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Human mobility data and analysis for urban resilience: A systematic review

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Abstract

The impacts of disasters are increasing due to climate change and unplanned urbanization. Big and open data offer considerable potential for analyzing and predicting human mobility during disaster events, including the COVID-19 pandemic, leading to better disaster risk reduction (DRR) planning. However, the value of human mobility data and analysis (HMDA) in urban resilience research is poorly understood. This review highlights key opportunities for and challenges hindering the use of HMDA in DRR in urban planning and risk science, as well as insights from practitioners. A gap in research on HMDA for data-driven DRR planning was identified. By examining human mobility

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studies and their respective analytical and planning tools, this paper offers deeper insights into the challenges that must be addressed to improve the development of effective data-driven DRR planning, from data collection to implementation. In future work on HMDA, (i) the human mobility of vulnerable populations should be targeted, (ii) research should focus on disaster mitigation and prevention, (iii) analytical methods for evidence-based disaster planning should be developed, (iv) different types of data should be integrated into analyses to overcome methodological challenges, and (v) a decision-making framework should be developed for evidence-based urban planning through transdisciplinary knowledge co-production.

Keywords
Human mobility, mobile phone data, location information, disaster resilience, systematic review

Introduction

The urban design and availability of services in metropolitan areas result in high human mobility. By 2050, 68% of the global population is projected to live in cities (United Nations, 2018). People travel within and between cities for daily commutes, business, leisure travel, and education. Human mobility has brought about social, economic, and technological advancements in cities. However, this high volume of human mobility from and within cities poses various challenges in disaster risk reduction (DRR) planning.

With high population densities and levels of human mobility, cities provide efficient and comfortable environments during normal times. However, disasters can have severe consequences. In 2020 alone, disasters displaced 30.7 million people worldwide (The Internal Displacement Monitoring Center, 2021). After the earthquake in Haiti in 2010, 630,000 people were displaced temporarily (Bengtsson et al., 2011; Lu et al., 2012). During a disaster, people can be stranded and unable to go home because public transportation is interrupted. For example, during the Great East Japan Earthquake, approximately 5.15 million commuters were stranded (Cabinet Office of the Government of Japan, 2015). Interconnectivity and efficiency, contemporary information technologies, and networked communication can help address this issue (Blondel et al., 2015). Digital transformation enables more informed and evidence-based decisions in managing assets and delivering services in cities during disasters (Engin et al., 2020; Man et al., 2018).

Within a metropolitan area, people commute to offices and schools, leading to significant fluctuations in human mobility throughout the course of a day. In addition, visitors from outside cities attend large events and meetings, with changes in the volume of human mobility on the scale of weeks and years (e.g., differences between weekdays and weekends and between seasons). However, most disaster risk management plans are "static," in that the times and locations of people are considered fixed. In reality, human mobility is nonlinear, chaotic, and spans across temporal and spatial scales (Oomori et al., 2014; Sawada et al., 2013; Wang and Taylor, 2016). Moreover, people travel both horizontally and vertically in cities, and the volume of human mobility fluctuates over the course of a day, week, and year. DRR planning should be "dynamic" to reflect the reality of dynamic mobility across space and time more accurately and to address the diverse needs of people with different demographic characteristics more effectively.

To facilitate DRR planning and promote urban resilience, urban planners and policymakers can utilize human mobility data and analysis (HMDA), which requires addressing the technical and analytical challenges associated with and the socioeconomic implications of human mobility data to achieve evidence-based DRR planning and decision-making. In practice, however, time-sensitive decision-making in DRR is often based on limited experience rather than evidence or data because

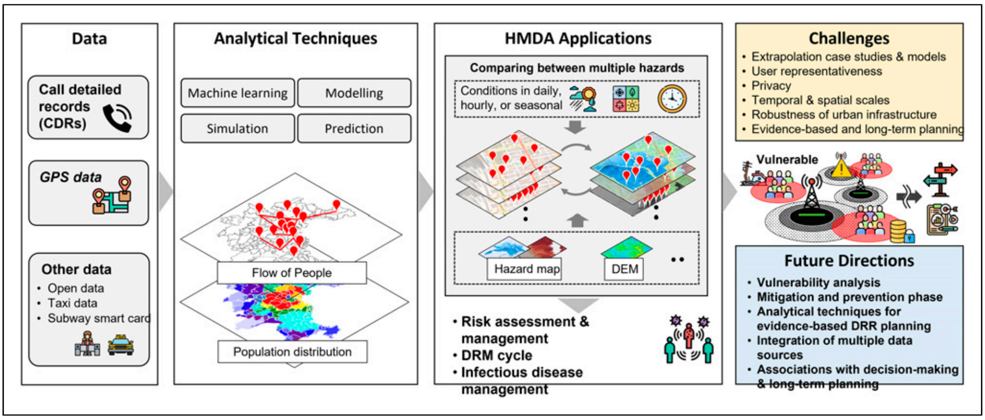

Figure 1. Overview of this review paper.

local governments lack timely access to locational information both during and after such events. The conventional approach to analyzing mobility patterns is based on household surveys and information provided by census data (Oliver et al., 2015). This suffers from recall bias and limited sample size. However, it has been demonstrated that human mobility data gathered using smartphones and geographical information technologies have the potential to overcome these shortcomings in public health (e.g., Oliver et al. (2015)), transportation management (Ilbeigi, 2019; Rahimi-Golkhandan et al., 2021; Roy et al., 2019), and evacuation modeling (e.g., Chen et al., 2020; Jiang et al., 2021), among other applications.

