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Zooming into mobility to understand cities: A review of mobility-driven urban studies

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ABSTRACT

Emerging big datasets about human mobility provide new and powerful ways of studying cities and addressing various urban issues. However, human mobility has usually been defined narrowly in prior research that limits the understanding of its values for urban applications. The aim of this study is to reveal the complexity and multiplicity of human mobility concept for various urban application scenarios, and present a comprehensive review of mobility-driven urban studies through four re-conceptualized urban mobility perspectives. Using a systematic review approach, existing mobility-driven urban studies are classified based on whether they interpret urban mobility as spatial movements, a social phenomenon, an economic indicator or a policy tool. Then, the core values of knowledge about urban mobility for addressing contemporary urban challenges are analyzed, and the current trends and future directions of mobility-driven urban studies are also discussed. Moving forward, the application of urban mobility knowledge can be further advanced by the evolution of mobility concepts, the improvement of mobility data quality and the innovation of mobility analytical methods. This review can contribute to the understanding the state of the art of mobility-driven urban studies, and provide inspiration and guidelines for studies of this area in the future.

1. Introduction

Big geodata concerning human mobility provides a powerful tool to support the discovery of complex knowledge and enable innovative applications in cities (Batty et al., 2012). Motivated by the recent explosive growth of geolocation datasets related to human digital traces, human mobility has attracted considerable attention from different fields of studies and has advanced various urban applications ranging from traffic engineering to infrastructure management, urban planning and epidemic control. The latest advancements in mobility analytical methods and mobility applications have been well documented in a few review papers (Pirozmand et al., 2014; Wang et al., 2019; Zhao et al., 2016). However, in spite of the upsurge of concern with mobility in urban residents' lives, these reviews understand and define the notion of mobility quite narrowly. Human mobility is traditionally defined as the human movement behaviors reflecting certain spatiotemporal characteristics. For example, Barbosa et al. (2018) defined human mobility as "the movement of human beings (individuals as well as groups) in space and time", and reviewed studies related to this kind of spatiotemporal behaviors from perspectives of metrics, models and applications. Their argument of the significance of mobility is clearly confined to the geographical characteristic of human behaviors. A similar perspective has been adopted by most other reviews.

The above conceptualization of mobility only as human movement behaviors limits the deep understanding of urban mobility and potential value of mobility-driven applications in cities. In fact, human movements are crucial to the functionality of cities and the wellbeing of their inhabitants. This has encouraged the emergence of various traditions and trends from the field of mobility research to reveal how mobilities are inscribed into different spheres of modern life. This has gradually led to the introduction of new paradigms of mobility (Kaufmann, 2014; Sheller, 2017; Sheller & Urry, 2006), which has in turn fostered enriched interpretation of urban mobility. For instance, in recent studies, the concept of urban mobility is sometimes introduced as "a complex system of social, economic and spatial interactions" (Jensen, 2013; Pucci & Colleoni, 2016; Sheller, 2017), or as critical contents in policy-making and planning of mobility practice (Cresswell, 2013; Pucci & Colleoni, 2016). Based both on such developing connotation of the human mobility concept, which is further discussed later on in the paper, and equally importantly on our comprehension of the role that mobility can

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play in addressing contemporary urban challenges, human mobility can be reconceptualized in multiple perspectives in urban contexts:

— as spatial movements: Mobility traditionally refers to geographic movement, i.e. the movement of individuals from an origin to a destination, along a specific trajectory within urban physical settings and natural environment, that can be described in terms of space and time (Pucci & Colleoni, 2016);
— as a social phenomenon: Mobility can be considered as individuals' social capital that may depend on the availability, quality and accessibility of mobility related resources, reflecting the capacity of each individual to appropriate them and then realize mobility. As such, mobility reflects and creates differences in a society (Kaufmann, 2014);
— as a policy tool: Observed individuals' trajectories are the results of individuals'"real use of the city"(Ahas et al., 2010). The mobility knowledge emerges based on observations of individuals' daily trajectories and then can be used and reproduced by the local authorities to support appropriate policy and regulatory actions, leading to advancement in mobility-related policy design and governance (Pucci & Colleoni, 2016).
— as an indicator for economic activities: People access various goods and services around the city through their movements. Human mobility gives rise to extensive economic activities in urban areas by integrating spaces and human activities (Colmenero Fonseca & Cruz Ramírez, 2020; Yang, Kaewunruen, et al., 2018), and thus could serve as an indicator for economic activities in the city (Chang et al., 2015).

Collectively, these four perspectives can be considered as a frame for understanding the nature of human mobility and its role in substantially shaping various aspects of the cities. A remark on the underpinning conditions to the frame is that by no means should it be thought to be an all-embracing analysis of mobility, as the connotation of human mobility evolves over time. Yet, the frame is valuable for understanding the interactions between humans and cities and related applications in urban processes through the complex nature of human mobility.

The main objectives of this study are to provide a comprehensive and synthetic assessment of how big datasets about human mobility inspire and enable solutions to urban issues, and to provoke new ideas for future studies in this area. This review focuses on the intersection of human mobility analytics and the relevant urban issues. To set the scope of the review, on the one hand, the human mobility analytics should be based on emerging big geodata, such as GPS (global positioning system) log data from mobile devices, CDRs (call detail records), smart card data, floating car data, VGI (volunteered geographic information), geotagged social media data, and so on. Traditional data sources such as travel surveys are not considered; On the other hand, urban issues covered in this review are limited to problems and challenges facing contemporary cities whose solutions, based on evidence from the literature, can benefit from human mobility knowledge. A list of the issues will be developed based on literature research results, as explained later in Section 2. The review will be conducted through the above broadened perspectives of human mobility. The specific questions this literature review aims to answer include: What are the main urban issues being investigated by mobility-related big data under each of the four perspectives of mobility? How are these issues addressed with mobility-related big data? What drives the increasing use of big datasets about urban mobility to inform solutions to the above urban issues? What are the future directions in this area?

This paper is organized as follows: Section 1 describes the background, motivation and expected contribution of this review; Section 2 explains the literature search method and screening criteria; Section 3 presents a detailed review of existing mobility-driven urban studies organized based on the four perspectives of human mobility; Section 4 discusses the findings, and Section 5 concludes the paper.

2. Methodology

2.1. Systematic literature review

The systematic literature review (SLR) is selected as the research method for this study because of the nature of the research questions, which aim at understanding trends and detecting existing gaps in the scientific literature (Lagorio et al., 2016). This study followed the guidelines provided in prominent articles (Keele, 2007; Lagorio et al., 2016; Touboulic & Walker, 2015) to develop a three-step protocol.

2.1.1. Step 1: inclusion/exclusion criteria

Related literatures exploring regional & urban issues through big datasets about human mobility should be included in this review. In order to do this, search algorithms were incorporated based on the definition of three analytical components (see Fig. 1), making our research as comprehensive as possible.

The Web of Science Core Collection database was used to search for related academic publications. To yield a comprehensive set of search results that could reflect the current trends in this area and their changes over time, the search did not set any restriction on the year of publication. With respect to the document type, the search items were limited to journal articles and reviews written in English. As a result, 1216 papers were extracted.

2.1.2. Step 2: selection based on title and abstract

First of all, we reviewed the titles and abstracts of all papers in the initial search results. Following a discussion, papers out of the review scope were removed from the corpus. Specifically, 226 papers that focused on irrelevant topics, such as animals, genes, vehicle design, communication protocols, and so on, were excluded.

Then, we used the following criteria to select articles for this systematic review: (1) articles should focus on applications of human mobility in urban contexts, rather than mobility behavior analytics, such as mobility pattern analysis, modeling and prediction (for comprehensive reviews of mobility patterns, models and prediction, see Barbosa et al., 2018) (422 papers were excluded); (2) considering the spatial scale of urban practice this review aims to cover, articles should focus on intra-city level applications, which means that we only focus on studies based on the movement of households and individuals within the geographic area of a municipality, rather than across cities or countries (69 papers were excluded).

2.1.3. Step 3: evaluating the eligibility based on full text and snowballing

The last step of the protocol involved the refining of the list of selected papers. The authors conducted readings and applied the following criteria for inclusion: (1) articles should be relevant to emerging big datasets covering large-scale human digital traces, rather than datasets with limited coverage or traditional mobility data such as survey and interview data (16 papers were excluded); (2) articles should be direct to provide solutions to urban issues, rather than focus on mobility data analytics, such as methods for preprocessing data uncertainty and sparsity, or evaluating data representativeness (122 papers were excluded). We then checked the references of all remaining papers in the search results, i.e. backwards snowballing, and identified a number of additional relevant and well-cited papers (50 papers were included).

The above protocol led to a final corpus of 411 papers. The results in terms of the number of papers resulting from each step of the selection protocol in the SLR are summarized in Fig. 2.

