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Using human mobility data to quantify experienced urban inequalities

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The lived experience of urban life is shaped by personal mobility through dynamic relationships and resources, marked not only by access and opportunity, but also inequality and segregation. The recent availability of fine-grained mobility data and context attributes ranging from venue type to demographic mixture offer researchers a deeper understanding of experienced inequalities at scale, and pose many new questions. Here we review emerging uses of urban mobility behaviour data, and propose an analytic framework to represent mobility patterns as a temporal bipartite network between people and places. As this network reconfigures over time, analysts can track experienced inequality along three critical dimensions: social mixing with others from specific demographic backgrounds, access to different types of facilities, and spontaneous adaptation to unexpected events, such as epidemics, conflicts or disasters. This framework traces the dynamic, lived experiences of urban inequality and complements prior work on static inequalities experience at home and work.

Cities emerged about 10,000 years ago as 'central places' where people, goods and services converged. The spatial agglomeration of opportunities has become the engine of prosperous urban economies and the driving force of increased urbanization, and modern cities now account for more than 55% of the world population and 80% of the world gross domestic product (GDP). Nevertheless, urban spatial agglomeration is not uniform. People, opportunities and infrastructure networks are unevenly distributed, as is manifest in racially segregated residences and unequal facility and amenity distributions[1]. This unevenness leads to a wide variety of explicit and subtle inequalities in how different people can leverage urban resources for education, employment, healthcare and more, which is reflected in urban mobility behaviour. Accordingly, quantifying experienced urban inequality via the lens of mobility behavioural data is an important starting point for equitable and inclusive urban policy design.

The idea of measuring urban interactions can be traced to the seminal work of Torsten Hägerstrand[2], which proposed 'space–time prisms' to depict the boundaries of personal activities through feasible 'space–time paths'. This work gave rise to the vibrant research community of time geography, which focused on the personal boundaries of human activities[3]. Increasingly available human mobility data gradually directed more attention from spatiotemporal constraints to realized

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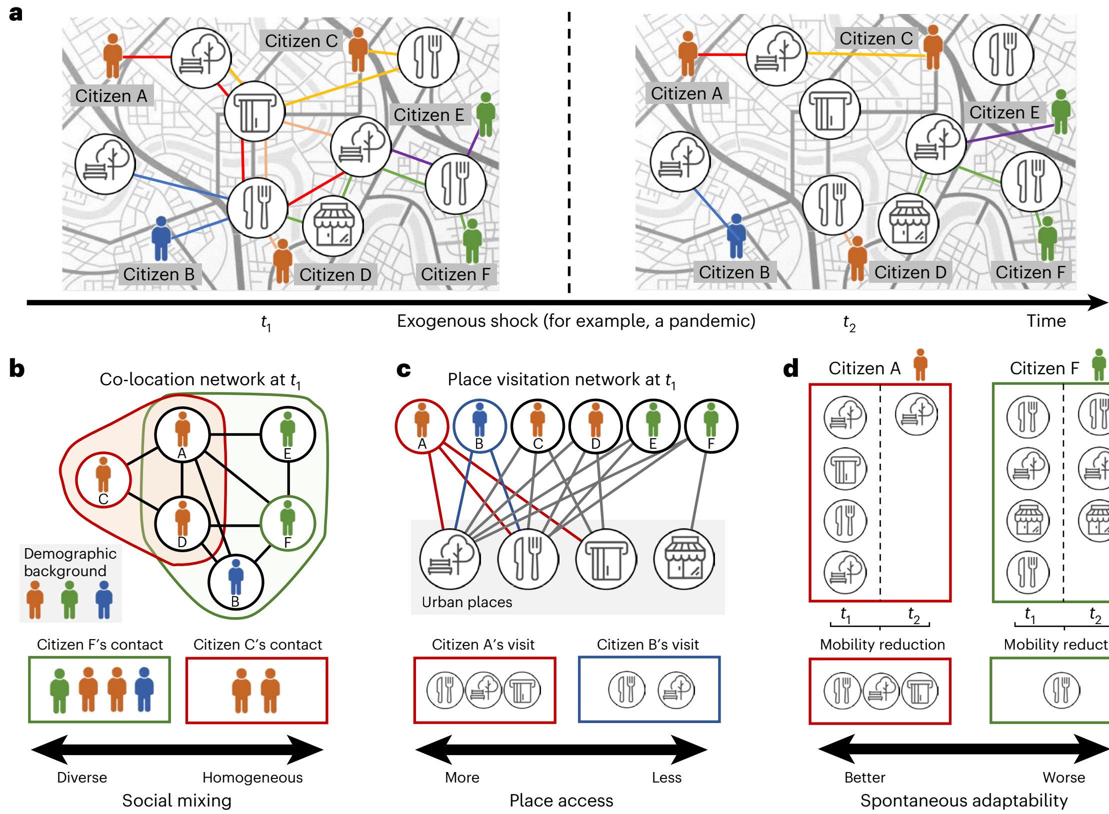

Fig. 1 | Conceptualizing experienced inequalities in urban mobility. **a**, Examples of urban mobility data, showing how citizens with different demographic backgrounds (represented by colours) visit various urban places across time. **b**, 'Social mixing' characterizes the unequal opportunities for human interaction. In the extracted co-location network at time t_1, citizen C only encounters persons with same demographic background (orange), whereas citizen F encounters persons with three different demographic background (orange, blue and green). Hence, citizen C has more opportunities to interact with a diverse population. **c**, 'Place access' captures urban place functions (for example, bank, park, restaurant) one can access through daily mobility, which measures the opportunity gap in leveraging urban resources. In the place visitation network at time t_1, citizen A can access more urban facilities and amenities (for example, a bank) than citizen B. **d**, 'Spontaneous adaptability' characterizes how well citizens can adapt their mobility behaviour in response to exogenous shocks. As an example, if we compare the mobility behaviour at t_1 and t_2 timestamps, citizen A shows better 'spontaneous adaptability' than F, because A can reduce mobility more dramatically during a pandemic.

human behaviours. Early work proposed the use of self-reported travel diaries from 5,000 residents in three US counties to quantify experienced segregation[4], and recent work uses Global Positioning System (GPS)-based indicators to measure urban activities on a much larger scale[5]. Partly triggered by the data requirements for COVID-19 control, an unprecedented trove of large-scale high-precision mobility data and the associated context attributes (for example, demographics and venue types) has become available, and this has attracted substantial scholarly attention to measure the inequality embedded in urban mobility behaviour. In this Perspective we argue that such mobility behaviour data could provide an important complement to previous research that focused on static urban spatial arrangements and surveys, revealing experienced inequalities in large-scale, passively sensed urban interactions.