HMDA can help improve existing disaster risk assessment and management strategies. For example, the accuracy of damage prediction and the service level of the emergency response can be increased. Rapid advances in information technology now enable us to capture, integrate, and store data associated with disasters in real time. For instance, sensing technologies, such as the global navigation satellite system in smartphones, enable us to monitor human movement at high temporal and spatial resolutions (Nishino et al., 2016; Sekimoto et al., 2011; Shibasaki, 2013). Advances in technology for the integration and storage of big data have led to the potential to utilize large volumes of geographical information and data on human movements to predict human mobility and damage and to model emergency responses in the long term for dynamic data-driven DRR decision-making.

Furthermore, the role of HMDA has become increasingly important during the COVID-19 pandemic. Research using human mobility data in the United States during COVID-19 has predicted higher infection rates among disadvantaged racial and socioeconomic groups, solely due to differences in mobility (Chang et al., 2021). Another study using human mobility data in Japan during the COVID-19 pandemic revealed the heterogeneous impacts of the pandemic, demonstrating that households in higher-income regions can better reduce their amount of social contact and thus the risk of COVID-19 transmission than households in lower-income regions (Yabe et al., 2020b). These studies indicate that HMDA could reveal social inequality during the pandemic, which is crucial for city policymakers during a disaster.

The objective of this review paper is to provide an interdisciplinary review of the current state of human mobility studies in the context of DRR planning for urban resilience by integrating the fragmented literature on data analysis, modeling, simulation, and planning. The remainder of this paper is organized as follows. The section Methodology describes the methodology used to select the existing literature on human mobility that is summarized in this review. The section Human Mobility Data and Analytical Approaches discusses the types of HMDA data and primary analytical

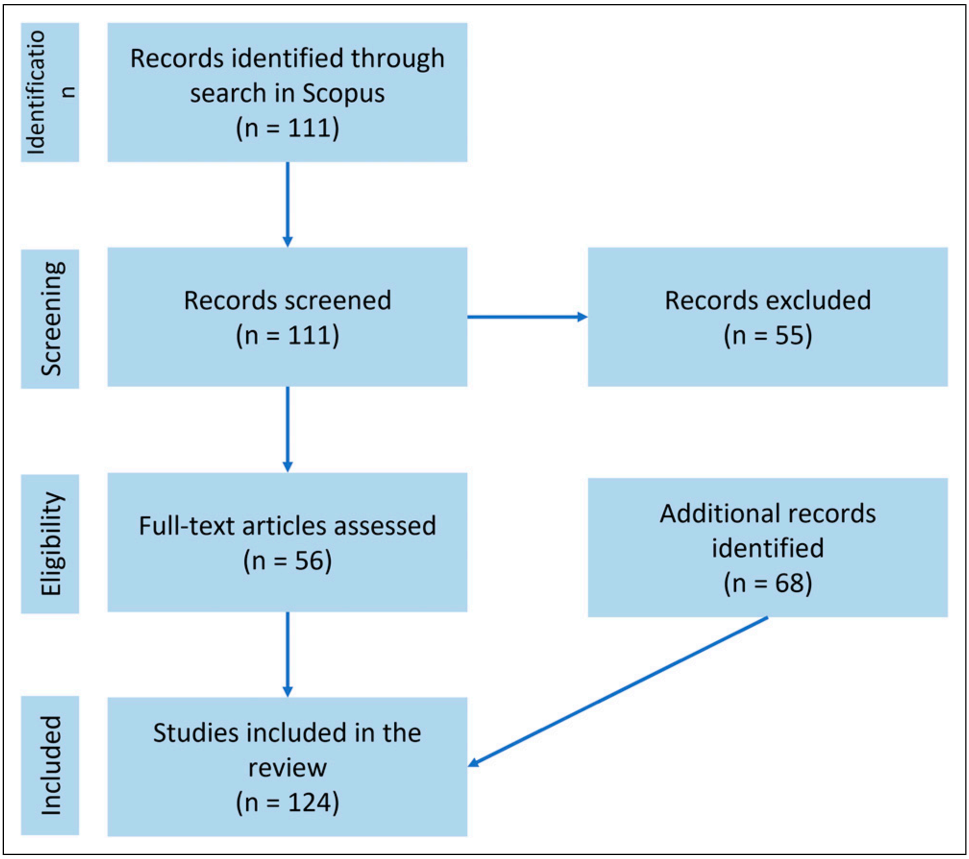

Figure 2. Procedure for literature search and selection.

techniques. The section Human Mobility Data and Analysis Applications in Disaster Risk Reduction Planning describes theoretical and practical applications of HMDA for DRR, and The section Challenges discusses the current challenges associated with HMDA. Finally, the section Future Directions identifies promising areas for future HMDA research. Figure 1 provides a schematic overview of this review.