2.2. Keywords clustering analysis

The keywords in academic publications are the refinement and induction of the main contents, hence the co-occurrence analysis of keywords is often used in literature review to reveal the distribution of

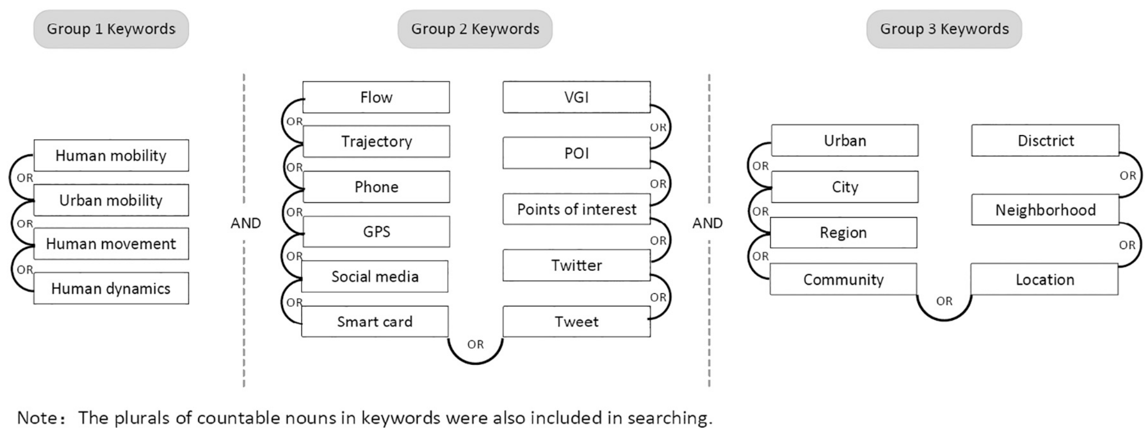

Fig. 1. The three groups of searching keywords.

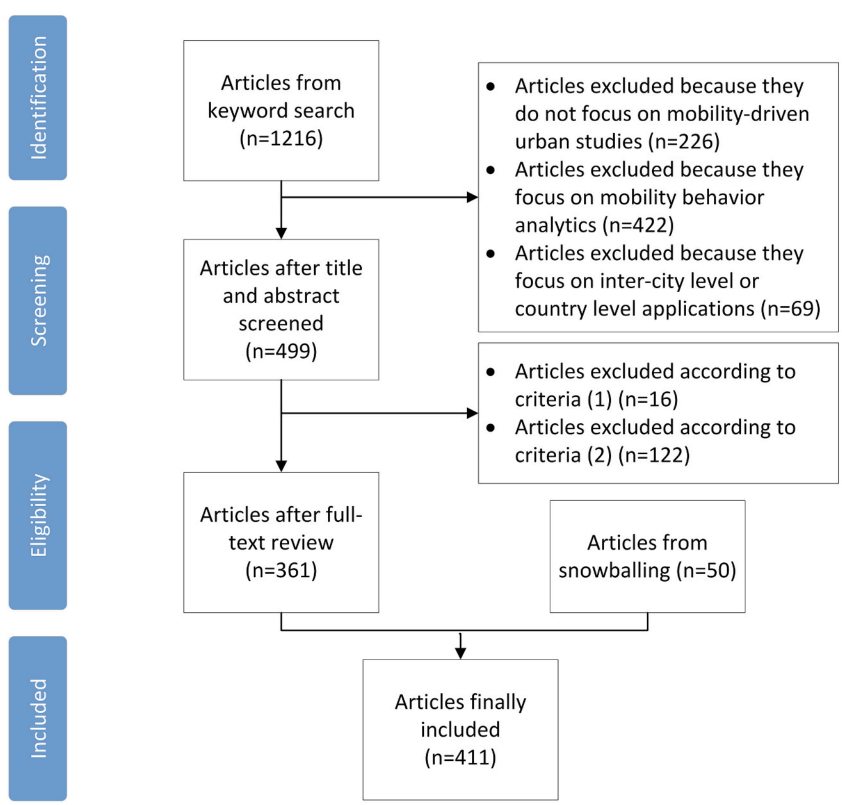

Fig. 2. The systematic workflow and results.

research clusters (Liao et al., 2019). In the case of a large amount of literature data, the keyword co-occurrence atlas drawn by VOSviewer has the advantages of clear clustering and good readability (Li et al., 2022). Therefore, VOSviewer is used for keyword co-occurrence analysis in this review to present the distribution of clusters of mobility-driven urban studies. There were 1579 keywords in the 411 articles. In VOSviewer, the minimum threshold of word frequency statistics was set as 2. Of all the co-occurred keywords, 428 passed the frequency threshold. The label view of co-occurrence of keywords is shown in Fig. 3.

In Fig. 3, each node represents a keyword, while the size of the node represents the level of word frequency. The larger the node, the higher the word frequency. The connection between the nodes reflects the co-occurrence relationship between keywords, according to which different research clusters can be formed. The results indicated that there were eleven emerging clusters in our literature data, each represented by a different color in Fig. 3. For each cluster, we reviewed the corresponding articles, and identified the main research themes for the cluster. The eleven clusters, together with their research themes and the numbers of included articles, are summarized in Fig. 4. In addition, there were a small number of articles classified as outliers by VOSviewer. Based on our review, these articles mainly discussed issues about business site selection, real estate appraisal, advertising strategy making, and friend or location recommendation. Considering that these issues were all closely related to improving retailing and entertainment services, which were of notable importance for the prosperity of cities and citizens' well-being, we grouped these articles in a twelfth cluster focusing on the research themes of business services improvement.

Lastly, the research themes are matched to the aforementioned four perspectives of mobility, based on how human mobility knowledge is interpreted and employed to solve the relevant urban issues. To be

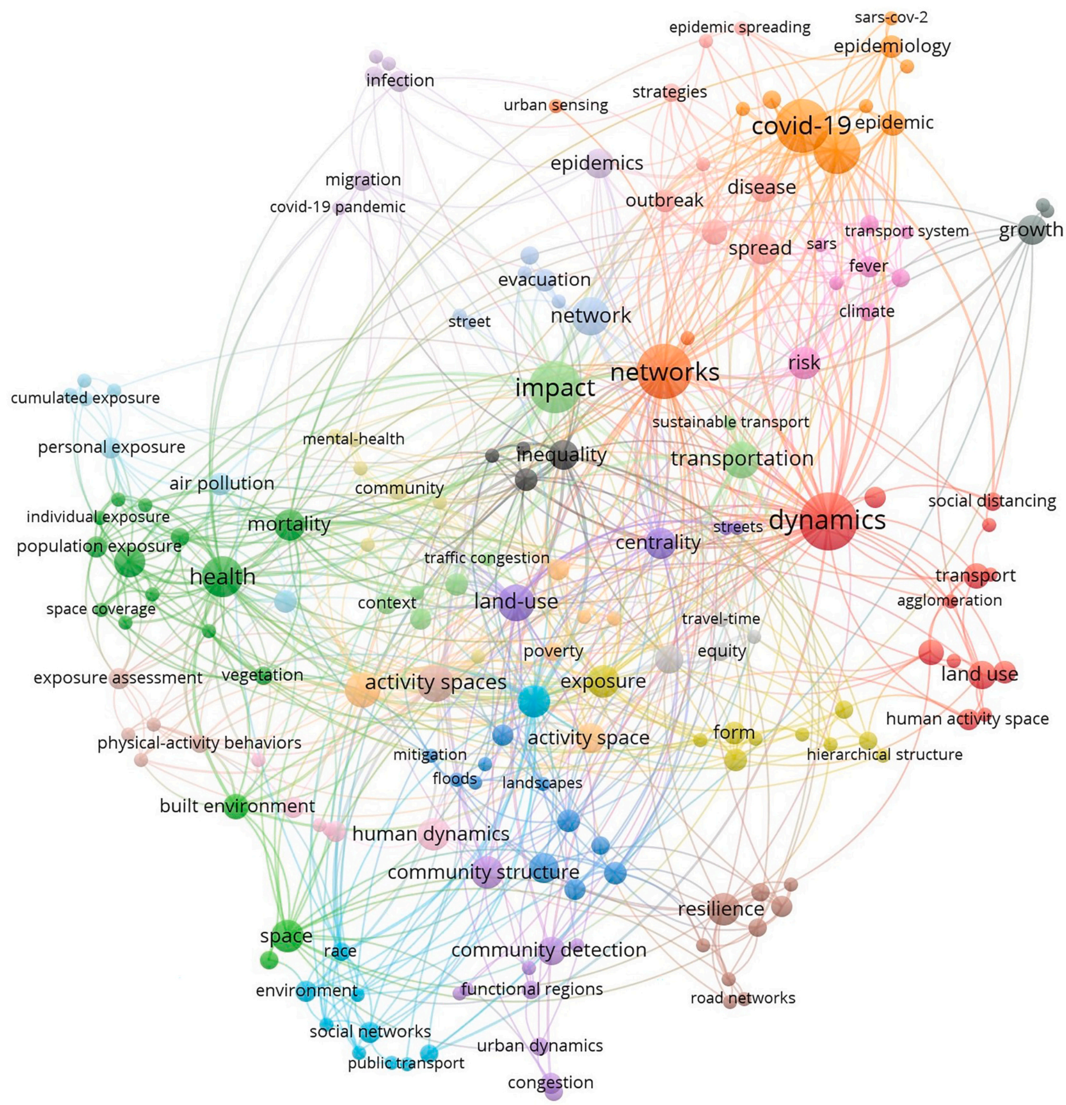

Fig. 3. Keyword co-occurrence tag view of mobility-driven urban studies.