Here we present a general analytic framework to quantify experienced inequalities in urban interactions via the lens of big mobility data. We model urban mobility behaviour as a temporal bipartite network (Fig. 1), where nodes represent people and places, and dynamic edges represent visitation at specific times. Temporal connectivity reflects mobility behaviour changes over time, which can capture residents' adaptability to exogenous shocks, such as the COVID-19 pandemic. This general formulation allows researchers to model inequality embedded in social encounters as uneven person–person co-locations, and inequality of opportunity access as uneven person–place visitations. This framework can thus facilitate urban inequality quantification along at least three conceptual dimensions: (1) social mixing—unequal opportunities to interact with people from different demographic backgrounds; (2) place access—uneven access to urban amenities and facilities with distinct functions; and (3) spontaneous adaptability—the dynamic capacity to adapt mobility behaviour to unexpected exogenous shocks, such as extreme weather events, public health crises or emergent urban conflict. Moreover, the meaning of projected person–person or place–place connections can be deepened by considering the context provided by the intermediary nodes of places or persons. For example, the social implications of eating together in a restaurant are markedly different from those associated with random encounters in a supermarket. Incorporating such contextual information may allow researchers to infer more nuanced social interactions embedded in mobility patterns. To introduce state-of-the-art methodologies that support the proposed framework, we provide a systematic review of pioneering work that maps mobility behaviour data to forms of experienced inequality in urban life.

A large body of literature has sought to provide formal guarantees for equal opportunity among citizens, and legal statutes have sought to incorporate these in policy. Nevertheless, these are often of limited worth to disadvantaged and marginalized urban populations. For example, most COVID-19 prevention policies are non-discriminatory, but empirical studies found extensive evidence that disadvantaged urban communities faced higher infection and mortality risks because they could not afford to reduce mobility behaviour for a sustained period[6,7]. The proposed framework allows us to systematically measure the effective equality of urban opportunities with real-world mobility

Table 1 | Various data sources for urban mobility behaviour

Data source	Example dataset	Brief description of typical datasets
Shared bike	BikeRio, EcoBici, Divvy, NYC Citi	Often include trip duration, start and end locations and timestamps, capturing short-range, flexible, green urban mobility
Ride-hailing	Uber, Lyft, NYC TLC, Chicago TNP	Often include trip origins, destinations, ride duration and timestamps, capturing on-demand mobility in urban space
E-scooter	US BTS, Chicago E-scooter Pilot	Often include trip origin stations, trip end stations, ride duration and timestamps
Public transit	Jakarta Data, Toronto Data, NYC MTA	Often include ridership numbers, routes, timestamps and public-transit modes, for example, buses, trains and subways
Social media	Foursquare, Gowalla, Weibo, Brightkite	Often include venues visited, timestamps and sometimes semantic-rich metadata such as user reviews or ratings
Mobile device	GeoLife, SafeGraph, MIT Reality Mining	Provide fine-grained and dense movements information of anatomized individuals or aggregated population at scale

behaviour. We demonstrate that subtle but important urban inequalities, such as experienced segregation, gaps in facility access, and vulnerability to pandemics and climate crises, can be quantified at scale with this approach. Such measurements carry profound implications for equitable policymaking under scenarios of pandemic prevention, climate adaptation and sustainable lifestyle adoption. For example, as citizens increasingly adopt local lifestyles and sustainable modes of transportation, opportunities can be more equitably distributed by changing or relaxing zoning regulations. Moreover, our measurement framework allows us to more accurately identify communities exposed to disproportionate damage in increasingly extreme weather events and engineer more resilient city systems. These use cases highlight the potential of mobility behaviour data for reducing experienced inequalities in urban space.

Sensing mobility behaviour in urban space

The advance of information technology has opened unprecedented opportunities to study urban inequality with ubiquitously collected fine-grained mobility behaviour data. Promising data sources include platforms for shared bicycles, e-scooters, public transit, ride-hailing, social media and mobile devices. Table 1 summarizes exemplary datasets. Recent years have seen substantial advancements in sensing technologies and machine-learning techniques that enhance the richness of mobility behaviour datasets. For example, algorithms have been developed to identify stay points from GPS trajectories in mobile devices[8], linking them to points of interest and enabling the inference of trip purposes. Additionally, data-mining algorithms have been designed to predict unobserved locations[9] and hidden context in urban mobility[10]. Furthermore, the advent of lightweight mobile sensors has facilitated portable sensing[11], which unobtrusively captures associated activities. Moreover, computer vision models have been used to characterize urban environments using satellite imagery and street views[12,13], providing contextual data that enrich urban mobility analyses.

The contextual attributes associated with mobility behaviour data can be leveraged to infer social implications encoded in person–place visitations and person–person encounters. For example, a recent study proposed the consideration of industry categories and areas of co-located places when modelling the probability of person–person virus transmission[6]. Moreover, contextualizing the frequency of person–place visitation with counterfactual random walks can facilitate more rigorous analysis of income and racial gaps in place access[14]. Similar techniques can be used to enrich the edges of mobility networks with attributes such as interaction strength, importance and types of social opportunity. By doing so, researchers can more effectively characterize complex social processes within mobility networks, including the spread of ideas, the formation of friendships and access to services. This enriched understanding enables a deeper analysis of urban inequalities, revealing how different social dynamics are facilitated or hindered by physical mobility patterns.

