al., 2015). The recency model operates in much the same way as the EPR model with the same probability for exploration, however, the preferential return probability is altered to adjust the jumps to return locations to be selected from both frequently visited locations and recently visited locations (Barbosa et al., 2015). This additional nuance captured by the recency model enhances the overall output of the EPR model, making it more applicable to use in generating trajectories in urban environments. By combining recency and frequency, the frequency of visits can be broken down to better understand the human motivation for visiting a location.

Agent-Based Models (ABMs) represent another approach in individual mobility modelling, simulating the decision-making process of individuals based on a set of rules and interactions. While previous models like EPR and recency models focus on predicting movement patterns based on historical behavior, ABMs allow for more complex decision-making processes that incorporate both individual preferences and environmental factors. In these models, agents are programmed to make autonomous decisions about their movement patterns while responding to both environmental conditions and the behavior of other agents (Serena et al., 2023).

ABMs are particularly valuable for their ability to represent heterogeneous types of agents with varying decision conditions and to handle only partial data in complex urban environments, reducing the need for large training datasets (Maggi & Vallino, 2016). One key advantage of ABMs over other mobility models is their ability to capture how individuals adapt their route choices, departure times, and transportation modes in response to dynamic conditions such as congestion, availability of services, and the presence of other agents in the system (Heppenstall et al., 2012). This makes them especially suitable for studying complex urban environments where multiple factors influence movement decisions. However, ABMs struggle with validation because they produce emergent behaviours that cannot be easily observed or verified in the real world (Heppenstall et al., 2021).

Recent advances in big data analytics, particularly from smartphone GPS data and financial transactions, have given researchers the ability to understand human mobility patterns and can be used to help validate theoretical models. High-resolution smartphone GPS data enables researchers to track individual movements with precision, allowing for detailed examination of how movement patterns vary across different temporal and spatial scales, and in response to different environmental conditions. The ability to track individual movements has proven especially valuable for analysing specific population segments, from commuters to tourists, revealing how different demographics interact with urban spaces (Rout et al., 2021). When combined with other data sources like financial transactions and social media check-ins, researchers can create rich behavioural profiles that capture not just where people go, but also the purpose and context of their movements (Andrade et al., 2020; Birkin, 2019). Studies using mobile phone data have opened up the possibility to reveal how socioeconomic factors shape mobility patterns. For example, research in Bogotá demonstrated how lower-income groups maintained higher mobility levels during COVID-19 due to necessity, while higher-income groups could more easily adapt their movement patterns through remote work (Guzman et al., 2021). This type of granular mobility data analysis helps validate theoretical models while uncovering critical patterns in how different demographic groups navigate and access urban spaces. Such insights contribute to understanding the real-world implications of accessibility disparities and evaluating the effectiveness of urban interventions across different population segments.

Individual mobility models have great potential in assessing the movement of people through urban environments, particularly regarding greenspace accessibility. Random walks and their variants, such as Lévy flights, establish foundational principles for modelling movement trajectories, though their limitations in capturing real-world behavior require more sophisticated approaches. The EPR model and its extensions offer valuable insights into the balance between exploration and routine behavior, with the recency model adding nuanced understanding of temporal decision-making patterns. ABMs further enhance our understanding by incorporating complex decision-making processes and environmental interactions, though their validation remains challenging. The integration of big data analytics, particularly from smartphone-GPS, has significantly improved these models' accuracy and applicability, however, there are concerns surrounding the ethical usage of this data.

While each model type has specific limitations, collectively they provide complementary insights into how individuals navigate and utilize urban spaces. Collectively, these models for understanding greenspace accessibility are capable of capturing both routine usage patterns and exploratory behaviours, resulting in factors such as distance, quality, and temporal variations in visitation patterns. Future research could enhance these approaches by better integrating environmental quality metrics, social dynamics, and seasonal variations, potentially leading to more robust predictions of greenspace usage patterns in the context of the x-minute city.