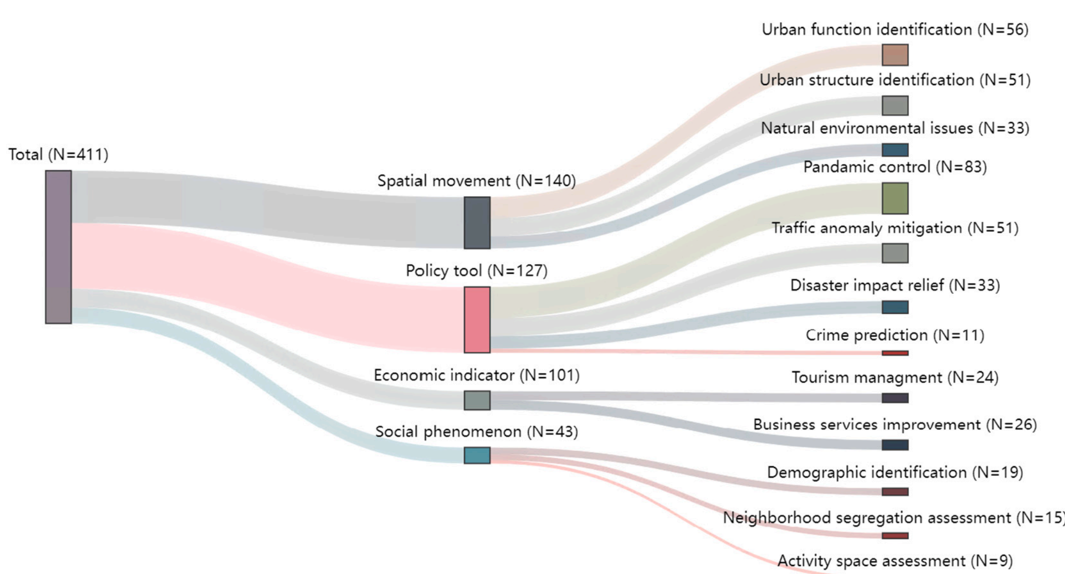

Fig. 4. The four perspectives and associated research themes.

specific, research themes "urban structure identification", "urban functions identification" and "natural environmental issues" require the understanding of how human mobility interacts with and is shaped by physical and natural environments. These research themes are associated with the "spatial movement" perspective, as human mobility is regarded as the movement of individuals within physical settings and natural environments. Research themes "demographics estimation", "activity space assessment" and "neighborhood segregation assessment", which focus on describing individuals' mobility capability and linking it into individuals' characteristics, are associated with the "social phenomenon" perspective. Most papers under these research themes adopt mobility as a proxy to analyze the availability, quality and accessibility of urban resources with the aim to address social issues such as social equity. Research themes "tourism management" and "business services improvement" mainly concern mobility-related economic activities, therefore, they are associated with the perspective of "economic indicator". As for "traffic anomaly mitigation", "crime prediction", "disaster impacts relief" and "pandemic control", papers under these research themes use mobility to reflect citizens' experience within the city and their use of urban resources, with the aim to support appropriate policy and regulatory actions, and thus are associated with the "policy tool" perspective.

3. Mobility-driven research on urban issues

3.1. Mobility as spatial movements

From a tangible and material perspective, mobility refers to movement in space within physical settings and natural environment. Places seem to "draw" people and activities in by offering effective facilities for their activities (Lawson, 2001). People not only observe the environment whilst moving through it, rather their mobility is shaped by the environment and reshapes the environment (Jensen, 2013). From this perspective, mobility is the outcome of the physical interactions between individuals and their surrounding environments. As such, mobility data can be used to investigate the relationship between individuals' mobility and urban environment.

Based on this interpretation of the concept of mobility, this section reviews existing mobility studies applied to address urban physical and natural environment related challenges in three themes. Studies relate to urban structure, which refers to the spatial distributions of physical environments and social-economic resources in a city, are firstly reviewed. The analyses of urban mobility patterns have greatly contributed to the understanding of urban structure and its dynamic features in recent two decades. Relevant findings provide new insights about the spatial interaction patterns of urban space, and new means for detecting urban structure and its evolution. The next subsection reviews the contribution of big geodata to classifying urban regions and physical settings. In recent years, related mobility studies in this theme have played an important role in urban planning and design. Finally, mobility studies focusing on urban natural environment treatment are reviewed. In this subsection, how urban mobility analyses are applied to solve issues related to ambient air pollution, climate change and resource depletion are discussed.

3.1.1. Identifying urban structure

City structure is closely related to the allocation of resources within a city, which generates travel demands and facilitates mobility (Liu et al., 2015; Zhang, Liu, Tang, et al., 2019). With the increasing recognition of relationship between urban structure and human mobility patterns, empirical analysis of the influence of urban structure on human mobility patterns has been taken as the first step to understand the interplay between urban structure and urban mobility. Relevant findings showed that human mobility patterns, such as the tendency of long-distance travel (Kang et al., 2012), regularity in commuting behaviors (Huang & Wong, 2016) and distance decay patterns (Forghani & Karimipour, 2018), are significantly affected by urban structure.

Inversely, human mobility patterns have been extensively studied to reveal the latent urban structure from a functional perspective. The functional structure of a city can be defined as collections of internal spatial interactions, such as how the city centers interact with their vicinities, rather than as static artifacts (Sun et al., 2016). It used to be difficult to identify urban functional structure, especially across space and time, due to limited data sources (Zheng et al., 2018) and the complexity and dynamics of urban structure that result from continuous urbanization process (Yu et al., 2019). Analyzing human mobility data within urban contexts provides a detailed view of the human flow, which could help reveal typical spatial interaction patterns in the urban space.

Specifically, massive travel flows extracted from various human mobility data sources enable researchers to model an entire city in a spatially embedded flow network to reveal urban functional structure (Batty, 2013). Community detection methods are widely used to explore the complex organization of spatial interactions by analyzing mobility-based flow network. Existing studies have used community detection algorithms to reveal community structures (Huang, Yang, et al., 2018; Tang et al., 2016; Wang et al., 2020), compare detected community structures with official boundary alignments (Amini et al., 2014), and investigate how large infrastructure projects such as metro line extension would influence urban community structures (Sun et al., 2014). Another attractive research topic in this theme is detecting essential elements in urban spatial structure. Prior research has explored the possibility of urban centers and hub detection (Liu, Yan, et al., 2021; Zhong et al., 2014), urban hotspots detection (Yang et al., 2016) and urban boundaries identification (Long et al., 2015) by mining urban mobility data. Findings of the above studies about urban structures reflect the distribution and division of collective activities of citizens. These findings can be further used to help find better solutions to boost commercial activities, enhance public security, and foster social interactions.

In addition, to further understand the liquidity of urban spatial structure, recent studies have begun to explore the short-term dynamics and long-term evolution of urban structures based on mobility data. Since daily urban mobility is highly dynamic showing different characteristics at different times of the day (e.g., peak hours vs. off-peak hours), there is significant and continuous variation in urban structure shaped by mobility flows across both space and time. A few studies attempted to detect the daily dynamic patterns of urban structure using community detection methods (Yu et al., 2019), network metrics (Tang et al., 2016) and eigenvectors (Gong et al., 2017). The extracted patterns were further applied to model and predict the dynamics of urban structure (Gong et al., 2017). For capturing the long-term evolution of urban structure, prior research has relied on detecting the changes in key properties of the mobility networks, such as community structures, city hubs and city centers (Sun et al., 2014; Zhong et al., 2014). The influence mechanism was also explored in these studies by investigating how mobility networks were affected by various factors, such as expansion of infrastructure, population density, and so on. These findings provide important empirical evidence about how the spatial interactions gradually shape the structural evolution of a city.

3.1.2. Classifying functional areas, buildings and infrastructures

Mobility is the outcome of the interaction between individuals and the surrounding environments. Areas, buildings and infrastructures with differentiated characteristics in a city are major reasons for the spatio-temporal diversity of mobility patterns in urban areas (Sevtsuk & Ratti, 2010; Yang et al., 2019). Thus, urban mobility turns out to be an effective basis for classifying them. By identifying different types of functional areas, buildings and infrastructures in a city, and understanding their correlations with population density (Li, Li, et al., 2019), mobility patterns (Kim et al., 2018) as well as traffic demand (Li, Cai, et al., 2019; Liu, Sun, et al., 2020), urban planners and policymakers can make more informed decisions concerning urban planning to improve urban habitat and the efficiency of the urban system. To be more specific, the applications in this theme are twofold.

Firstly, human mobility patterns could serve as an indicator of the function of urban areas, namely land use. Early land use classification methods were mostly based on physical properties of certain areas extracted from remote sensing data (Hu & Wang, 2013), point of interests (POI) data (Hu et al., 2016), and so on. However, land use is difficult to infer purely from physical characteristics of the region, especially in mixed urban environments. The emergence of big geodata makes it possible to combine social functions of lands, which are reflected by the temporal and spatial dynamics of human mobility, with their physical characteristics in land use classification (Pan et al., 2013; Zhou et al., 2019). The same methods have also been adopted and used for analyzing the spatial organizations of lands (Lenormand, Picornell, et al., 2015) and extracting traffic patterns in different functional areas (Liu et al., 2012; Zheng & Zhou, 2017).

Apart from identifying land use, urban mobility analysis also contributes to classifying buildings and infrastructure in the city, which is essential for evaluating and improving the effectiveness of planning schemes. For example, since urban mobility patterns can reveal the relationship between human dynamics and urban complexes, urban mobility analysis has been adopted to identify buildings of different functions (Niu et al., 2017) or different level of attractiveness (Lenormand et al., 2020) and accessibility (García-Albertos et al., 2019). Another example is that human mobility could be adopted to classify transportation facilities, given that people's mobility in transportation network can reflect the relationships between those facilities. For instance, several recent studies identified the spatiotemporal functions (Fan et al., 2021; Wang et al., 2017) and the importance (Xia et al., 2020) of subway stations by analyzing human mobility patterns of subway passengers. The findings of these studies enable a deeper understanding of the subway system, and could be applied in improving its operational efficiency, evaluating the robustness of subway networks and making evacuation plans.