Mapping mobility behaviour to experienced inequality in urban life

The increasing availability of mobility behaviour data is promoting the quest for methodologies that map mobility behaviour to experienced inequalities in urban life. To conceptualize recent methodologies in a unified analytic framework, we propose to model urban mobility behaviour as a temporal bipartite network between people and places (Fig. 1a). This framework allows researchers to measure inequality in the following three dimensions: social mixing and experienced segregation, unequal access to urban places, and spontaneous adaptability to exogenous shocks.

Social mixing and experienced segregation

The diversity and density of interactions in cities catalyse innovation, opportunities, jobs and economic development[15]. Cities are becoming more segregated, and also a significant force in creating inequalities and eroding the social fabric of neighbourhoods, institutions, companies and society. Income and racial segregation have been shown to affect access to critical urban resources, such as housing, community facilities, health services and clean environments. Despite this, our current understanding of segregation and its relationship with other urban problems such as transportation, gentrification and even social participation is based primarily on residential information collected via census or survey, which is coarse-grained and updated infrequently. Recent years have witnessed substantial progress in technologies for augmenting census data. Researchers have designed methods to use satellite images and mobile phone records to downscale census population data into finer spatial and temporal resolutions[16,17]. Several bottom–up approaches have also been proposed to estimate the population distribution in the absence of national census data[18], which is particularly important for developing regions that have limited resources to sustain accurate and updated population information. Despite this recent boost in progress in the resolution and coverage of census data, we remain limited in our ability to capture personal movements and social encounters in resource-constrained regions, and hence cannot provide a full picture of how social interactions unfold across all cities.

Using recently available large-scale data on mobility and its associated social and cultural context, researchers have begun to document unequal patterns of mobility among different socio-demographic groups and, more importantly, how spatial residential segregation in cities extends to the activity spaces where most of our working hours, leisure and social interactions occur[19,20]. As individuals move around the city, they encounter and interact with more diverse people than they could within their own neighbourhoods. Even though residents of disadvantaged neighbourhoods travel widely, they predominantly visit poor or underprivileged communities, so their relative isolation and segregation persist[21,22]. Diverse social interactions do not happen everywhere: commercial venues such as restaurants, retail shops and office workplaces are particularly strong forces that pull against segregation[19]. By contrast, amenities such as schools or churches, cultural and entertainment spaces, and single-status workplaces such as factories or warehouses are more segregated. As a result, segregation can occur at the street level or even inside a classroom. Places located in the very same block can have a very different composition of

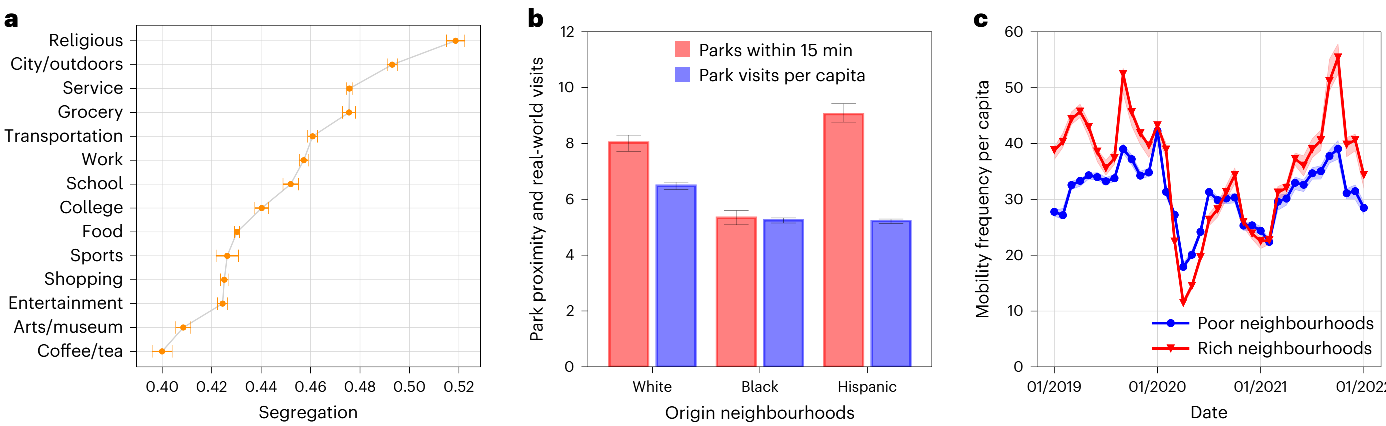

Fig. 2 | Demonstrating experienced inequalities with empirical mobility data collected from New York City. a, Different places show distinct patterns of experienced segregation (by income). Specifically, neighbourhood places that provide groceries, services, religious and natural experiences are visited by less diverse income groups. On the other hand, places such as coffee shops, museums or entertainment venues are more diverse[19,23]. **b**, Majority-Hispanic neighbourhoods have the most parks accessible within 15 min via public transit (red bars). Nevertheless, empirical mobility data show that majority-white neighbourhoods have significantly higher park visits compared with both majority-Black and -Hispanic neighbourhoods (blue bars), revealing the importance of leveraging empirical mobility traces. Error bars in **a** and **b** represent 95% confidence intervals. **c**, Rich neighbourhoods (top income decile) have higher per capita mobility frequency than poor neighbourhoods (bottom income decile) before the COVID-19 pandemic. This pattern reversed during the COVID-19 pandemic in 2020 due to a higher mobility drop in rich neighbourhoods, which gradually returned to the pre-pandemic norm in 2021. This suggests that rich neighbourhoods have better spontaneous adaptability in their capacity to reduce mobility and minimize viral exposure risk due to their outsized economic opportunities and abundance[7].

visitors[23]. Segregation can also occur at different times of the day due to the distinct urban mobility rhythms of different socio-demographic groups[20,24]. Because individuals spend most of their time away from their neighbourhoods, these findings challenge our traditional understanding of segregation and inequality in a city. Segregation is not only reflected in economic or racial sorting within neighbourhoods—it is encoded in our behaviour as we move, interact and communicate with the rest of the city.