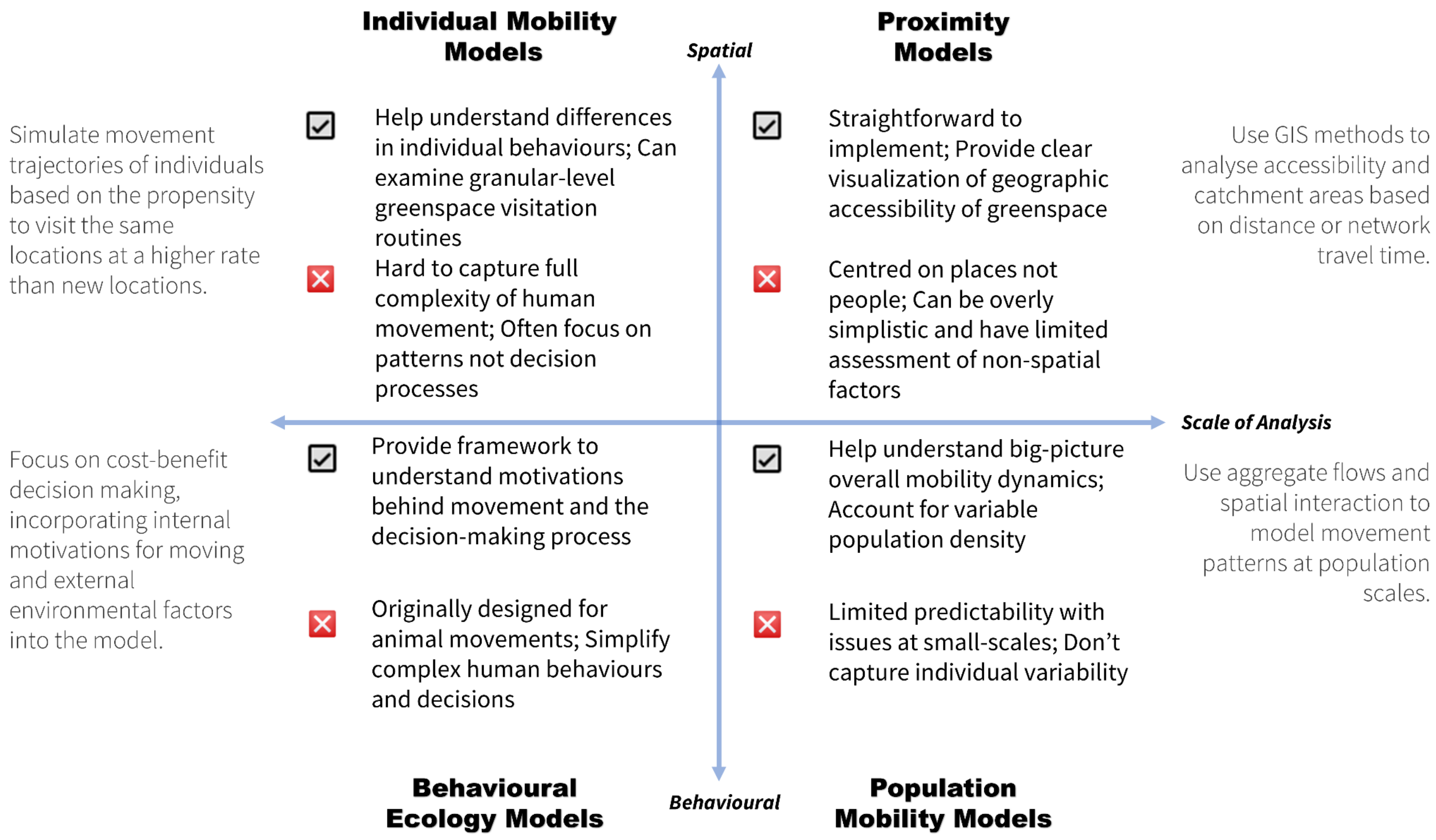

Figure 1. A summary of the advantages, denoted by ticks, and limitations, denoted by crosses, for each family of models.