3.1.3. Addressing urban natural environmental issues

Addressing urban natural environmental issues, such as ambient air pollution, climate change and resource depletion, is of great importance to public health, urban planning (Ng, 2012) and city management (Dunne & Ghosh, 2013). According to the present literature, in this theme, urban mobility analyses have been mainly adopted to assess people's exposure to air pollution as well as their vulnerability to adverse weather events.

Firstly, urban mobility analyses have been adopted to assess people's exposure to air pollution (Dewulf et al., 2016; Yu et al., 2020) and extreme heat (Schlink et al., 2014). Traditional methods could only roughly estimate region-average pollution exposure at the census tract level (Gray et al., 2013) or zip code level (Cao et al., 2011), or estimate individual exposure based on home address (Huang & Batterman, 2000), which usually leads to biased exposure assessment (Setton et al., 2011). By tracking individuals' actual locations based on mobility data, exposure assessment could be conducted at the individual level and with higher accuracy, especially for exposures to traffic-related pollutants (Yu et al., 2020). Moreover, incorporating individual mobility patterns into air pollution exposure assessment could help policymakers to analyze the impact of any given policy or event on public health (Dewulf et al., 2016). Similar methods have also been adopted in studies of estimating traffic emissions (such as CO_2 emissions and NO_X emissions) (Veratti et al., 2020; Zhao et al., 2017) and urban greenspace exposure (Song et al., 2018).

In addition, a few studies were conducted to investigate the effect of weather on urban human mobility. It has been discovered that weather has a substantial impact on human activities (Tucker & Gilliland, 2007), which motivated studies that aimed to analyze the correlation between human mobility patterns and different weather conditions, such as rain, wind, humidity and heat (Brum-Bastos et al., 2018; de Montigny et al., 2012). Findings in these studies have significantly contributed to the prediction accuracy of human mobility and traffic volumes under various intense weather conditions (Borowska-Stefańska et al., 2021; Dunne & Ghosh, 2013), which has been proved valuable for improving the capability of cities to respond to adverse weather events. Moreover, prior studies have revealed the impact of weather on people's behaviors, which highlights the necessity of considering the effect of natural environment in urban planning (Ng, 2012) and city management (De Freitas, 2015).

3.2. Mobility as a social phenomenon

For studies included in this section, mobility is considered as a social phenomenon, where the analysis of mobility teaches us about the composition of and changes in a society (Pucci & Colleoni, 2016). Mobility can be understood under the notion of motility proposed by Kaufmann et al. (2004), which is the consequence of all those factors that determine an individual's "potential to move or be mobile (i.e. physical ability, income, aspirations (to move or be sedentary), technical systems (transportation and telecommunication) and their accessibility, and skills acquired through training (driver's license, international English for travel, etc.)". From this perspective, mobility is the way an individual appropriates and makes use of the field of possibilities, and thus can be considered as social capital (Kaufmann et al., 2004). This implies seeing mobility as a tool that can be used to "read" a society.

Pertaining to the social aspects of cities, the use of mobility data in the current literature has mainly focused on (1) inferring citizens' demographics, based on the relationship of individuals' mobility and their demographic characteristics; (2) measuring the activity space of individuals and the neighborhood isolation; and (3) quantifying neighborhood segregation. Existing studies in the above three themes of applications are reviewed and discussed as follows.

3.2.1. Inferring population demographics

Characterizing how human mobility patterns are affected demographic characteristic is essential for understanding human mobility behaviors. Information of population demographics plays a critical role in public health, urban planning, transportation engineering and related fields. By coupling large scale mobility datasets and urban demographic datasets, prior studies have discovered that the patterns of individuals' mobility, characterized by radius of gyration, number of activity locations and recurrent mobility patterns, are affected by individuals' demographic features such as age, gender, income, race/ethnicity group, and so on (Luo et al., 2016; Xu et al., 2018). For instance, it is found that phone user groups that are relatively richer tend to travel shorter in Singapore but longer in Boston, and women tend to travel with a larger value of radius of gyration than men in Beijing (Xie et al., 2016; Xu et al., 2018).

While demographics is essential information to various public and commercial services, such as urban planning, personalized recommendation and commercial site selection, this information is traditionally difficult to acquire timely and on a large scale. Inferring demographics from human trajectories provides an alternative route. A number of studies explored rules or patterns from recorded mobility data, and then used extracted rules or patterns as assumptions for further estimation of people's demographic characteristics. For example, based on the basic idea that people within a given social class tend to have similar lifestyles by virtue of their income levels and common tastes, Filho et al. (2014) defined the wealth of a neighborhood according to the income of residents and then used a twitter dataset to predict users' socioeconomic class by the wealth of neighborhoods they frequently visited. They reported predictive accuracies up to 73 %. By observing the commuting patterns of residents and workers, Kontokosta and Johnson (2017) identified the variation between weekend and weekday Wi-Fi access activities, and used it to estimate real-time population classified by residents, workers, and visitors/tourists in a given neighborhood. The predicted population counts were within ±15 % of corresponding census data. Moreover, using mobility data as input, non-parametric models can be constructed to infer individuals' demographics. Specifically, spatiotemporal features extracted from mobility data can be used to reflect individuals' activities such as the number of visits, radius of gyration, travel length, and so on. Then these features can be input to supervised learning models to infer demographics such as gender, education, age, and so on (Arai & Shibasaki, 2013; Zhong et al., 2013). The prediction accuracies of such non-parametric models varied from 53 % to 85 % in different studies.

3.2.2. *Assessing activity space*

An activity space is generally defined as a geographic extent delineated by a number of locations. Individuals have direct contacts due to social activities in those locations, and travel between and around those locations during a certain time period – daily, monthly or yearly (Järv et al., 2020). Activity spaces are fundamental to the assessment of individuals' dynamic exposure to social and environmental resources, opportunities, risks and so on. Human mobility data has opened up new opportunities for the assessment of activity space and serves as a valuable data source for uncovering individuals' activity anchor points such as home and work locations (Xu et al., 2015), and their use of space around these locations (Chen & Dobra, 2020). Various mobility-based measures have been developed to estimate individuals' activity space. Examples of these measures include the average distance between home location and activity locations (Hu, Li, et al., 2020), the area covered between home and activity locations (Chen & Dobra, 2020), home-centered standard distance (Xu et al., 2015), mobility-based scale and shape metrics (Yuan & Raubal, 2016), and so on. These mobility-based measures provide an intuitive way of describing the general characteristics of human activity spaces and shed light on how individuals move around in a geographical context. Beyond delineating and measuring activity spaces, mobility data that tracks individuals' activity spaces provides new opportunities to consider how activity space varies across social groups when in company with demographic information (Hu, Li, et al., 2020; Järv et al., 2020). Findings in these studies suggest that differences in individual activity space are related to neighborhood-level social-spatial characteristics, such as density of road network, population density and employment density (Chen & Dobra, 2020), and individuals' ethnicity or self-estimated affiliation to social status (Järv et al., 2020).

3.2.3. *Quantifying neighborhood segregation*

Neighborhood segregation in urban areas has grown rapidly in the past few decades in the world, especially in the U.S. and some European countries (Xu, Belyi, Santi, Ratti, 2019b). This phenomenon has been traditionally analyzed using surveys or census data. These traditional methods ignore that individuals are mobile, and are limited to individuals' neighborhood of residence (Park & Kwan, 2017) without a timely and dynamic view (Morales et al., 2019). To address these limitations, a large number of studies leverage individual-oriented mobility analysis to improve the understanding of segregation beyond residential spaces with timely and dynamic views. For instance, some recent studies made use of human mobility data to identify the neighborhoods that individuals live in and those that they travel to (Wang, Phillips, et al., 2018) and measure the distance and frequencies of their trips (Prestby et al., 2020; Sampson & Levy, 2020; Xu, Belyi, Santi, Ratti, 2019b). These measurements are used to reveal more reliable and realistic segregation experience of the individuals.

Moreover, social cohesion depends on bridging network relations across social groups, which requires the existence of opportunities for communication (Amini et al., 2014). Apart from observations of individuals' mobility in physical space, a social-network structure can be constructed from day-to-day communications to reflect interactions among different social groups and quantify segregation in the social space at the population scale (Sun et al., 2013). Therefore, using mobile phone-based big geodata, mobility-based metrics and communication-based metrics, such as encounter probability and contact strength, could be calculated to delineate people's interaction and segregation in both physical and social space (Xu, Belyi, Santi, Ratti, 2019b). The level of segregation can also be quantified by network-based measures. The structure of a city could be characterized by mobility networks, and then the strength of detected communities in mobility networks could be evaluated for quantifying segregation in the city (Gallotti et al., 2021; Prestby et al., 2020). Coupled with census data, mobility datasets were also explored to investigate the different levels of segregation among diverse racial groups and income classes, which found that inequalities vary across social groups (Prestby et al., 2020; Wang, Phillips, et al., 2018). Findings in these studies enable a deeper understanding of the dynamics of human segregation in the social and physical spaces, which can assist social scientists, urban planners and city authorities in achieving more integrated cities.