Methodology

This paper synthesizes perspectives and results from computer science, information technology, geography, disaster studies, civil engineering, and urban planning to increase the understanding of the current opportunities and challenges in HMDA research. To select papers, we followed "the preferred reporting items for systematic reviews and meta-analyses" framework (Moher et al., 2009) (Figure 2). We first created a broad set of search strings that included terms associated with human mobility, disasters, and urban areas (see the exact strings in the Supplementary Material). The initial search was conducted on 10 August 2021, and 111 articles were returned. The titles and abstracts (and, in some cases, the main texts) of these articles were carefully read to select those that were relevant to HMDA for DRR based on the following criteria: (1) focus on urban areas, human mobility and movement, and disasters (including pandemics); (2) implications for urban planning and development; (3) a clear application going beyond purely method development; and (4) shortterm human mobility (i.e., the temporary movement of people during disasters and their subsequent return) rather than long-term movement such as migration (i.e., situations in which people permanently move and never return). We also excluded preprints, selecting only published journal articles, including both original research papers and reviews. We have limited the papers to those written in English. After screening, 56 papers remained. An additional 68 papers were identified as relevant via Google Scholar while reading these 56 papers. This led to a systematic scrutiny of 124 papers in total.

Human mobility data and analytical approaches

Sources of human mobility data

With the spread of mobile phones, continuous, real-time, anonymized location information of individuals is becoming increasingly available for DRR planning at low cost. There are two primary sources of human mobility data: call detail records (CDRs), which are generated every time a cell phone communicates using a mobile phone network, and global positioning system (GPS) data, which are recorded by a variety of smartphone apps and other devices. Table 1 presents the advantages and disadvantages of utilizing each type of human mobility data.

Call detail records

For every mobile phone call, text message, or data communication, the mobile phone network records which mobile phone tower is connected to the mobile device. In addition, mobile phone companies store CDRs for billing purposes. Thus, the mobile phone network possesses geographic information for each mobile phone communication. The high usage of cell phones provides a large amount of call and text message data with high spatial resolution. These advantages make CDRs a popular source of cell phone data in human mobility research (Rahimi-Golkhandan et al., 2021; Wang et al., 2018). However, this approach has some limitations, that is, the datasets are not easily accessible because of privacy concerns, and the accuracy of the locations reported using CDRs depends on the cell tower density (Rahimi-Golkhandan et al., 2021) (Table 1).

Table 1. Advantages and disadvantages of different types of human mobility data.

	Description	Advantages	Disadvantages
CDRs	Data collected when cell phones communicate with mobile phone networks	- Reports call timestamps and the geolocations of users - Provides a large amount of data - Spatial coverage is large	- Not easily accessible - Cell tower density can influence the accuracy of reported locations - Privacy concern if data are not anonymized
GPS	Data collected by apps or other devices when used by users	- Provides the geolocations, timestamps, and content of social media posts such as tweets - Provides a large amount of data - Reports high-resolution geolocations	- Coverage may not be as extensive as that of CDRs - Can detect only the locations from which users post - Users of GPS services may be biased - Positioning indoors is less precise

Source: Rahimi-Golkhandan et al. (2021).

Call detail records have been utilized in HMDA studies to examine human activity during disasters. For example, Solmaz and Turgut (2017) tracked pedestrian movement during disasters by developing a network model that uses mobile sinks, which store and carry pedestrian smartphone messages. Similarly, Lu et al. (2012) and Bengtsson et al. (2011) analyzed the CDR data of 1.9 million mobile phone users to analyze human mobility 42 days before and 158 days after the devastating Haiti earthquake in 2010.

Furthermore, CDRs have been used to fill the gaps in hazard data. For instance, Yabe et al. (2018) detected anomalous behaviors of individuals using mobile phone location data to infer flooded areas in rural Japan, where conventional sensors and cameras for flood detection were lacking.

Global positioning system data

An alternative source of human mobility information is geotagged data from social media and smartphone applications. GPS data can include not only location information, but also the content of posts (e.g., messages, photos, and videos), which can contain diverse user information, such as sentiment, needs, and preferences. This feature has immense potential for analyzing multifarious situations and the needs of people during disasters. However, GPS data are limited in that the coverage may not be as extensive as that of CDRs (Table 1).

Various scholars have used geotagged social media data, such as data from Twitter (Rahimi-Golkhandan et al., 2021; Wang and Taylor, 2014, 2018; Wang et al., 2020) and Weibo (Liu et al., 2021). Wang et al. (2020) utilized aggregated location data from Twitter to compute and compare network-wide indicators before, during, and after disasters in a case study of Hurricane Harvey and the floods that followed in Greater Houston, Texas, in 2017. Similarly, Rahimi-Golkhandan et al. (2021) employed geotagged Twitter data from 1 month before and after Hurricane Sandy in New York City to understand mobility patterns and measure transportation diversity.

In addition to social media applications, other smartphone applications can be used for HMDA. For instance, Yabe et al. (2017) used human mobility and disaster warning information data stored in the Yahoo Japan Disaster Alert application to predict irregular human mobility in Tokyo. The application stores the human mobility data of 1 million users and disaster warning information corresponding to earthquakes and typhoons since 2014. Other examples include Google Location History data to examine rare, long-distance, and international trips (Ruktanonchai et al., 2018); Google Mobility data for analysis during the COVID-19 pandemic (Sadowski et al., 2021); and Baidu Maps to analyze the changes in congestion patterns in Shanghai (Jiang et al., 2021).