3. Building a Holistic Framework: The Multi-context Inclusive City Framework

The previous sections explored different models and approaches to understanding human movement and accessibility within the x-minute city, examining methods from GIScience, behavioural ecology, and human mobility research (Figure 2). Each approach encompasses particular aspects of both the urban environment and human behavior, providing distinct perspective on urban accessibility. These approaches have been developed largely in parallel to each other. However, while this parallel evolution has led to sophisticated methods within each domain, it has also created methodological "silos" that limit the processes in which we examine urban mobility and accessibility.

Recent studies demonstrate this limitation. For instance, GIScience approaches excel at identifying spatial inequalities in greenspace access (Wu et al., 2022), but may miss the behavioural factors that influence actual usage patterns. Similarly, mobility models can reveal movement patterns through urban greenspaces (Zheng et al., 2024), but often lack environmental and social context. Behavioral ecology approaches offer insights into decision-making processes but may not fully account for spatial constraints. This fragmentation of approaches mirrors a broader challenge in urban planning, the disconnect between physical infrastructure, human behavior, and movement patterns (Smith & Walters, 2018).

To address this knowledge gap, while acknowledging practical constraints, these approaches can be combined in various ways to address specific urban planning challenges, particularly in understanding access to greenspace. We propose the Multi-context Inclusive City (MIC) approach as a flexible framework that can be adapted based on data availability and research needs (Figure 3).