3.3. *Mobility as an indicator for economic activities*

Cities are known to possess concentrating population, economic activities and services (Lenormand, Gonçalves, et al., 2015). Understanding the spatial distribution and the dynamics of human economic activities helps with business site selection, advertising as well as marketing. Drawing upon existing theories, the mobility of people, which occupies a central role in integrating spaces and events (Colmenero Fonseca & Cruz Ramírez, 2020), provokes extensive economic activities in urban area (Yang, Kaewunruen, et al., 2018). To be more specific, people access various goods and services around the city through their movements or, to put it in another way, human mobility produces economic consequence in the city (Massobrio & Nesmachnow, 2020). From this perspective, human mobility could be regarded as a fundamental enabler and a good indicator of economic activities in the city (Chang et al., 2015). In recent years, mobility data has been increasingly used to extract semantic information of human mobility, based on which various economic activities taking place in the city are revealed and analyzed.

Existing mobility studies have been applied to analyze people's access and preference to services (or goods) as well as uncover the spatial distribution of human economic activities in the city, which shows considerable practical value in commercial applications. In this section, these studies are divided into two themes, namely tourism-related studies and retailing-and-entertainment-related studies. For studies in the first theme, the analyses of tourists' mobility patterns have provided a new way to predict tourists' flows, understand their travel preferences and evaluate the attractiveness of scenic spots. Studies in the second theme primarily focus on another two typical business forms in cities, namely retailing and entertainment, and discuss the applications of mobility research in business site selection, advertising, friend/location recommendation, and so on.

3.3.1. *Enhancing tourism management*

With big data technology gaining its momentum in recent years, the use of spatiotemporal big data that tracks tourists' mobility, such as geo-tagged photos and texts in social media, GPS traces and Bluetooth data, has played an increasingly important role in enhancing tourism management (Li et al., 2018). Various applications that have been explored in prior research can be generally divided around three topics, including managing visitor flow, enhancing tourism market segmentation, and providing guidance for long-term tourism development, as reviewed in detail below.

Tourism related travel has strong seasonal characteristics (Ahas et al., 2007). Various data mining methods, such as statistical analysis and frequent pattern mining, have been adopted by a number of studies to analyze the generalized patterns of tourist mobility (Li et al., 2018; Shoval & Ahas, 2016; Xu et al., 2021). The findings enrich the understanding of tourists' travel patterns, and have an extensive application prosperity for visitor flow management. For example, Edwards and Griffin (2013) analyzed the mobility patterns of tourists in Sydney and Melbourne and revealed the space of high use, co-presence as well as co-absence, which uncovered problems in local destination management and travel service. Similarly, Modsching et al. (2006) explored the spatial distribution of tourists and their behaviors based on real-time tracking data, shedding light on optimizing resource allocation and improving travel services in cities. In a more microscopic perspective, existing studies also investigated the mobility patterns of tourists intra certain urban scenic spots, such as museums (Yoshimura et al., 2014), theme parks (Birenboim et al., 2013) and zoos, and provided valuable guidance on the strategies of directing tourists and managing visitor flows.

Tourist profiling is another important issue in smart tourism. With the help of clustering and classification algorithms, prior studies were able to identify tourists with different visit preferences based their mobility patterns (Asakura & Iryo, 2007). These approaches have been widely applied to extract preferable scenic spots (Maeda et al., 2018), typical travel patterns (Rodríguez et al., 2018), and possible routing strategies (Asakura & Iryo, 2007) of different groups of tourists, which remarkably contributes to tourist profiling. By classifying tourists with different characteristics into distinct groups, travel agencies could provide targeted information, recommendation and services to meet tourists' individualized needs, hence realizing tourism market segmentation and personalized service customization, which are essential for the boosting of local tourism.

The analyses of tourists' mobility patterns could also help city councils to plan for long-term tourism development. On the one hand, identifying the mobility patterns of tourists can help local travel authorities understand the status quo of local tourism and identify problems at issue. For instance, by mining the massive trajectories collected from visitors, hot spots and the most popular travel sequences could be extracted from visitors' travel histories (Wei et al., 2012; Zheng et al., 2009). These locations and travel sequences represent the most interesting scenic spots and popular travel routes in the region, based on which the local travel authorities could infer tourists' preferences and better design local tourist lines. Moreover, mobility-related analyses also contribute to the evaluation of the attractiveness of touristic sites (Maeda et al., 2018). By identifying and understanding the spatial distribution and attractiveness of scenic spots in the city, local travel authorities can assess the connectivity of the city's scenic spots and enhance tourism development either by improving the current spatial arrangement of scenic spots or by establishing necessary transportation infrastructure for local tourism.

Lastly, the analyses of tourists' trajectories could also help with investigating the factors that affect tourists' behaviors. Existing studies have analyzed the spatiotemporal distribution of tourists' visits and time budget expenditures based on geo-located data and identified its links with factors such as the distributions of attractions (Hallo et al., 2012) and hotels (Shoval et al., 2011). With a deep understanding of such correlation, local travel authorities could manage the overburden of visitors at some popular sites and attract more tourists by improving the spatial arrangement of the attractions.

3.3.2. Improving retailing and entertainment services

Retailing and entertainment are also typical business forms in cities that have significantly benefited from analyses of human mobility. The rapid development in ubiquitous computing and communication technologies has enabled various types of businesses to collect human mobility data and mine the mobility patterns to inform their business strategies and improve the quality of their services. This subsection reviews three major applications of human mobility analysis in this area, including business site selection, advertising, and friend or location recommendation.

The prosperity of an urban area, characterized by region popularity, region demands and peer competitiveness, could provide useful decision basis for business site selections (Lu et al., 2020). Given that people's mobility pattern is an effective indicator of the above variables, existing studies have involved mobility pattern analysis in the process of business site selection and real estate appraisal (Fu et al., 2014; Lu et al., 2020). Mobility pattern analysis also plays an important role in advertising. The exploration of users' mobility patterns can help companies build user profiles and identify their target users more accurately, which improves the effectiveness of advertising (Goulet Langlois et al., 2016). Big geodata also helps retailers and service providers to find best places to put on advertisement, which facilitates targeted marketing and personalized advertising. For instance, using trajectory clustering methods, advertisers could better decide where to set their billboards to maximize the influence (Zhang et al., 2018; Zhang, Li, Bao, et al., 2019). Recent studies also explored the prediction of the location and time of people's next activity (Ozer et al., 2016; Yuan et al., 2014), based on which retailers and service providers could generate appropriate advertisement messages to their target consumers according to their predicted movements.

Last but not the least, measuring mobility similarity between individuals has drawn considerable attention in recent years (Yang, Cheng, et al., 2018). This has inspired increasing application of mobility analysis in recommendation algorithms. Specifically, since people with similar mobility pattern tend to exhibit similar interests, daily activities and preferred destinations (Li et al., 2008; Yang et al., 2015), methods of calculating mobility similarity has been widely adopted by social media platform to promote friend recommendation (Hu, Tang, et al., 2020). Furthermore, since geographical proximity and social ties would influence human mobility, people's historic travel experience as well as the travel preference of their friends have been widely considered in existing location recommendation methods (Huang, Ma, et al., 2020; Yuan et al., 2014). By involving people's historical mobility patterns in recommendation algorithms, existing studies have largely improved the performance of personalized geographical recommendation, which then enhances the service of related businesses. For instance, for social media platforms, recommending more proper friends for users would advance their user experience and increase their usage time. As for navigation or business directory applications, a more accurate prediction of suitable routes and preferred locations for their users would enhance the effectiveness of advertising, improve the quality of service and eventually bring more business opportunities.

3.4. Mobility as a policy tool

Mobility, as the result of individual behaviors and habits, is a useful source of information on citizens' "real use of cities", or their "urban practices" (Pucci et al., 2015). Knowing the intensity and the rhythms of urban practice (urban dynamics) becomes a necessary condition to ensure efficiency, livability and equity in making urban policies (Järv et al., 2014; Ratti et al., 2006). Mobility can be considered as a policy tool on the basis of the observation of citizens' daily practices, so as to construct policies coherent with the emerging demands being made by diverse populations using the city and its services, at varying rhythms and intensities.

This section reviews existing studies that consider mobility as a policy tool to address various challenges in managing urban dynamics under both normal and abnormal conditions. The first subsection focuses on studies that concern traffic management. The findings of these studies can benefit traffic managers and planners at strategic, tactical and operational levels. The second subsection focuses on studies apply mobility analysis in managing social events such as festivals, sports matches, concerts, and so on. The third subsection focuses on studies that aim to support urban disaster management with mobility-based applications. These studies provide important implications for planners and policymakers to enhance urban resilience through a better understanding of the vulnerability of the city to disruptive events.

Lastly, motivated by the current global pandemic, a good number of studies have been carried out in the past two years looking into epidemics-related problems from the mobility perspective. These studies are reviewed in the last subsection.

3.4.1. Monitoring and mitigating traffic anomaly

A large volume of existing literature focuses on predicting regular traffic states, which is a classical and extensively studied problem in transportation engineering, with the aim to help fulfill the mobility needs of city inhabitants (Moreira-Matias et al., 2016; Toole et al., 2015). Efficient computational methods have been developed to perform many aspects (it can be the volume, speed, density, or behavior) of traffic estimation based on the input of mobility information. These methods play an important role in intelligent transportation in terms of guiding route planning of drivers and supporting dynamic traffic control, such as opening/closing lanes, dynamic parking pricing and adaptive traffic lights (Nagy & Simon, 2018). Details of these traffic prediction methods and algorithms are beyond the scope of this paper. A detailed review of them can be found in (Nagy & Simon, 2018).