This recent work demonstrates how experienced segregation can be measured with co-location networks extracted from the temporal bipartite network of human mobility, which reveals the distribution of social encounters across urban space (Fig. 1b). Specifically, it allows researchers to easily quantify the segregation individuals experience in daily life with diversity metrics over the demographic profiles of individuals connected in the co-location network. As an example, we have computed the co-location network of New York neighbourhoods with real-world mobility data from SafeGraph[25]. Figure 2a shows the percentages of racial backgrounds of neighbourhoods connected to focal neighbourhoods. It reveals that majority-white, Black and Hispanic neighbourhoods all experience segregation in their daily activities because their members undertake more frequent trips to neighbourhoods with similar backgrounds than the average.

Unequal access to urban places

The spatial agglomeration of people and infrastructures in cities enables convenient access to facilities and opportunities across urban space, a crucial factor in the quality of urban life. A large literature has documented long-term negative consequences from limited access to high-quality schools, banks, green spaces and other urban places on household finance, physical health and subjective well-being[26,27]. Nevertheless, opportunities for accessing urban places are often unevenly distributed, creating inequalities between neighbourhoods. Researchers have long sought to develop methodologies that measure inequality in urban place access with a variety of data sources, including surveys, spatial information and mobility behaviour traces[28]. Surveys collect direct feedback from urban residents, but tend to be expensive and challenging to scale in sample size and measurement frequency. Studies using spatial information differentiate between place- and people-based measures[29]. Place-based measures assess the spatial distance between a focal neighbourhood and urban amenities or services, and people-based measures also consider individuals' activity schedules and spatiotemporal constraints. These measures provide valuable insights based on static urban configurations. For example, a recent study found that alternative financial institutions, such as payday lenders, are more frequently located closer to racial/ethnic minority neighbourhoods than regular banks, even when accounting for poverty rates and other factors[30]. Moreover, previous work has considered the spatial configuration of road networks and determined that redistributing facilities could reduce average travel distance by half[1]. Although spatial information can measure available urban places with travel costs, it may not accurately predict the actual mobility patterns of urban residents. For example, studies have demonstrated that models solely based on spatial information tend to produce biased estimates of realized place visits[31].

Hence, mobility data offer crucial insights into the experienced inequality of urban life[31–34]. To integrate methodologies using mobility data into our analytic framework, we represent recorded urban place visits as a bipartite people–places network, where edges indicate visitation frequency or duration (Fig. 1c). Variability in edges linked to each individual or subpopulation, gauged by metrics such as total out-degree or number of places serving specific functions, acts as a reliable proxy for experienced inequality in access to urban places. This enables researchers to transcend mere spatial distance, providing a holistic view that accounts for subtle inequalities rooted in social or cultural contexts, such as disparities in time spent waiting for basic services[35]. We conducted a case study on park visits in New York City (Fig. 2b), and found majority-Hispanic neighbourhoods have the most parks available within 15 min via public transit. Both Hispanic and Black neighbourhoods register significantly fewer actual park visits compared to white neighbourhoods, however, echoing previous work on the discrepancy between park proximity and park visitation[31]. These results underscore the value of mobility data in revealing the effective inequalities of urban life.

Spontaneous adaptability to exogenous shocks

Exogenous shocks include unexpected external events that can significantly affect society, often leading to alterations in human mobility behaviours. Such changes in mobility patterns can result directly from events such as natural disasters[36,37], climate change[38], pandemics[39,40] and geopolitical conflicts[41], or indirectly due to impaired socioeconomic capability[21,42]. These shocks often exacerbate pre-existing inequalities in urban space, disproportionately affecting vulnerable populations and widening the gap between different social groups[42,43]. Research on exogenous shocks has uncovered significant effects on both short-term mobility fluctuations and long-term immigration patterns, emphasizing the need to comprehend the interplay between these events and human mobility. Traditional studies, which rely on household surveys, census data, panel data and qualitative interviews, provide valuable insights but are limited in capturing the subtle intricacies of mobility change. Furthermore, their static nature precludes real-time prediction or the capacity for intervention.

In response, researchers are increasingly turning to alternative mobility datasets, either to supplement or replace traditional data sources, offering finer-resolution metrics such as travel distance, number of trips, evacuation distance and evacuation percentage. These recent methodologies can be understood as measurements capturing dynamic changes in the proposed bipartite network linking people and places. We illustrate this concept with a toy example in Fig. 1. Specifically, citizen A demonstrates greater spontaneous adaptability than citizen F, as evidenced by a more significant reduction in number of trips following a pandemic outbreak. We analysed this phenomenon with real-world mobility data in New York City during the COVID-19 outbreak (Fig. 2c) and found that rich neighbourhoods (top 10% income) had greater mobility reduction compared with poor (bottom 10% income) at the outbreak onset, and swifter recovery after vaccines became available. Such differences probably exist because low-income and marginalized populations have fewer options to work remotely or access essential services without travel[6,7]. This shows how mobility data can capture the disproportionate effect of exogenous shocks. Furthermore, graph-based approaches have been employed to investigate the role of social networks in mobility during emergencies[36]. A notable example of these advanced models is the spatiotemporal decay model proposed by Li and colleagues[42], which captures the interplay between geographic distance and time in mobility during disasters. This mathematical framework allows for a more comprehensive understanding of the complex dynamics governing human mobility under exogenous shocks, contributing to the development of more effective disaster response, recovery and policy intervention.

Example use cases

We introduce three example use cases featuring our proposed framework to underscore its applicability in scenarios such as pandemic prevention, climate change adaptation and promoting locality in urban lifestyle.