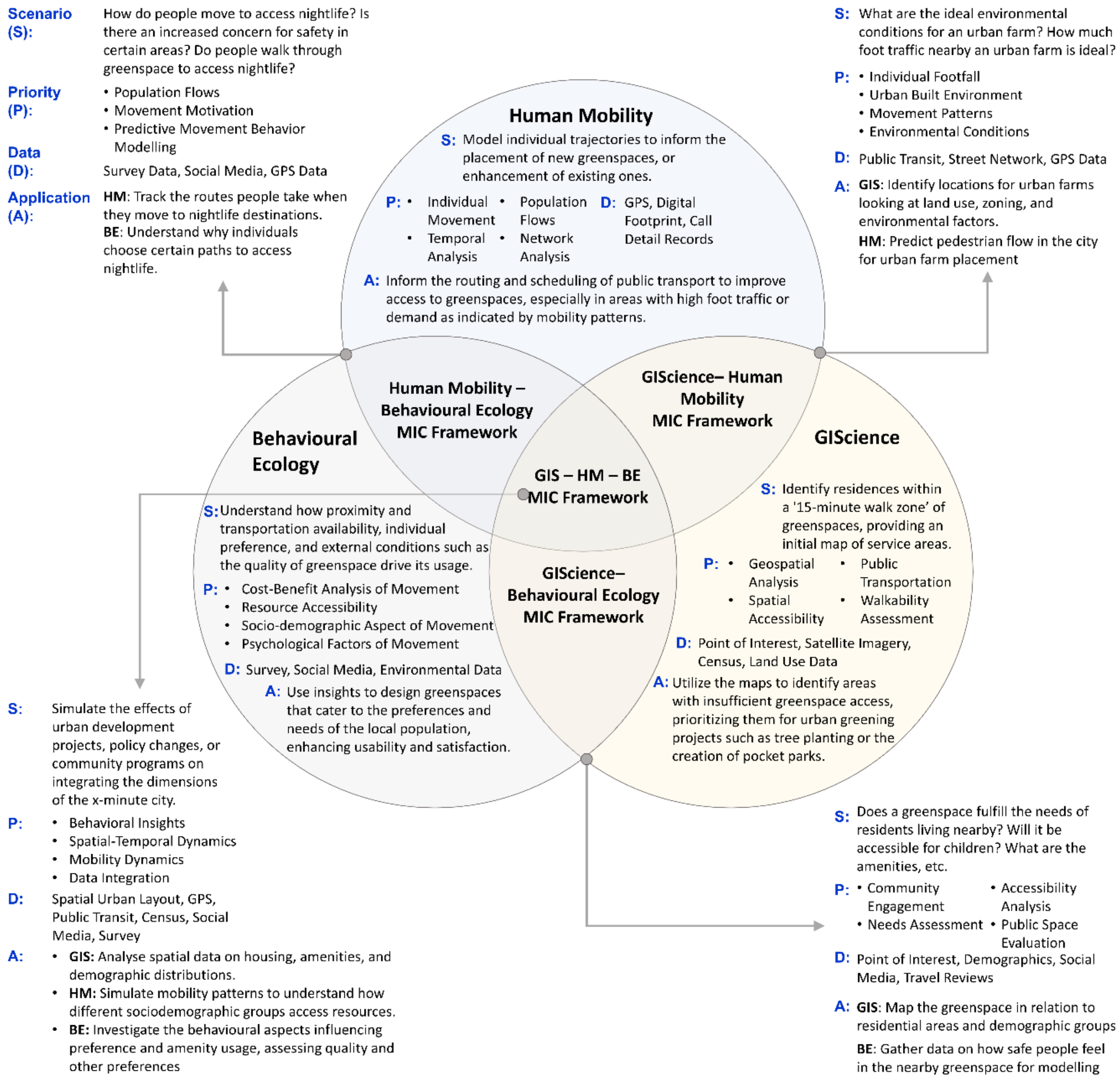

Figure 2. A general overview of the different Multi-context Inclusive City (MIC) models. Each of the circles represents the three approaches used to model human movement in the city: Human mobility (HM), Behavioral Ecology (BE), and GIScience (GIS). These sections describe the reason for using the individual model, as well as the priorities for using this type of model. The overlapping areas describe the different MIC frameworks by describing a potential scenario or application, and giving a brief example of the types of data that could be used.

The MIC framework represents a new perspective in how we conceptualize and analyse urban accessibility. Rather than treating spatial distribution, human behavior, and movement patterns as separate phenomena, we recognize them as interconnected dimensions of urban life that influence each other. The framework identifies four distinct approaches for combining different analytical methods: GIScience-Behavioral Ecology (GIS-BE), Human Mobility-Behavioral Ecology (HM-BE), GIScience-Human Mobility (GIS-HM), and a combined GIScience-Human Mobility-Behavioral Ecology approach. Each integration pathway within the MIC framework opens new possibilities for examining urban accessibility.

The GIS-BE approach combines spatial analysis with behavioural insights to understand how environmental conditions, the built environment, and individual perceptions influence movement patterns. This integration proves particularly useful for scenarios where understanding both spatial distribution and human behavior is crucial. GIS analysis reveals critical spatial patterns in urban resources distribution and accessibility barriers (Jin et al., 2023; Leboeuf et al., 2023), complemented by behavioural movement analysis that quantifies how people navigate through based on environmental factors and resource availability such as greenspace crowdedness (Mears et al., 2021; Vallejo et al., 2015; Xu et al., 2024). Together, these approaches provide a robust framework for evaluating both the spatial and behavioural dimensions of urban accessibility.

The HM-BE approach integrates individual movement patterns with behavioural principles to understand the motivations behind urban mobility. This combination provides unique insights that neither field can achieve alone (Demšar et al., 2021). Rather than treating movement patterns as purely spatial phenomena, this integration acknowledges that human mobility emerges from complex decision-making processes shaped by both individual preferences and environmental contexts. Empirical research demonstrates how behavioural frameworks enhance our understanding of human mobility patterns. Ladle et al. (2018) used smartphone GPS data combined with behavioural resource selection analysis to quantify how university students select greenspaces. Their integration revealed that students' selection of greenspaces and trails varied significantly by season and day of week, with stronger selection during summer months and weekends. Oliver et al. (2020) demonstrated how mobile phone data could track behavioural responses to public health measures, showing how people adjusted their mobility patterns in response to interventions during the COVID-19 pandemic. These studies show how integrating mobility data with behavioural analysis helps explain both the temporal dynamics and underlying motivations driving urban movement.