Companies also sell offline location data to businesses and provide free access to academics. Examples include LocationSmart (www.locationsmart.com), Foursquare (www.foursquare.com), Cuebiq (www.cuebiq.com), and SafeGraph (www.safegraph.com). Using mobile phone GPS data (Safegraph), Yabe et al. (2020c) detected the effects of hurricanes on the performances of 635 businesses in Puerto Rico after Hurricane Maria. Meanwhile, international aid agencies such as UNICEF and the World Bank use human mobility data for real-time humanitarian purposes (Marx et al., 2020). The location information associated with these various applications, combined with user demographic information, can be valuable for analyzing human mobility, but privacy considerations must be considered, as discussed in the section Challenges. Also, a large portion of GPS data is generated from Internet data communications. Mobile phone ownership has increased and become decoupled from socioeconomic status, leading to reduced disparities in Internet access (Ilieva and McPhearson, 2018; Quercia and Saez, 2014). In the United States, Internet users account for more than 93% of the population as of 2021 (Pew Research Center, 2021). Hence, the potential usability of human mobility data for research and DRR is increasing.

Other human mobility data

In addition to CDR and GPS data from mobile phones, other data, such as open data, are widely used for HMDA research. Examples include data from subway smart cards (Ma et al., 2017), Wi-Fi usage (Alessandretti et al., 2017), and taxi trips (e.g., Ilbeigi, 2019; Roy et al., 2019).

Combining human mobility data with other data such as hazard maps and remote sensing data is common for HMDA. For example, Song et al. (2017) used diverse data sources (e.g., GPS data records of 1.6 million users over 3 years, news report data, and transportation network data) to understand and simulate human evacuation behavior and routes during different disasters. Later, Liu et al. (2021) provided more detailed and effective disaster information by combining Weibo data with hazard maps. Xing et al. (2021) proposed a method of integrating crowdsourced data, such as social network service (SNS) data, and mobile phone data from the Jiuzhaigou earthquake in Sichuan, China, to identify the effects of a disaster, the disaster type, and the location of the affected population in response to emergency management. Although it is challenging to couple human mobility data with data in other formats, heterogeneous data sources complement human mobility data collected from mobile phones.

Categories of human mobility data

There are two categories of HMDA: population distribution and human flow. Population distribution data are human mobility data that are derived, analyzed, or simulated on a grid basis using datasets representing a population, such as census data. They tend to be combined with other grid data, such as hazard maps (Liu et al., 2021; Renner et al., 2018) and digital elevation maps (Khakpour and Rød, 2016). Population distribution analysis is better suited for detecting large spatiotemporal scale patterns and changes, such as daily, hourly, or seasonal fluctuations (Chen et al., 2020; Freire and Aubrecht, 2012; Renner et al., 2018).

On the other hand, human flow data pertain to human mobility, which is analyzed or simulated based on individuals (e.g., individual humans or mobile objects). Changes in the locations of these individuals are calculated along a timeline in hours, minutes, and seconds, and can be combined with relevant attributes and information on SNS. Human flow data are better than population distributions for analyzing the dynamic flow of individuals because they are collected at a finer spatiotemporal scale. For example, the longitude and latitude information of data collected by SafeGraph is accurate to within a few meters (Yabe et al., 2021b). Table 2 summarizes the advantages and disadvantages of each category of data.

Data analysis

HMDA research uses four main types of analytical techniques: machine learning, modeling, simulation, and prediction.

Machine learning

Machine learning is a powerful technique for dealing with a large amount of data and has been applied in various HMDA studies, including the analysis of social inequality during the COVID-19 pandemic (Huang et al., 2021), categorization of human mobility types (Fan et al., 2014), and prediction of human mobility (Song et al., 2017; Yabe and Ukkusuri, 2019). Fan et al. (2014) used an algorithm (non-negative tensor factorization) to separate mixed human flow into several basic flows which could represent the characteristics of the mobility patterns in a city. The method was applied to the cell phone GPS data of 1.6 million users to model the changes in human flow before

Table 2. Categories of human mobility data.

	Description	Advantages	Disadvantages	Studies
Population distribution	- The data are in grid format- Recorded on a mass basis	- Large-scale spatiotemporal patterns can be detected- These data can be analyzed with other map data	- The spatiotemporal scale is less fine than that of human flow data	Chen et al. (2020); Freire and Aubrecht (2012); Khakpour et al. (2016); Renner et al. (2018)
Human flow	- The data are in vector format- Recorded on an individual basis	- The temporal scale is high (accurate up to within a few meters)- These data can be analyzed with SNS data	- Large-scale patterning is more challenging than with population distribution data	Lwin et al. (2018 b); Ma et al. (2017); Sasabe et al. (2020); Sekimoto et al. (2011); Solmaz and Turgut (2017); Wang et al. (2014); Yabe et al. (2021b); Yabe et al. (2020b)

and after the Great East Japan Earthquake of 2011. Song et al. (2017) built an intelligent system called DeepMob that collects large amounts of heterogeneous data to predict human evacuation behaviors and routes in various disaster situations. Using Twitter data, Yabe and Ukkusuri (2019) proposed a machine learning framework that integrates information such as GPS data acquired from heterogeneous networks on social media via smartphone apps to predict individual behaviors when returning home after disaster evacuation.