Equitable policymaking in pandemic response

As human movement and social interaction are key drivers of infectious disease spread across a population, the availability of fine-grained mobility data allows us to measure such processes with unprecedented detail, providing valuable information to guide policymakers in response to epidemic outbreaks[44]. For example, by leveraging the high granularity of large-scale mobility data and integrating mobility flows into epidemic agent-based models, several studies have investigated how differential responses to mobility restrictions are explained by differences in socioeconomic status[6,45]. Furthermore, by using dynamic neighbourhood–place interaction networks (similar to Fig. 1a) in several US metro areas, and combining them with an epidemic susceptible–exposed–infectious–removed (SEIR) compartmental model, Chang and colleagues[6] explained higher infection rates among disadvantaged groups. Counterfactual scenarios on large-scale mobility data-driven simulations were also used to assess the viability of contact tracing and quarantine policies during the first waves of the pandemic[46]. Similar simulation studies can help to analyse trade-offs between economic output and public health[47]. Finally, our proposed framework to quantify urban inequality can inform data-driven simulations of pharmaceutical interventions during a pandemic, such as vaccination distribution. Chen and colleagues[7] demonstrated how an epidemic model combining mobility data with socio-demographic information offers valuable guidance for vaccine prioritization (Fig. 3a). This approach can simultaneously improve utility and equity across different vaccination rates and timing. These findings should inspire stakeholders to design vaccine distribution schemes that simultaneously pursue enlightened self-interest and benefit overall population health[48].

As the need to address socioeconomic inequalities in infectious disease modelling becomes more pressing[49], the integration of high-resolution mobility data in epidemic models represents a key ingredient to fill the gap. This is especially important as changes in behaviour during the pandemic from social distancing have changed continuing co-location and mixing patterns in our cities[50,51], increasing experienced segregation. Our framework can guide epidemiologists and public health officials to define comprehensive modelling approaches that inform improved policies.

Adapting to extreme weather events

Climate change is exerting a heterogeneous adverse effect on urban populations[52,53]. This effect has a pronounced correlation with urban residents' exposures to environmental stressors[54–57]. Consequently, urban mobility research is paramount, not only to comprehend the complex implications of climate change, but also to weave the threads of social justice into climate adaptation strategies, ensuring equitable solutions for all urban residents[55,58].

Figure 3b illuminates the spatial correlations in human mobility across the Greater Houston area amid the 2021 tropical storm Imelda, as captured by Moran's *I*. During the storm's zenith, a marked decline in this spatial correlation was observed, indicating a transition towards more randomized movement patterns among neighbouring grids. This transition could be attributed to a myriad of potential factors: unpredictable flood patterns, areas perceived as refuges, or the operation of essential services in specific locations. For policymakers and emergency responders, such irregularity not only signals the necessity for adaptive strategies, but also underscores a departure from monolithic approaches toward tailored interventions. Certain locations might become inundated with displaced populations, necessitating amplified resources. Other locations characterized by diminished movement might be those most severely affected and thus warrant more immediate attention and assistance. This underscores the urgent need for robust infrastructure and agile mobility plans during extreme weather events, which are crucial for safeguarding residents and preserving indispensable city functions during crises.

Promoting locality in urban life

To reduce traffic congestion and curb emissions, policymakers worldwide are exploring innovative urban planning models that aim to reduce the reliance on automobiles. One prominent vision is the '15-minute city' model, which suggests that cities will be more energy-efficient and socially cohesive if residents can access most necessities within a 15-min walking or cycling distance from home[59,60]. Previous studies examining the potential of residential neighbourhoods to provide essential services within walking distance have primarily focused on assessing the proximity of amenities such as grocery stores and restaurants[61–63]. However, simply arranging amenities close to residences does not guarantee utilization, because mobility decisions are driven by diverse behavioural factors that vary across social groups and locations. Understanding the effects of reorganizing cities around walkable amenities necessitates the utilization of large-scale data based on actual trips.

A recent work has analysed local trip behaviour in US cities by analysing the GPS data from 40 million mobile devices[64]. Using such data,

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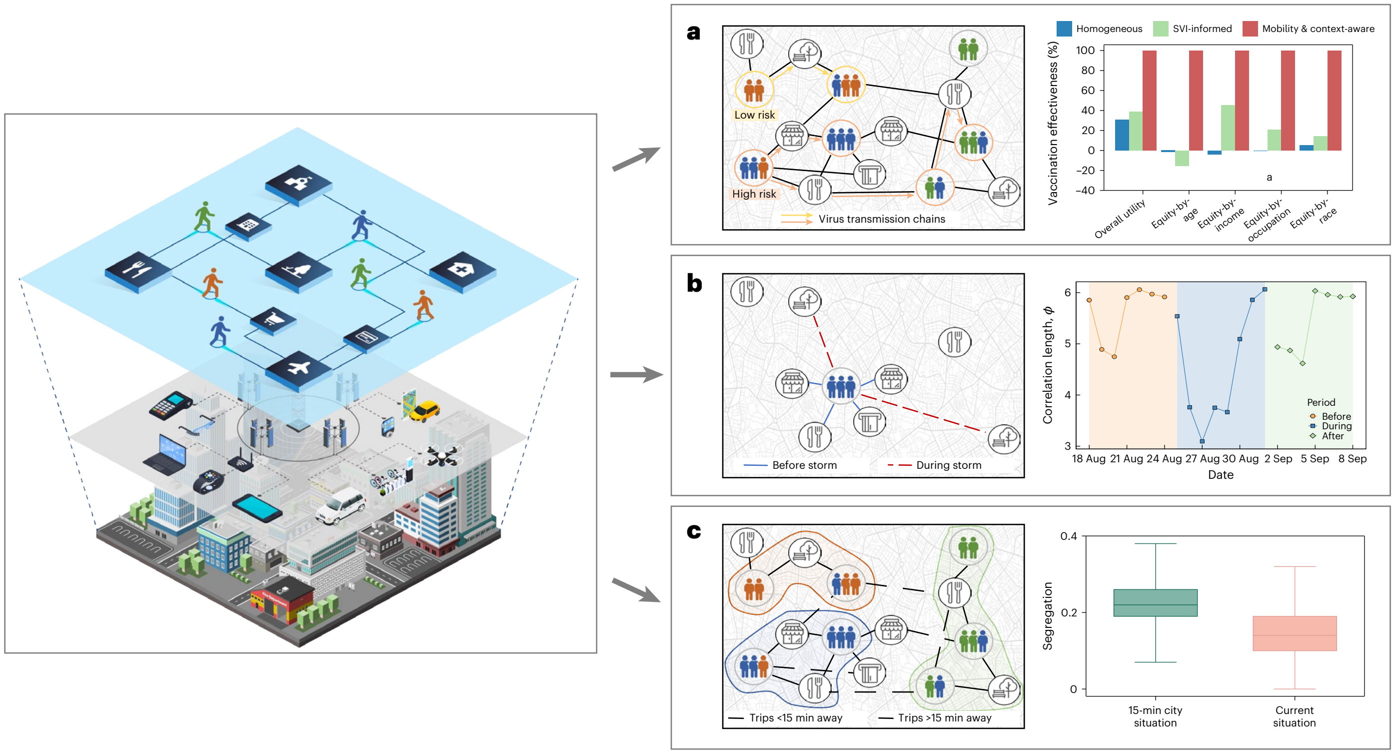