Meanwhile, mobility data has also been employed to study irregular traffic patterns. Describing traffic dynamics is the first step to infer traffic anomalies. Traffic dynamics are different to observe directly and timely due to their spatiotemporal complexities. Traditional anomaly detection methods require substantial human efforts or extensive monitoring infrastructure (e.g., fixed sensors), which are usually inefficient, costly and delayed in time (Zhang, Li, Shi, et al., 2019). Alternatively, it is possible to infer traffic dynamics from urban mobility data (Zhang et al., 2020), as it can contain information of moving vehicles that are employed as "sensors" to perceive the traffic states in nearby areas. Traffic flow, traffic speed, traffic density, travel time/delay and OD (origin-destination) metrics (Xu, Cui, et al., 2019) are common parameters computable from mobility data. By setting proper threshold for these parameters, traffic anomalies at the road segment level (Wang et al., 2016) and irregular mobility patterns caused by special events (e.g., festivals and sport events) (Marques-Neto et al., 2018; Zhou et al., 2020) can be detected. However, the thresholds for identifying urban anomalies may vary across different locations, time and anomaly types, causing inconformity and subjectivity problems in threshold setting (Zhang, Li, Shi, et al., 2019). To address this challenge, methods that do not require the use of thresholds, such as mobility-based hierarchical clustering of vehicles' trajectories (Liu & Ban, 2013), principle component analysis (PCA) analysis of the spatial distribution of traffic flows (Kuang et al., 2015), and graph embedding technique (Zhang, Li, Shi, et al., 2019) were developed to establish mobility tensors and then detect anomalous urban mobility patterns at the road segment level.

Moreover, traffic dynamic information extracted from mobility data can also be used as the primary input for forecasting traffic anomalies. Prior studies on this topic use two different classes of approaches, namely parametric approaches and non-parametric approaches. The parametric approaches, such as the volume-delay functions (VDFs) (Huntsinger & Rouphail, 2011), time series model (Williams & Hoel, 2003) and Markov model (Yuan et al., 2011), are typically based on certain assumptions or require prior knowledge. The non-parametric approaches, based on techniques such as support vector machine (SVM) (Deshpande & Bajaj, 2016) and recurrent neural network (RNN) (Guo et al., 2021), have a relatively more flexible and sophisticated structure. They are able to capture the non-linearity in the data and use mobility data as the primary input for prediction models. In addition to traffic anomaly prediction, several recent studies also explored anomaly simulation based on mobility data. By importing mobility-based metrics such as OD matrices, travel times and travel flows, simulation models can induce backward the causes of traffic congestion based on the simulation results (Wu, Liu, et al., 2019) or test the efficiency of mitigation measures to traffic congestion (Qian et al., 2020).

3.4.2. Understanding and predicting urban crimes

Crime is a highly dynamic and complex challenge for public safety. Crime explanation and models traditionally leverage the crime history, and demographic variables such as sex, income and age, and so on. However, such information is almost constant or only changes slowly over time. Meanwhile, individual and aggregate patterns of human mobility reflecting the structure and dynamics of the cities have been implicated in a host of criminological theories. Prior research has pointed out that the mobility–crime linkages can be understood from the following perspectives (Browning et al., 2021): (1) the spatial perspective, where existing studies have focused on the interaction of potential offenders, victims and guardians at the neighborhood level; (2) the person-centered perspective, where existing studies have focused on individuals' spatial trajectories that have been employed in the investigation of the spatial dynamics of victimization (i.e. lifestyle routine activities, criminal decision-making, and situational action theories); and (3) the collective perspective, where existing studies have considered links between persons or collectivities based on shared activity locations.

By investigating the above mobility–crime linkages, prior studies have improved the empirical assessment of classical criminological theories by tapping into novel mobility data sources. From the spatial perspective, Malleson and Andresen (2015) and Hipp et al. (2019) used geo-tweets density data to improve the census block-level crime rates estimation that traditionally relied on the population information only. From the person-centered perspective, Griffiths et al. (2017) analyzed the mobile phone geo-records of terrorists to explore their spatial mobility patterns and identify their activity spaces, in order to validate existing crime pattern theories. From the collective perspective, mobility flows across places indicating social structures may have implications for understanding the place effects on crime. For instance, prior research constructed mobility networks at the neighborhood level for assessing neighborhood isolation, and the results showed that the high levels of segregation in the mobility networks were associated with higher violence (Sampson & Levy, 2020) and higher local crime rates (Graif et al., 2017). Another important but challenging objective of crime-related studies is crime prediction. Recent literature shows that there is an emerging trend to reinforce the crime prediction models with spatiotemporal features extracted from urban mobility data. With advanced deep learning techniques, recent studies have reported prediction accuracies up to 70 % in crime area prediction (Zhao & Tang, 2017) and up to 89 % in yearly counts prediction (Kadar & Pletikosa, 2018). For the sake of brevity, kindly refer to (Browning et al., 2021) for a more detailed review of the literature on mobility and crime.

3.4.3. Understanding and relieving disaster impacts

Natural disasters pose serious threats to cities. Understanding human movements is critical for evaluating urban population's vulnerability and developing plans for disaster evacuation, response and relief. Several studies, by analyzing big geodata, found that human mobility patterns would be perturbed in times of extreme natural events. For instance, major disasters such as earthquakes could cause regional population migration (Bagrow et al., 2011), and extreme weather events such as heavy rainfalls or strong winds could diversify population activities (Long et al., 2015). More recently, using voluntarily reported Twitter data in the New York City during Hurricane Sandy, Wang and Taylor (2014) revealed that human mobility displacements during the disaster followed a truncated power-law distribution, and that the perturbed human mobility was resilient, as the radius of gyration of human trajectories during the hurricane was strongly correlated with that of human trajectories during normal days. However, when impacted by more powerful natural perturbations, human mobility might be much less resilient (Wang & Taylor, 2016). These studies have advanced the knowledge on human mobility patterns under the impact of natural hazards, which would be valuable for predicting mobility pattern of urban population under similar extreme events.

On the other hand, human mobility is considered as a key proxy to understand and manage the impacts of disasters to social, economic and physical aspects of cities (Ilbeigi, 2019; Roy et al., 2019). Recent studies have begun to explore the possibility of inferring the states of disaster-disturbed urban system from human mobility data. Traditionally, observations on performance of urban systems are limited to discrete measurements at a few numbers of timings, failing to provide a quantifiable, continuous and longitudinal understanding of the post-disaster recovery process of urban systems (Yabe et al., 2020). The access to mobility data generates actionable insights for the implementation of real-time recovery monitoring for cities (Pastor-Escuredo et al., 2020). For instance, mobility is considered as a key to supporting business and maintaining engineering and social infrastructures: network-based metrics calculated from mobility networks are used as indicators to track social resilience (Mirzaee & Wang, 2020); the recovery process of business can be monitored by approximating business performances from the number of visits to business establishments per day, observed from continuous real-time mobile phone data (Yabe et al., 2020). Knowledge about urban human mobility patterns is also playing an increasingly important role in understanding the resilience of transport infrastructures (Nogal & Honfi, 2019). Mobility perturbations of the users of transport infrastructures may reflect the capability of the infrastructures to adapt to changes caused by extreme events. Hence, tracking human mobility perturbations has been widely considered as a novel and effective approach for assessing the resilience of transport infrastructures, based on mobility metrics such as displacement (Zhang, Li, Li, et al., 2019), travel flows (Ilbeigi, 2019) and OD pairs (Nogal & Honfi, 2019). Relevant findings have led to better understanding of the strengths and vulnerabilities of transport infrastructures against disaster impacts. Lastly, Individuals' behavior during evacuation, an effective protective strategy adopted to minimize the deadly threat of incoming disasters, can be inferred from mobility data. Along this line of research, people's movement patterns during evacuation (Solmaz & Turgut, 2017), how their evacuation decisions are influenced by demographic characteristics (e.g., race, age and gender) (Martín et al., 2020), as well as their sentiment time series affected by disasters in online social media have been investigated for evacuation decision prediction (Yabe et al., 2021). These studies have advanced the understanding of evacuation decision-making of people at risk, and hence provide critical support for disaster evacuation simulation research (Lu et al., 2015) and evacuation planning in practice (Li et al., 2020; Zamichos et al., 2018).

3.4.4. *Predicting and mitigating the spread of pandemic*

The world is currently facing a global public health crisis due to the COVID-19 pandemic, which has caused devastating life and economic losses. Epidemic control is gaining burgeoning attention from academia in an attempt to mitigate the ongoing COVID-19 pandemic and better prepare us for future epidemics. Human mobility is widely considered a critical factor in the spread of infectious disease, thus an increasing volume of literature has looked into the relationship between mobility and pandemic transmission. It is revealed that mobility patterns, depicted by travel volume (Jia et al., 2020; Zhao et al., 2020), the number of individuals trips (Badr et al., 2020) and network metrics (De Souza Freitas et al., 2020), are strongly correlated with the number of confirmed cases for the most affected cities and countries. Knowing this has motivated countries to tackle the COVID challenge with a variety of non-pharmaceutical interventions (NPIs), ranging from complete regional lockdowns to closures of non-essential businesses and to different forms of travel restrictions (Flaxman et al., 2020). Meanwhile, researchers have started to utilize large-scale mobility datasets to estimate the effectiveness of these NPIs. Mobility metrics, including the radius of gyration, travel distance, OD pairs and network-based metrics, were used to show the overall reduction of population mobility restricted by NPIs in China, Japan, Poland, Canada, the United States, and so on (Borkowski et al., 2021; Faruqui & Harris, 2009). These studies indicated that social distancing is the most effective NPI and has remarkably delayed pandemic transmission (Tian et al., 2020; Zhang et al., 2021).