Modeling

Model-based studies seek to represent a system, entity, phenomenon, or process physically or mathematically to understand its characteristics better (Loper and Register, 2015). Various models with diverse purposes have been built in HMDA studies. For example, Aubrecht et al. (2012) developed a conceptual setup and subsequent implementation for DynaPop, a seamless spatio-temporal demographic model. The model is intended to provide basic information for social impact assessment in crisis management and is implemented through a gridded spatial partitioning approach based on population data.

Simulation

Once a model has been developed, it can be advanced through time in a simulation in an attempt to learn how the modeled system works (Loper and Register, 2015). There are three main simulation approaches in HMDA studies. The first is discrete simulation, such as Monte Carlo simulation. For example, Liu et al. (2021) integrated commuter mobility patterns and road inundation records to calculate the quantity, structure, and spatial distribution of a population affected by flooding using Monte Carlo simulations. Mobility patterns were constructed by the gravity model using point-of-interest data and detailed into individual routes by simulation.

The second approach is continuous simulation, such as system dynamics. Wang et al. (2020) focused on human-spatial systems, which were designed to understand the complex and dynamic interactions between urban spatial structures, human mobility, and natural hazards. They generated spatial networks by aggregating location information from the Twitter streaming application programming interface.

The third approach is agent-based simulation, which simulates the actions and interactions among autonomous decision-making agents. Agent-based simulations are often used in HMDA research to study multiple scenarios. For example, by running a multi-agent simulator, Sudo et al. (2016) estimated the population distribution, including stationary people, using a particle filter and generated multiple scenarios to provide the next step in the distribution of people. By acquiring anonymous GPS data in real time, they estimated the movement of people without using pre-trained models. The limitation of agent-based simulations is that the process is often computationally intensive (Yin et al., 2020). Nevertheless, agent-based simulations can help predict human mobility, which can contribute to damage assessment and future DRR planning, as discussed in the section Human Mobility Data and Analysis Applications in Disaster Risk Reduction Planning. These simulation-based approaches, some of which are model-based, can effectively contribute to DRR planning by identifying patterns of human mobility during past disasters and predicting future individual behavior.

Prediction

By changing variables in a simulation or using patterns discovered from machine learning, predictions can be made about the future behavior of a system (Loper and Register, 2015). The prediction of human mobility has been studied for various purposes. Lu et al. (2012) predicted the locations of disaster victims by analyzing the mobility of 1.9 million cell phone users from 42 days before to 341 days after the 2010 earthquake in Haiti. Furthermore, Wang and Taylor (2014) predicted the visited locations and mobility flow of Twitter users in New York City during and in the days following Hurricane Sandy. Information about where disaster victims are and how they move helps local officials provide prompt rescues. In addition, Yabe et al. (2017) predicted individual travel delays during frequent disasters using multiple types of features, such as the usual travel patterns of commuters, location information, and disaster information. Their method could predict the irregularity of commuting behavior in the event of disasters such as earthquakes and typhoons in Tokyo using GPS data from one million users of Yahoo! Apps. Studies that enhance the predictability of human mobility during disasters contribute to simulating evacuation behaviors in the DRR planning phases. In another study, Lwin et al. (2018b) attempted to overcome a long-standing challenge in HMDA studies, namely, enhancing temporal resolution by predicting population links and flow directions at a scale of hours. They used origin–destination paired CDR data and conducted a citywide shortest path analysis using geographic information systems. Their model predicted and visualized the hourly flow of people on a map and thus could be used for various urban and transportation planning purposes. All told, these simulation-based approaches, some of which are model-based, can effectively contribute to DRR planning by inferring patterns of human mobility from past disasters to predict future individual behavior.

Human mobility data and analysis applications in disaster risk reduction planning

Numerous studies have demonstrated the advantages of using HMDA for pre- and post-disaster planning to enhance urban resilience. The opportunities that new data sources and analytical techniques can bring to DRR planning are considerable, ranging from monitoring and managing all types of human mobility and needs in real time to better preparedness for future disasters and designing and testing plausible future scenarios.

Risk assessment and management

Collecting and analyzing human location data is effective for investigating and assessing the components of disaster risk (i.e., hazard, exposure, and vulnerability).

Hazard analysis. HMDA has been used to estimate the spatiotemporal characteristics of hazards. For instance, Pastor-Escuredo et al. (2014) demonstrated the possibility of using CDR data to understand the characteristics of floods. They created maps that identified floods by comparing the communication activity signals contained in CDR data to rainfall data from Landsat 7 imagery. Yabe et al. (2018) proposed a method of estimating flooded areas in real time by detecting the abnormal behavior of individuals. This approach combines cell phone data with topographical information, such as digital elevation models and river trajectory data. Further, Chen et al. (2020) used human mobility data collected by Baidu Maps to analyze dynamic patterns over time for detailed spatiotemporal assessment of the impacts of extreme weather events on cities. This analytical framework is valuable not only for understanding the risk of hazards, but also for assessing the vulnerability and resilience of cities and planning for disaster mitigation. Thus, by adding people flow and population distribution data to meteorological observation data and geospatial information, hazards and risks can be analyzed more accurately by conducting analysis in multiple layers.