Fig. 3 | Example use cases featuring our proposed framework for advancing sustainable urban development. a, Designing pandemic policy: an epidemic model integrated with mobility data and socio-demographic profile can accurately identify high-risk neighbourhoods in viral spreading, which not only face higher mortality risk but may also cause more secondary infection[7]. SVI is the CDC's social vulnerability index, which uses demographic variables to identify vulnerable communities. **b**, Adapting to extreme weather: the temporal bipartite network of neighbourhoods and places captures mobility behaviour change in the Greater Houston area amid the 2021 tropical storm Imelda. Spatial correlations, measured by Moran's *I*, dropped sharply during the storm, indicating a transition towards more randomized movement patterns among nearby neighbourhoods. **c**, Promoting the '15-minute city' lifestyle: shaded areas show neighbourhoods connected through co-location encounters when trips for more than 15 min are removed. Using GPS data from 40 million mobile devices in US cities[64], we find that this lifestyle could exacerbate socioeconomic segregation.

the study establishes a baseline of local living in the USA to examine the relationship between trip length and access to nearby amenities. This allows for an exploration into whether shorter trips might aggravate socioeconomic segregation (Fig. 3c). The results suggest that adopting less restrictive zoning regulations, such as allowing for more mixed-use development, could reduce trip lengths. However, such policies also carry the risk of increasing social isolation for low-income individuals. Thus, these findings highlight the importance of our behaviour-centric framework, which can shed light on the trade-off between enhanced access to diverse local amenities and opportunities for encountering diverse populations. Moreover, a trade-off emerges between the environmental goal of promoting shorter trips and social goals that necessitate intensive mobility to facilitate social mixing. This urges stakeholders to comprehensively consider all relevant factors when formulating policies.

Future directions

Exploring higher-order structures

Our framework offers a complementary network perspective to urban inequality research, enabling researchers to explore more complex mobility patterns as higher-order structures within mobility networks. We provide three illustrative examples in Fig. 4. First, the betweenness of a node captures its mediating role in effectively bridging other nodes (Fig. 4a), which can be quantified by the number of shortest paths passing through it[65]. It can be an effective measure for identifying de facto 'hub' neighbourhoods or infrastructures that serve as critical bottlenecks for mobility throughput[66], as well as bridges facilitating interactions across different social groups. Future research may investigate the temporal dynamics of infrastructure betweenness to understand how the importance of different locations evolves over time and the effect on urban space. Second, network communities emerge from heterogeneous network connections as groups of nodes that are more densely connected internally than with other nodes outside the group[67] (Fig. 4b). To detect communities on people–places bipartite networks, one can adopt modularity-based techniques such as bi-clustering[68] and Louvain[69] or random walk-based techniques such as Infomap[70]. These identified communities can reflect multiple dimensions of experienced urban inequalities in terms of commuting patterns, activity modes, resource access[32] and social interaction structures, which are jointly shaped by infrastructure distribution, transportation accessibility and individual travel budgets. For example, the fragmentation of urban mobility networks indicated by distinct community structures is found to be correlated with increased income inequality[71]. Third, the backbone of a network (Fig. 4c), identified by percolation analysis[72], can reveal the 'core' set of nodes and edges that account for the most connectivity. In the context of urban mobility networks, the network backbone corresponds to the critical neighbourhoods and infrastructures that sustain the overall integrity of the urban mobility network, especially during times of shock and disturbance[73,74]. Meanwhile, neighbourhoods excluded from the network backbone tend to be more susceptible to isolation during crises, thus suffering a disproportionate effect from reduced place access and people encounters.

Implications for sustainable urban development

The discussed use cases in pandemic prevention, climate adaptation and the '15-minute city' connect our urban mobility analytic framework to broader sustainable development goals (SDGs). As illustrated in Fig. 5, mobility big data enable researchers to measure experienced