Another major application of mobility analysis in fighting the pandemic is to model and forecast the distribution of confirmed cases, through investigation of the correlation of human mobility and pandemic transmission, so as to support early warning and proactive policy making. Prediction methods can be classified as individual-centric methods and spatial-centric methods. As an example of individual-centric methods, smart card datasets were used to construct individual-level contact networks in urban public transit networks, based on which the spread of disease was modeled and studied (Mo et al., 2021; Qian et al., 2021). For spatial-centric methods, the space of a city is divided into small local areas such as grids, neighborhoods or census block groups. Big geodata is then used to capture real-time mobility flow between the local areas. By considering local areas as nodes and mobility flows as edges, mobility networks can be constructed and serve as a proxy for social contacts, hence enabling the prediction of the pandemic spreading (Chang et al., 2021; Granell & Mucha, 2018; Liu, Zhang, et al., 2020). The above individual-centric and spatial-centric methods can be used by policymakers in any nation and city where mobility data is accessible to make rapid and accurate risk assessments and to plan the allocation of limited resources ahead of ongoing outbreaks (Gan et al., 2020).

4. Discussions

Based on the above review of existing literature on mobility-driven urban studies, this section is aimed at 1) illustrating the underlying reasons why urban mobility has been increasingly used to inform and guide various applications that target diverse urban issues, and the limits of such applications that require further research efforts; and 2) discussing a few factors which have substantially influenced the evolution of the past mobility-driven urban studies and are likely to continue to direct the future trends in this area.

4.1. *Opportunities and challenges of human mobility in urban applications*

4.1.1. *Opportunities*

Objectives of urban planning and management can be addressed at least in part by the construction of networks of sensors across urban space. The emerging concept of "citizen as sensors" is largely benefited from the advent of geo-positioning technologies. It offers new opportunities and avenues to the utilization of digital traces left by electronic device holders. The mobile nature of humans can be leveraged to help urban applications collect high quality or semantically complex data that might otherwise require sophisticated hardware and software. Specifically, as the above review of mobility-driven urban studies reveals, leveraging human mobility to "sense" urban characteristics and dynamics has the following two advantages, viewed from temporal and spatial aspects, respectively:

4.1.1.1. Real-time awareness and feedback. The traditional understanding and conceptualization of the city, which are usually founded on the idea of the city as being a stable and constant structure or a collection of static entities, has drastically changed: from being viewed as a static system to being seen as a complex, dynamic, adaptive, and evolving system in terms of its behavioral patterns (Bibri & Krogstie, 2017). Such increasing complexity and dynamics have made sensing and understanding the cities more challenging than ever. In recent years, mobility-related big geodata with potential value in the real-time awareness and real-time feedback (Zhao & Hu, 2019) shows increasing advantages in investigating the dynamic properties of cities, such as daily dynamics modeling of urban structure, real-time social events detection, traffic anomaly analysis, and so on, which used to be challenging for studies relying on traditional data, such as questionnaires, surveys, and statistical yearbooks. Real-time awareness is achieved since mobility data promotes fine-grained representation of the reality related to urban dynamics through its high temporal resolution and continuity. Real-time feedback is made possible since, based on the real-time and uninterrupted collection and analysis of mobility-related big geodata, the effects of urban management measures can be monitored and assessed on the fly, and adjustments and optimization can be made in a timely manner. The speed at which mobility data is generated is unparalleled to that of most other data sources employed in urban studies, and can substantially reduce the time lag between the start of an event, a phenomenon or a trend and when authorities are able to realize and respond. As such, mobility data has inspired and benefited a range of urban studies that aimed to e.g. improve the accuracy of pandemic spread prediction (Fokas et al., 2020), track traffic dynamics (Zhao & Hu, 2019), quantify neighborhood isolation in a dynamic and timely fashion (Wang, Phillips, et al., 2018), and so on.

4.1.1.2. Finer spatial resolution and wider coverage. Human mobility varies across urban space because of the spatial heterogeneity of sociodemographic, environmental and other conditions within the city (S. Liu et al., 2019; Sun, 2016). Traditional survey or census data usually face the limitations of low spatial resolution and restricted coverage when used to describe human mobility and support related mobility-driven studies. The emergence of big geodata with wide spatial coverage and high spatial resolution has provided a unique opportunity to analyze large-scale and spatially-refined mobility patterns (Long & Liu, 2016), the results of which usually have better representativeness and statistical power. Such mobility-related big geodata allows information to be associated with individuals and their featured locations. The high sampling frequency and positioning accuracy of tracking data offer rich details on individual movements. As such, quantitative studies are better supported to uncover information of hidden patterns, correlations, trends and preferences at the individual level, which, after necessary privacy protection measures are applied, can be used to help city authorities and other organizations make informed decisions. This has enabled individual-level implementation of various urban studies that once could only be done at the regional, city or neighborhood levels. Examples of such studies include estimating the distribution of economic activities (Östh et al., 2015), quantifying disaster-induced impact (Fang et al., 2020), assessing traffic congestion levels (Pirra & Diana, 2019), measuring exposure levels to air pollutions (Yu et al., 2020), and so on. Moreover, the usability of mobility datasets at a finer spatial resolution has also inspire innovative urban applications, such as inferring individual demographics (Wu, Yang, et al., 2019), geo-advertising (Zhang, Li, Bao, et al., 2019), locations recommendations (Huang, Ma, et al., 2020), travel route planning (Chen et al., 2014), and so on.

4.1.2. Challenges

4.1.2.1. Limits of human mobility data. Despite its above advantages, the emerging human mobility data is not limit-free. Firstly, human mobility data can be biased, due to the fact the samples in a mobility dataset may not fully represent the entire population or the studied group. For instance, for mobility trajectories collected from mobile devices or social media, which are typical sources of mobility data, the sample representativeness may be limited, since mobile phone usage is lower among certain populations such as children, the elderly, the poor, and women (Bengtsson et al., 2011; Giles, 2012). In addition, during extreme events, such as extreme heat, earthquakes and hurricanes, some people may lose access to digital devices (Longo et al., 2017), hence their whereabouts may not be tracked and represented in mobility datasets. Secondly, the privacy issue of human mobility data also needs to be addressed. Mobility-related analysis could enable producing the knowledge about a person's daily routine, lifestyle, demographic information and social network, which may cause significant threats to privacy. The rising awareness of the privacy concern has led to various technical measures for enhanced privacy protection in mobility-related studies, examples of which include obfuscating spatial and temporal data, replacing raw location data with semantic places, and publishing privacy-preserving data (Barak et al., 2016; Duckham et al., 2006; Zhao et al., 2021). In addition, higher research ethical standards can be adopted to guide mobility-driven urban studies which may involve identifying information in their data (Liu, Fan, et al., 2021; Smolak et al., 2020).

4.1.2.2. Need for combination with other datasets. Considering the above limits of mobility-related big geodata, there is increasing necessity to combine it with other types of data, such as trip survey data, demographic data, POIs, and so on, when addressing the growing intricacies of urban problems. The benefits can be multifold. Firstly, integrating multiple types of data into analyses is a possible strategy to overcome the sample bias issue. By combing human mobility data with demographic data or triangulating different sources of human mobility data, researchers could assess and reduce the biases about the studied populations and improve the representativeness of their results (Bengtsson et al., 2011; Song et al., 2017). Secondly, traditional data could also contribute to the validation of human mobility analyses. For example, Kyaing et al. (2020) utilized trip survey data to validate their findings derived from CDR data. Thirdly, human mobility data has its limit in producing semantics-rich information about human movements (Wang, He, & Leung, 2018). This makes the combination of large-scale semantically enriched data with human mobility data important for discovering complex knowledge of urban dynamics and enabling innovative applications in cities. For instance, recent research has begun to associate individuals' stops extracted from their trajectories with POIs that contain the stops' semantics, such as schools, shops, restaurants and cafes. Demographic data of individuals (such as age and gender) and attributes of public events (such as festivals, concerts and sports games) can also be incorporated in mobility-driven urban studies, as such information is vital for understanding why individuals move, what activities they participate in, and what resources or social capital they mobilize. Such combination of semantic information with mobility trajectories is vital for understanding why and how individuals move, where they visit, what activities they participate in, and what resources or social capital they mobilize, which has enabled a variety of innovative applications explored in recent urban studies. Examples include identification of urban functions (Wei et al., 2020), understanding spatial inequality (Cagney et al., 2020), real-time traffic flow prediction (Nagy & Simon, 2018), business site selection (Wang, Fan, et al., 2018), and so on.

4.2. Current and future trends of mobility-driven urban studies

Another important observation we drew from the reviewed literature is that the advancements of the mobility-driven urban studies and their success in addressing contemporary urban issues are largely promoted by two important factors, namely the evolving conceptual understanding of urban mobility, and the emerging novel mobility data and mobility mining methods. The influence of these factors as well as their implications for future research are discussed as follows.