Exposure analysis. HMDA can be valuable for assessing the hazard exposure of a population. Necessary for such assessment, population data based on administrative units are usually available and are often collected through conventional methods, such as national censuses. However, the spatial and temporal scales are not sufficient for timely and accurate risk assessment (Khakpour and Rød, 2016; Renner et al., 2018). For example, national censuses record populations based on residences, but business districts generally have fewer residences. However, during the day, the actual number of people in business districts can be much higher than that recorded by a census. Similarly, the actual numbers of people at tourist locations can fluctuate considerably across days and years. HMDA can be used to fill the spatiotemporal gaps in conventional population data to reflect the actual population exposed to hazards more accurately.

To refine our understanding of human mobility across temporal scales, models can be used to improve the estimates of daily, weekly, and seasonal changes in population distribution (Chen et al., 2020; Freire and Aubrecht, 2012; Renner et al., 2018) or human flow (Solmaz and Turgut, 2017). For example, Khakpour and Rød (2016) built a cellular automation model assuming that the human mobility pattern is similar to that of a contagious disease. They produced spatiotemporal maps at resolutions of 50 m and 5 min that could estimate population distribution changes between daytime and nighttime. Freire and Aubrecht (2012) classified nighttime and daytime population densities and combined them with the seismic intensity level to derive a composite population exposure map for the four spatial classes.

Improving spatial resolution is also critical, particularly for congested areas, in which many people can be exposed to hazards. Using diverse data sources, Renner et al. (2018) estimated population distributions at a spatial resolution of 100 m in congested areas such as tourist locations. Solmaz and Turgut (2017) developed a method of tracking pedestrians in a crowded theme park during disasters using ad-hoc mobile communication architectures. In their network architecture, pedestrian smartphones store and carry messages to a limited number of hubs, contributing to improved simulation results and the rescue of more pedestrians. Advancements in communication technology and data availability have increased the spatiotemporal resolution of HMDA, enabling it to contribute effectively to population exposure risk assessment.

Vulnerability assessment. Although the application of HMDA in vulnerability assessment is still in its infancy, it is gaining increasing attention in the field of disasters due to natural hazards (Marx et al., 2020; Yabe et al., 2020c; Yin et al., 2021) and the COVID-19 pandemic (Huang et al., 2021). Yabe et al. (2020c) utilized location data collected from mobile phones to analyze the causal impacts of hurricanes on the economic vulnerability of the business sector. To quantify the impacts, they employed a Bayesian structural time-series model to predict the counterfactual performance of the affected businesses. Using foot traffic data provided by a location information company (SafeGraph), Yin et al. (2021) proposed a heat vulnerability index to monitor vulnerability to heat at finer timescales at more vulnerable locations in the urban environment. Marx et al. (2020) proposed an algorithm that uses pseudonymized location data collected from individual cell phones to detect community depopulation caused by a massive earthquake in Puebla, Mexico, in 2017. This approach can provide humanitarian response organizations with an inexpensive, accurate, and automated method of detecting the communities most severely affected by a major disaster, such as those that have no other means of reporting or are reluctant to share information with local authorities or the international community. When assessing vulnerability, it is important to clarify the causal relationship between the actual state of human mobility based on location-based analysis and the affected communities, sectors, and areas and to propose indicators and methods.

The literature review of HMDA and associated risk components (i.e., hazard, exposure, and vulnerability) shows that more papers are related to exposure than to the other components. In contrast, research on vulnerability is limited, although some studies have been published recently (e.g., Yabe et al., 2021b; Deng et al., 2021) (Table 3).

Disaster risk management cycle

DRR involves four phases: mitigation and prevention, preparation, response, and recovery (FEMA, n.d.). The existing literature reveals that HMDA can be used to manage disaster risk more appropriately in at least three of these phases: preparation, response, and recovery.

Preparation phase. To prepare for disasters in urban areas effectively, scenarios must be created to reflect probable threats to identify resource capabilities and develop proper courses of action. HMDA research offers a promising means of identifying possible threats and developing multiple scenarios that enable realistic risk assessment and planning. In their risk assessment research, Liu et al. (2021) developed a new approach to estimate flood-exposed populations based on human mobility patterns and road inundation records. Three scenarios were then designed with flood return

Table 3. Risk assessment and management components.

Risk component	Description of risk component	Studies
Hazard	A potentially damaging physical phenomenon; typical natural hazards include floods, tsunamis, cyclones, droughts, and landslides	Pastor-Escuredo et al. (2014); Yabe et al. (2018); Bengtsson et al. (2011); Wang et al. (2018); Chen et al. (2020)
Exposure	The value, location, and attributes of assets that are essential to communities (e.g., people, buildings, factories, and agricultural land) and that could be impacted by a hazard	Khakpour and Rød (2016); Renner et al. (2018); Freire and Aubrecht (2012); Chen et al. (2020); Solmaz and Turgut, (2017); Liu et al. (2021), Xing et al. (2021)
Vulnerability	The likelihood that assets will be damaged when exposed to a hazard	Huang et al. (2021); Yabe et al. (2020a); Yin et al. (2021); Marx et al. (2020); Yabe et al. (2021c); Deng et al. (2021)

periods of 10, 20, and 50 years, and the quantity, structure, and spatial distribution of the affected population were estimated. Another significant application of HMDA in evacuation scenarios is emergency planning. Chen and Zhan (2014) modeled the traffic flow of the collective behaviors of evacuating vehicles on three types of road network structures with different population densities.