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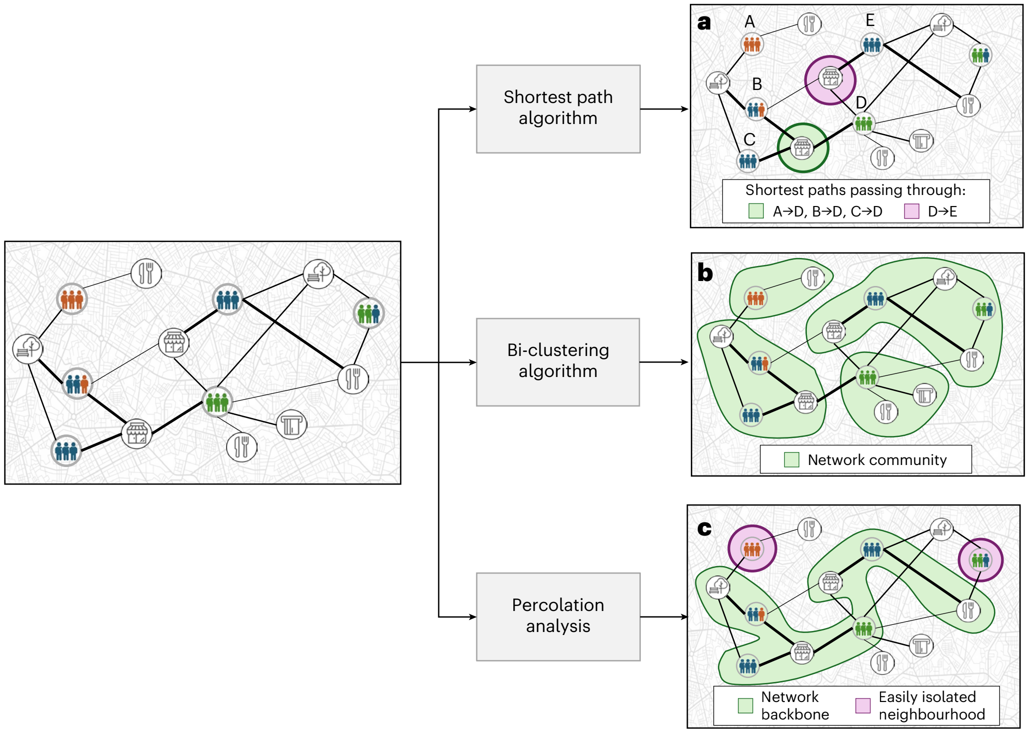

Fig. 4 | Exploring the higher-order structures in a mobility network. **a**, Network bridges: the mediating role of a node can be captured by computing its betweenness using the shortest path algorithm. As illustrated, the green circle node exhibits a higher betweenness than the purple circle node, as the green one is part of more shortest paths across the network. **b**, Network communities: social segregation is observed as residents tend to visit places within their own community, and the higher-order communities can be detected using a bi-clustering algorithm. **c**, Network backbones: the backbone identified through percolation analysis consists of critical nodes and edges that sustain the overall integrity of the network, especially when faced with unexpected shocks and disturbances. Consequently, neighbourhoods within the purple circles are more susceptible to isolation during crises.

inequality in place access, social mixing and spontaneous adaptability. Various combinations of these measurements can be used in '15-minute city' adoption, climate adaptation and pandemic prevention, which have important roles in a range of SDGs, such as SDG 3 (good health and well-being), 9 (industry, innovation and infrastructure), 10 (reduced inequality) and so on.

We also note that mobility behaviour data may have an even more important role in developing nations, where the classic survey methods, such as travel surveys, could be prohibitively expensive and time-consuming. By contrast, recent advancements in using mobile phone data and other passive data-collection sources[75] have enabled the generation of travel demands that cover a larger portion of the population at low cost, allowing for more comprehensive analyses of different subpopulations. Nevertheless, cities in developing and disaster-prone nations face unique challenges in modelling and planning due to limited economic resources, data scarcity and limited expertise. With the increasing frequency and severity of natural disasters induced by climate change, better decision-making tools are required to mitigate the effects of extreme events. For example, data from past landslide and flooding events in Freetown, Sierra Leone, have been used to simulate the effect of such events on transportation infrastructure[76]. Taken together, properly mining and analysing novel data sources of human mobility represents an important direction for informing urbanization policies and supporting sustainable development. The utility of these resources is maximized when traditional datasets and statistics are compared for calibration and context.

Data fairness and marginalized populations

As the utilization of novel mobility datasets substantially advances our understanding of human mobility dynamics, it is crucial to address the implications of data fairness and its effect on marginalized populations. This concern arises from the possibility that the available datasets may not represent the entire population, as ownership rates and usage patterns vary across socioeconomic and demographic groups. For example, work has identified modest income biases in mobility across large US cities[19], but those biases are more prevalent in rural cities and developing countries. These disparities can result in biased estimates and analyses, neglecting the challenges faced by marginalized populations in low-income, older or rural communities. Consequently, policies derived from these novel datasets and methods may inadvertently reinforce existing inequalities, exclude demographic groups or exacerbate disparities in resource access.

Addressing these fairness concerns requires a rigorous examination of bias in mobility data and the development of cutting-edge mitigation strategies, such as pre- or post-stratification methods to obtain representative demographic panels of users, or comparison with ground-truth and other datasets[7,19]. Moreover, integrating emerging mobility data with traditional survey and census data can provide a more comprehensive and representative picture of mobility patterns. Researchers can also harness machine learning to develop fairness-enhancing techniques that amplify data from underrepresented groups. Policymakers have a crucial part to play in ensuring data fairness. They should work towards reducing digital divides by investing in infrastructure, education and access to digital technologies, thereby ensuring that all demographic groups are represented in mobility research. Moreover, community engagement is vital for fairness. Researchers, institutions and policymakers should develop and adhere to robust data ethics guidelines that prioritize fairness and inclusion. Furthermore, researchers and policymakers should collaborate with marginalized communities to understand their unique needs and perspectives, incorporating their insights into research designs and policy interventions.