4.2.1. Conceptualization of urban mobility

Evidence from the literature indicates that the concept of mobility has evolved over time. Mobility used to be predominantly seen as movements for transportation in physical space, as evidenced by the World Bank documentation (1996). A similar concept is used in mobility studies that adopt a traditional geographical perspective, which generally understands mobility as the spatial movement between two geographical locations. This conceptualization of mobility, however, is strictly spatial in its nature, which limits its capability to capture the conjunction between mobility and social change and cause the ignorance of the hidden dependency of spatial mobility on social systems (Gallez & Kaufmann, 2009; Kaufmann, 2014). The beginning of the 21st century witnessed the emergence of "the new mobilities paradigm", in which mobility research combines social and spatial theory in new ways (Sheller & Urry, 2006). According to Urry's analysis, there is a "mobility turn" spreading into, and transforming, the social sciences, transcending the dichotomy between spatial research and social research (Sheller & Urry, 2006). With the latest advancements in information and communication technologies that are infiltrating various aspects of peoples' daily life, new forms of mobility such as digital and communicative mobilities are emerging, and are being combined with physical mobility in the "mobilities turn" (Sheller, 2014, 2017). At the same time, under the notion of "motility", Kaufmann (2002) proposed a conceptualization of mobility as "the intention and realization of an act of movement in physical space that involves social change". and then, the analysis of mobility could be used as a sociology tool and reveal "the composition of, and changes in, a society" (Kaufmann, 2014). The new mobility paradigm, focusing on the relationship between mobility and social science, significantly affected adjacent fields and opened up interesting perspectives on the interpretation of mobility from various disciplines such as urban design (Jensen, 2013), health studies (Gatrell, 2016), and so on. In summary, there is a progressive "slippage" towards a more complex conceptualization of mobility: from the focus on analyses of multiple movements and their spatial consequences, the current mobility paradigm has brought mobility across many different domains of research and drawn in ever-widening circles of interest and innovation (Sheller, 2017).

As the above historical evolution of the concept of mobility suggests, new ways of theorizing mobility have brought together the "social" concerns in sociology with the "spatial" concerns in geography. Consequently, mobility-driven urban studies are increasingly concerned with various contemporary social challenges, aiming to improve people's mobility experiences and ensure mobility rights at both the individual and collective levels (Cresswell, 2013; Kaufmann et al., 2004; Sheller, 2014). For individuals, mobility can be considered as a particularly indispensable resource for overcoming the spatial and temporal barriers in their daily lives (Kaufmann, 2014). Thus, the quality and experiences of individuals' daily lives can be read from their mobility. For example, by using activity space measurement, individuals' mobility can be profiled from a longitudinal (monthly, annual) perspective to observe how individuals' characteristics affect variations in their spatial experience (Järv et al., 2014). Similar empirical research has been conducted on a variety of topics such as extracting routines of daily mobility (Huang, Li, et al., 2020; Sevtsuk & Ratti, 2010; Wang et al., 2021), modeling transportation choice (Abdullah et al., 2020; Wang, Gao, et al., 2018), revealing job-housing dynamics (Huang, Levinson, et al., 2018; Ma et al., 2017), and so on. The revealed mobility profiles can enable urban planner to improve individuals' accessibility and travel experience by designing better neighborhoods (Calabrese et al., 2013). In addition, mobility equity, ethics and justice are among the most debated topics in recent studies, which attempt to understand individuals' mobility at the collective level. For example, a growing body of literature has looked into social isolation using mobility based data and methods, aiming to assess isolation assessment (Wang, Phillips, et al., 2018; Xu, Belyi, Santi, Ratti, 2019a) and reveal the impact of various factors, such as income and race, on the degree of isolation (Järv et al., 2020; Wang, Phillips, et al., 2018). Another example is that recent studies of disrupted mobility have explored the variances of individuals' evacuation behavior among different racial/ethnic and gender groups, in order to enhance the understanding of uneven mobility capabilities during disaster events (Dargin et al., 2021; Yuan et al., 2021; Zhang & Li, 2022).

In addition, with the emerging consensus about the significant role of human mobility in shaping urban society and economy, it is foreseeable that there will be an increasing number of mobility-driven urban studies that look into mobility applications in economic, commercial and societal contexts that are currently underexplored. For example, urban human mobility could serve as an indicator for the level of regional economic development, intensity of inter-regional economic activities and supply-demand relationships in urban systems, which is important for evaluating and regulating local economies. By bringing the dimension of geoinformation into the business data for analytics, the decision-making of business executives can be powered by accurate predictions of economic indicators ranging from macroscopic market changes to microscopic customer visitation and service usage patterns. Moreover, by inferring individuals' preference, social relations, economic situation, demographic characteristics, accessibility to services or resources and so on, human mobility could provide new insights for enhancing social safety net and social equity.

4.2.2. Emerging big geodata and mobility analytical methods

The development of smart infrastructures, location-aware terminals, internet-of-things and precise outdoor and indoor positioning technologies has remarkably increased the accessibility to different types of mobility data. The ever-evolving mobility data promotes our understanding of human mobility as well as the interactions between humans and urban spaces. Over a decade ago, mobility studies mainly relied on travel surveys, GPS trajectories from vehicles, smart card records and banknote records. Due to limited time and space resolution of these datasets, researchers primarily focused on macroscopic analysis of the mobility patterns of entire populations by quantifying people's visited locations, travel length, travel time, radius of gyration or OD matrices, with few discussions of their implications for managing urban issues. Gradually, mobile phone data and Global System for Mobile Communications (GSM) records with much higher spatiotemporal resolution and larger sample size have become accessible to mobility studies, which larges enables microscopically revealing individuals' behavioral patterns (Birenboim et al., 2013; Ozer et al., 2016; Shen & Cheng, 2016). More specifically, researchers are able not only to care about where people go, but also to characterize what their activities are and how they behave in their day-to-day lives, laying the foundation for applying the knowledge about human mobility in various urban scenarios. Over the past few years, a number of studies also began to involve social media data in human mobility analyses, based on which individuals' mobility can be connected with their social networks, providing new insights on urban planning, neighborhood segregation analysis, business advertising and recommendation service from a cyber-physical–social perspective (Huang, Ma, et al., 2020; Huang & Wong, 2016; Soliman et al., 2017).

Meanwhile, the fast growing amounts of mobility data and researchers' increasing interests in extracting the latent spatiotemporal characteristics of human mobility from these data have motivated the continuous advancement of mobility mining methods in the literature. Particularly in recent years, the introduction of machine learning methods, deep learning methods, graph algorithms and complex network algorithms has made it possible to efficiently extract rich sematic information and network characteristics of human mobility, which consequently promotes urban applications in multiple domains, including population demographics inference, neighborhood segregation analysis, and smart urban mobility. For example, deep learning methods, such as CNN (convolution neural networks) and RNN (recurrent neural networks), have been used to model the complex relationships between mobility patterns and people's characteristics (e.g., demographic characteristic, economic state, personality, and emotion), predict human mobility in different urban scenarios, and so on, which can eventually facilitate urban mobility management during normal conditions and special events.

The emerging big geodata and related analytical methods, empowered by other enabling technologies such as cloud computing, 5G and artificial intelligence, are expected to provide more in-depth and accurate mobility knowledge in a more efficient fashion, this inspiring new opportunities for future intelligent planning, development and management of cities. For example, the big geodata generated by ubiquitous computing infrastructure can be transferred through the 5G network with minimal delays, and processed in real with artificial intelligence methods to extract the information that authorities may rely on to predict the trends or upcoming states of different entities in the city, and to identify the optimal proactive or reactive measures for various tasks such as prevention of traffic congestions or early warning of irregular crowd gatherings. Another example is that the information extracted from emerging big geodata can advance the implementation of the city digital twin technology. The benefits are twofold: First, knowing the mobility states of residents in the city in real time may enable the incorporation of residents as an important element of the city digital twin, allowing to capture, simulate and predict the interaction between residents and the urban environment and the real-time feedback of residents' real use of the city. This has thus far been missing in most existing city digital twin applications; Second, the mobility knowledge may also act as a proxy for sensing the dynamic states of other elements of the city digital twin, which can strengthen the real-time interactions between the city and its digital counterpart. There are other opportunities that could also be explored in future research, and the resulting urban applications will provide powerful means for better making sense of, managing and living in the city.

5. Conclusions

Human mobility, gaining considerable attention across various research domains, is valuable for reading the lifestyles of urban residents and indicating the processes of cities. The main aim of this study has been to review the applications of mobility data, related analytics and the resulting knowledge in addressing various contemporary urban issues. Human mobility was re-conceptualized from four perspectives in this study to illustrate the role of mobility in enabling and driving applications in various urban contexts. Then, based on these four perspectives and a number of themes associated with each perspective, we reviewed the use of mobility data and analytics in various applications explored in recent urban studies, ranging from urban planning to traffic management, public safety, pandemic control, tourism management, and so on. Finally, the core values of knowledge about urban mobility for addressing contemporary urban challenges are analyzed, and the current trends and future directions of mobility-driven urban studies are discussed. It is anticipated that this work will provide a starting point for researchers seeking a sense of the work completed in the area of mobility-driven urban research, and provide urban policymakers and professionals with useful guidelines to transfer the human mobility knowledge into actionable planning and management measures towards the most appropriate domains of implementation.

CRediT authorship contribution statement

Ruoxi Wang: Conceptualization, Methodology, Investigation, Writing, Visualization. **Xinyuan Zhang**: Conceptualization, Methodology, Investigation, Writing, Visualization. **Nan Li**: Conceptualization, Methodology, Supervision, Writing, Funding acquisition.

Declaration of competing interest

None.

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