The GIS-HM approach merges spatial analysis with empirical movement data, creating a bridge between static data approaches and dynamic human behaviour. This integration reveals how people actually navigate and utilize urban spaces, expanding upon traditional accessibility measure. The incorporation of GPS-derived mobility data (or synthetically modelled movement data) allows for a more realistic representation of travel paths and individual behavior patterns (Mears et al., 2021). This creates the possibility to distinguish between potential accessibility—the theoretical opportunity to access a place based on its location and population demand—and realised accessibility, which accounts for actual mobility patterns, transport modes, and temporal dynamics (Filazzola et al., 2022; Lin et al., 2024; Tao et al., 2018). In terms of greenspace accessibility, mobility data and spatial analysis can be used to assess how accessibility fluctuates depending on factors such as the time of the day or the number of greenspace access points. It can also reveal how disparities in accessibility differ between different socioeconomic groups, to uncover barriers to safe and consistent greenspace access. The integration of human mobility approaches with traditional spatial analysis provides a more realistic lens for understanding how cities are experienced and accessed by different communities.

The GIS-HM-BE approach represents the most comprehensive integration within the MIC framework, combining spatial analytics from GIScience, movement pattern analysis from human mobility studies, and decision-making frameworks from behavioural ecology. For example, when analysing greenspace accessibility, the GIScience component provides spatial distribution and network analysis, human mobility models or data can reveal actual usage patterns and temporal tracking, while behavioural ecology frameworks help explain and quantify the underlying motivations for these patterns. The model can capture complex interactions between spatial contexts (e.g., demographics, socioeconomic status, neighbourhood segregation, transportation networks) and behavioural factors (e.g., individual preferences, social dynamics, temporal constraints).

While the GIS-HM-BE approach provides the most complete analysis of urban movement patterns, its implementation requires substantial data resources and processing capacity. Therefore, researchers should carefully consider whether their specific research questions necessitate this full integration or if a simpler MIC combination would suffice. Like other MIC approaches, the GIS-HM-BE approach serves as a complementary tool to existing urban analysis methods. One promising application is in urban digital twins, where the model's ability to simulate realistic human behavior patterns can help evaluate proposed urban interventions before implementation (Deng et al., 2021).

The selection of appropriate models and methods for analysing urban accessibility depends heavily on both data availability and specific research objectives. While comprehensive analytical frameworks offer powerful opportunities, their application is often constrained by real-world data limitations. For example, studies in regions with limited digital infrastructure may need to rely primarily on GIS approaches, as data for mobility tracking or behavioural analysis may be unavailable. Similarly, research questions themselves often dictate methodology choice—investigating spatial equity patterns might primarily require GIS techniques, while understanding temporal usage patterns would necessitate mobility data

(Figure 3). When combining these approaches, the balance between the methods needs to be carefully calibrated based on both the specific research objectives and practical constraints of data availability, while ensuring that the selected combination provides meaningful insights without unnecessary analytical complexity.

Conclusion

The Multi-Context Inclusive City framework presented in this review marks a collaborative approach in how we conceptualize and analyse urban accessibility, particularly concerning greenspace. While traditional approach to the x-minute city have focused on spatial proximity, this multidisciplinary approach attempts to bridge the divide between GIScience, human mobility analysis, and behavioural ecology, opening new pathways for understanding the complex relationship between urban residents and their environment. The framework's value extends beyond theory by providing practical tools for addressing persistent spatial inequalities in urban planning.