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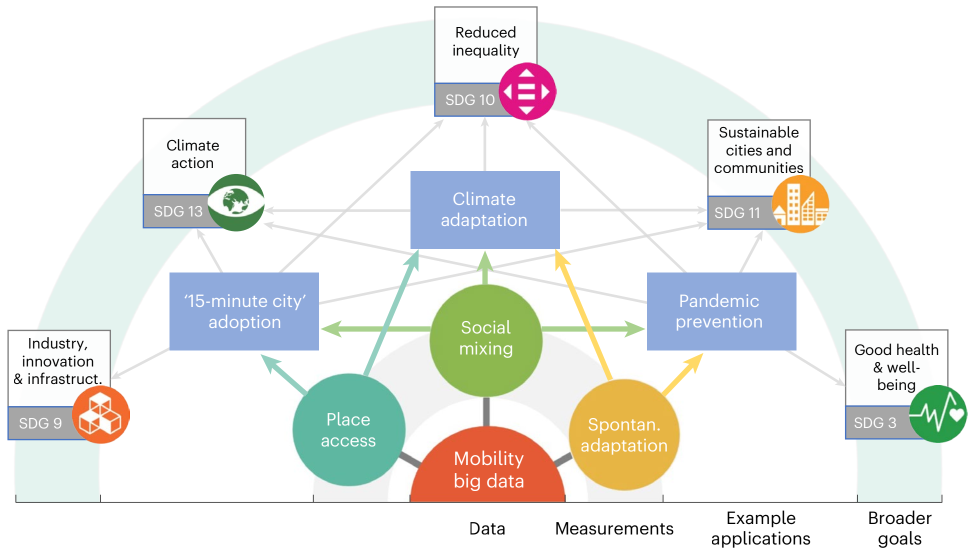

Fig. 5 | Linking mobility data to broader SDGs in cities. Measurements of experienced inequality in urban mobility provide a platform for addressing important city challenges such as pandemic prevention, climate adaptation and '15-minute city' adoption. Specifically, cyan, green and yellow arrows show how the measurements of place access, social mixing and spontaneous adaptation, respectively, contribute to the application of 15-minute city adoption, climate adaptation and pandemic prevention. For example, measurements of place access and social mixing can directly inform 15-minute city adoption. Light grey arrows show how these applications link to SDGs. These measurements provide a deeper understanding of urban mobility that channels equitable access and opportunity in urban space, facilitating researchers to quantitatively track SDGs over time.

Privacy risks in mobility behaviour data

Despite the great potential of mobility behaviour data, privacy risks are often a concern because such datasets can be easily linked with sensitive personal information. Anonymization and aggregation are two commonly used techniques to sanitize mobility behaviour data. Nevertheless, previous studies have demonstrated that anonymized mobility behaviour data can often be accurately reidentified using minimal side information[77,78]. Similar risks of reidentification have also been observed in anonymized credit-card transaction records[78]. More recent research has indicated that aggregated mobility data remain vulnerable to privacy breaches[79,80]. Adversaries can reconstruct individual trajectories from aggregate mobility data with high accuracy by exploiting the inherent uniqueness and regularity of individual mobility patterns[79].

In response to these risks, several advanced privacy preservation techniques have been proposed. A recent study introduced a data-coarsening technique designed to ensure that each individual is hidden within an anonymity group of a certain size[81]. Another promising avenue for the deidentification of personal data will probably involve federated learning, an approach that would obscure personal mobility traces within published models[82]. Synthesizing mobility behaviour data has also emerged as an encouraging new research direction[83], especially in light of recent generative AI advancements. Recent work has demonstrated how large language models can be adapted to generate plausible mobility behaviour data[84], offering the potential for privacy-preserving simulations that retain practical utility. Despite notable advances in privacy preservation techniques, achieving an ideal balance between data utility and privacy protection remains a challenge. Consequently, stringent privacy regulations and robust data management protocols are essential to ensure responsible practices in the analysis of mobility data. Policymakers, institutions and researchers must collaborate to establish enforceable mechanisms that guarantee that data access is properly authorized.

Data-driven urban simulation and policy evaluation

Accurate simulation of urban mobility is crucial for finding effective intervention policies to reduce urban inequality. Traditional urban simulations rely on intensive expert knowledge and simplified models[85]. By contrast, recently available novel mobility data sources, such as social media check-ins and mobile phone records, provide important opportunities for researchers to comprehensively model people's movement across urban environments. More importantly, by extracting and leveraging empirical patterns in observed mobility behaviour, data-driven simulation models have the potential to accurately identify vulnerable neighbourhoods under different scenarios[86]. Accurate simulation is also helpful for revealing potential mechanisms that produce the inequality in social mixing, place access and spontaneous adaptability. Moreover, data-driven urban simulations can serve as a useful tools for informing urban policymaking. For example, transportation planners can identify gaps in simulated public transit accessibility, and subsequently develop strategies to enhance service provision in disadvantaged neighbourhoods. Simulated urban mobility in disaster scenarios can inform the location choices of shelters and the design of evacuation routes, ensuring that residents receive equitable rescues when facing similar risks. By comparing the simulated outcomes of counterfactual policy scenarios, decision-makers can identify the most promising strategies to address urban inequality and promote social inclusion. The use of advanced data science techniques, including deep learning and complex system analytic frameworks[87,88], can facilitate the modelling of hidden patterns and correlations in urban systems. Recently available big mobility data provide important opportunities for accurate data-driven simulation of urban systems, which can serve as a useful toolset for understanding, modelling and mitigating inequalities in urban space.

Conclusion

This Perspective aims to highlight the critical role of mobility behaviour data in quantifying experienced inequalities across urban space. We present a general analytic framework, leveraging temporal bipartite networks, to capture the dynamics of access to urban opportunities. This framework summarizes recent advances in data-driven urban inequality measurement along three fundamental dimensions: social mixing, place access and spontaneous adaptability. These dimensions characterize the contemporary urban landscape shaped by the complex

interplay of social interactions, spatial access and the distribution of resources. We demonstrate how such measurements provide an important perspective on experienced urban inequality, complement conventional studies leveraging survey and static spatial information, and uncover the subtle experienced inequalities of urban life. Through case studies involving large-scale, high-precision mobility data, we show how insights derived from mobility data-based measurement are essential for equitable policy design. As we better harness the power of mobility data, we hope that it will enable the creation of more inclusive, resilient and flourishing cities for all inhabitants.

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Author contributions

All authors contributed content on the topic for the initial manuscript. F.X. drafted the initial manuscript and constructed figures. All authors edited the manuscript.

Competing interests

The authors declare no competing interests.

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