Analysis with high spatiotemporal resolution can help planners develop scenarios with similarly high resolutions. For instance, Ma et al. (2017) developed a model to calculate the hourly changes in the population at the community level based on subway smart card data. They estimated the population in six central districts of Beijing and examined the spatiotemporal patterns and diurnal changes in the population to explore the main sources and sinks of human mobility. These results can be used to calculate the potential number of evacuees per hour under different temporal disaster scenarios, which can help city officials prepare for disasters more accurately. The more spatially complex the target city or the more dynamic the human mobility, the more important it is to create detailed scenarios based on HMDA.

Response phase. Compared to the previous DRR phase, more HMDA studies have been conducted on the response phase, including evacuation, damage assessment, and provision of emergency assistance.

Transportation disruption

Human mobility data and analysis has been applied in studies to examine resilience and disruptions in transportation networks during disasters. Transportation disruptions directly impact human mobility, making this sector vital among critical urban infrastructure systems (Haraguchi and Kim, 2016).

Detecting abnormal flows by comparing flows during disasters with those during non-disaster times is an established method. Comparing human flow during non-disasters and evacuation situations, Sasabe et al. (2020) developed a method of assessing road network risks during response phases. As another example, Ilbeigi (2019) employed taxi GPS traces to detect unusual patterns in transportation networks during Hurricane Sandy in 2012. Further, a case study in Shanghai showed changes in urban road congestion patterns during the COVID-19 pandemic (Li et al., 2021a). After the lockdown in Shanghai, transit and bus users switched to driving or car sharing, and this change in human behavior contributed to an upward trend in traffic congestion after the pandemic in Shanghai. Understanding the dynamics of urban traffic operations in a complicated disaster context, such as a pandemic outbreak scenario, will help policymakers implement different management strategies.

Evacuation and rescue

Several scholars have found that social factors and connections are closely associated with evacuation behaviors. Previously visited places and social relationships are associated with evacuation destination choices (Jiang et al., 2021; Song et al., 2014). However, in contrast to other hazards, during severe winter storms, the most frequent locations are not good predictors of individual mobility patterns (Wang et al., 2017). In addition, a study using long-term human mobility data associated with sentiment analysis from social media data revealed that evacuated people travel for daily activities over longer distances and have smaller variances in long-term sentiments than non-evacuated people (Jiang et al., 2019).

Several tools and methods have been developed to model evacuation and to prepare effective plans. For example, Horanont et al. (2013) proposed a real-time evacuation monitoring method using a large-scale auto-GPS. They applied this method to the Great East Japan Earthquake and

Tsunami. Performing grid-based analysis, Chen et al. (2020) developed a model to assess the vulnerability to evacuation quantitatively using the location data of 17 million cell phone users in Shanghai for two consecutive days.

Agent-based modeling is often performed for evacuation modeling and planning, such as modeling evacuation vehicles (Chen and Zhan, 2014) and assessing warning messages with geographical targets (Gao and Wang, 2021). However, computational burden is a major limitation. To address this challenge, Yin et al. (2020) developed a database of evacuation plans for typical population distributions acquired from cell phone location data and enabled optimal evacuation plans to be searched in real time. Focusing on rescue activities during the response phase, Chaoxu et al. (2019) used cell phone location data from the Jiuzhaigou earthquake to investigate their potential use in emergency rescue operations in terms of several aspects, including quantity, location, rate of change, and epicenter distance. Thus, understanding human mobility trends can contribute to more effective and safer evacuation and rescue planning, as well as real-time responses.

Different data can be combined to improve understanding of the needs of diverse users during a disaster. For example, Wang and Taylor (2018) proposed an approach that combines sentiment and mobility data to assess disaster demographics. They collected 3.74 million geotagged tweets over an eight-week period to examine individual sentiment and mobility before, during, and after the 2014 South Napa Earthquake. They also examined time-series trends and seasonality to understand the temporal relationship between sentiments and mobility. These approaches to combining location and content information from SNS data are currently being studied to understand human behaviors, psychology, and needs during disasters.

Recovery phase. Several researchers have reported that human mobility during the recovery phase is associated with mobility during non-disaster times through social relationships and ties, such as after the Great East Japan Earthquake (Song et al., 2014; Yabe et al., 2019). Yabe et al. (2019) discovered that inter-city dependencies in social connectivity between cities contribute to the recovery of cities after disasters. They analyzed mobile phone location data from 78 counties in Puerto Rico, which included the GPS location data of more than 50,000 unique users over a period of more than 6 months before and after Hurricane Maria. Recovery of the transportation sector is also important for overall disaster recovery. Roy et al. (2019) developed a method of detecting extreme changes in mobility data and measuring their recovery times. They used taxi data for 1 month in New York City before, during, and after Hurricane Sandy. Rahimi-Golkhandan et al. (2021) examined the impact of the New York City transportation system on the recovery of human mobility after Hurricane Sandy by characterizing the diversity of transportation modes and mobility patterns before and after the disaster, using location information from Twitter data. Analyzing human mobility based on population and transportation data over a certain period can play a role in understanding the state of urban recovery.