Whilst the comprehensive MIC framework proposed here needs to be tested empirically as a unified approach, evidence already exists in support of individual components and specific integrations within the framework. The GIS-BE component is well-represented in studies by Comber et al. (2008) and Van Herzele & Wiedemann (2003), who combined spatial analysis with behavioural factors to understand how different demographic groups perceive and access urban greenspaces. The HM-BE component has been demonstrated by Ladle et al. (2018), who analysed human mobility data alongside behavioural decision-making processes to reveal patterns in greenspace selection and movement responses. For the GIS-HM component, Filazzola et al. (2022) and Lin et al. (2024) distinguished between potential and realised accessibility by incorporating empirical movement data with spatial analysis. While the full three-way GIS-HM-BE component of this framework is novel and has yet-to-be fully implemented, Mears et al. (2021) have made important contributions in this direction by combining GPS human mobility data with GIS analysis and behavioural factors influencing greenspace selection. These existing studies provide a strong foundation for the value of our proposed MIC framework, while highlighting the need for further research fully implementing the comprehensive integration.

Several key research directions emerge from this integrated approach. First, there is a need to develop more sophisticated methods for incorporating subjective experiences and perceptions into quantitative accessibility measures. While current approaches can map physical access to greenspace, they often fail to capture the qualitative factors that make greenspaces truly accessible to diverse communities. The behavioural ecology component of the MIC framework offers promising avenues for addressing this gap, particularly through the adaptation of movement ecology to urban contexts.

A critical area for future development lies in the framework's application to emerging urban challenges in greenspace access, particularly in understanding how different socioeconomic groups access key ecosystem services. The MIC approach could help planners understand how communities adapt their movement patterns in response to environmental stressors such as urban heat islands, extreme weather events, and air pollution. By integrating spatial analysis with behavioural and mobility data, planners can identify barriers that prevent certain communities from accessing these vital services and develop targeted interventions. For instance, the framework could reveal how low-income neighborhoods might alter their greenspace usage patterns during heatwaves, or how the distribution of tree canopy coverage affects walking routes in different communities. These insights would inform more equitable and resilient urban design strategies that ensure essential ecosystem services are accessible to all residents, regardless of their socioeconomic status (Masson et al., 2020).

The availability of big data and the rise in artificial intelligence presents both opportunities and challenges for implementing the MIC framework. While machine learning algorithms can process vast amounts of mobility data to identify movement patterns and predict behavioural responses to urban changes, these tools must be carefully calibrated to avoid perpetuating existing biases. For instance, GPS data from smartphones might underrepresent elderly populations or low-income communities who have limited access to technology, potentially skewing any analyses (Kang et al., 2020). AI-driven approaches could help integrate diverse data types—from social media check-ins to environmental sensors—but questions remain about data privacy, ownership, and the ethical implications of tracking urban movement patterns (Shanley et al., 2024). Future research should focus on developing frameworks for data governance and ethical AI implementation while ensuring that technological advances in mobility analysis serve to reduce, rather than exacerbate, existing urban inequalities.

The success of the MIC framework will depend largely on its ability to bridge the gap between theoretical understanding and practical implementation. This requires developing user-friendly tools and guidelines that enable planners, policymakers, and researchers to apply these integrated approaches. For example, the framework's flexible structure allows cities to leverage their existing data infrastructure while systematically incorporating new data streams and analytical capabilities. Comparative case studies will demonstrate the MIC framework's enhanced capacity to capture complex accessibility patterns and inform evidence-based planning decisions, particularly in optimizing greenspace distribution and identifying barriers to access. These applications will further refine the framework while expanding its utility across different urban planning challenges.

As urban populations continue to grow, the challenge of providing equitable access to urban greenspace becomes increasingly critical for public health and environmental justice. The multi-dimensional perspective offered by the MIC framework contributes to this goal by revealing the complex interactions between spatial distribution, movement patterns, and human behavior that shape urban accessibility. Through its integrated approach, the framework provides essential tools for evidence-based planning decisions that can address historically overlooked barriers to greenspace access. By combining GIScience capabilities, human mobility insights, and behavioural ecology principles, this approach enables planners and policymakers to develop targeted interventions that not only optimize the spatial distribution of greenspace but also account for how different communities perceive, access, and benefit from these vital urban resources. The MIC framework thus represents a significant step forward in creating more accessible, sustainable, and equitable urban environments for all residents.

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