Existing HMDA literature related to the disaster management cycle reveals that studies on the mitigation and prevention phase are lacking compared to those on the preparation, response, and recovery phases (Figure 3). Some researchers, such as Jia et al. (2020) and Gatto et al. (2020), used HMDA to demonstrate the ability to predict the transmission of COVID-19, contributing to the mitigation of the impacts of the pandemic. However, HMDA research on disasters caused by natural hazards is limited to the mitigation and prevention phase.

Comparison of human mobility among disasters

Comparing human mobility patterns and identifying trends across multiple disaster cases is useful for DRR planning. Using the location data of SIM cards held by the largest cell phone company in

Haiti, Bengtsson et al. (2011) compared human mobility during the 2010 Haiti earthquake and cholera outbreak and estimated the scale, distribution, and trends of human mobility. Based on Twitter data, Wang and Taylor (2016) contrasted the perturbations and steady-state of human mobility before, during, and after 15 disaster events. While working with three companies in the United States and Japan, Yabe et al. (2020a) analyzed the human mobility of more than 1.9 million cell phone users over 6 months during five disasters to improve understanding of post-disaster population movements and recovery patterns.

To identify general laws of human mobility, studies have shown that human mobility during disasters follows specific distributions, such as log-normal (Han et al., 2019) and power-law (Lu et al., 2012; Wang and Taylor, 2014, 2016; Wang et al., 2017) distributions, depending on the type of mobility. These studies on human mobility comparison and patterning can support comprehensive DRR planning and decision-making while addressing multiple hazards.

Combatting infectious diseases and the COVID-19 pandemic

HMDA has been used in research on infectious disease management in the field of digital epidemiology (Salathe et al., 2012; Wesolowski et al., 2016). In its application to conventional infectious diseases, HMDA has been used to monitor and predict the transmission of malaria (Buckee et al., 2013; Tompkins and McCreesh, 2016; Wesolowski et al., 2012), dengue (Kiang et al., 2021; Wesolowski et al., 2015), Ebola (Wesolowski et al., 2014), influenza (Venkatramanan et al., 2021), and rubella (Wesolowski et al., 2015), among other diseases. During the COVID-19 pandemic, the need for human mobility data has increased considerably because understanding human mobility is crucial for decision-making. As such, various open-sourced mobility datasets and scoreboards have been produced, including Apple and Google Mobility Reports, the University of Maryland Mobility Metrics and Social Distancing Index, the Unacast Social Distancing Index, and mobility indices from various companies such as Baidu, Descartes Labs, Cuebiq, and SafeGraph.

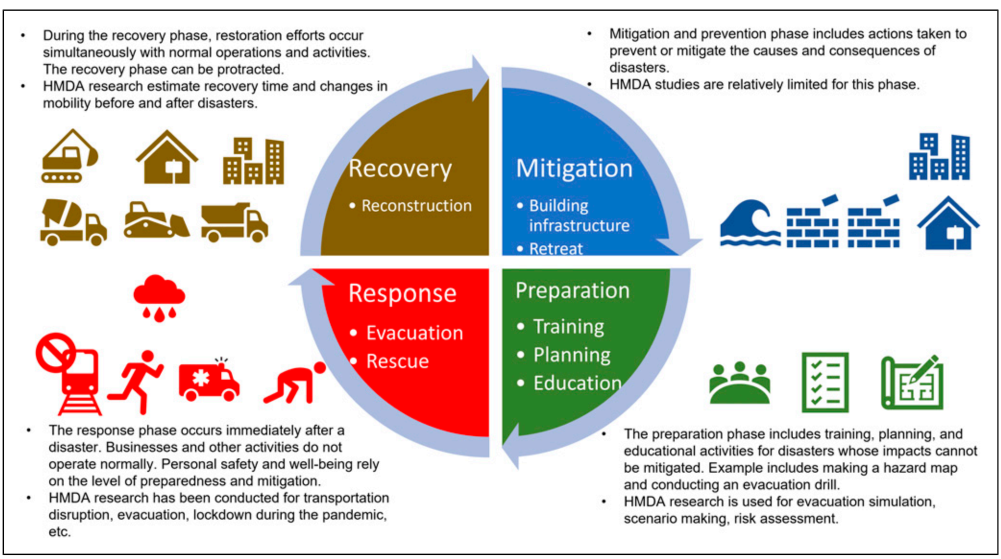

Figure 3. HMDA and DRR practice cycles. HMDA can be used to manage disaster risks more appropriately in at least three of these phases: preparation, response, and recovery.

HMDA has also been used to investigate the relationship between human mobility and COVID-19 transmission at various spatial levels, such as globally, nationally, and within a city. Twitter posts with embedded location data are sufficient to analyze mobility during the COVID-19 pandemic quantitatively at global, country, and U.S. state geographical scales (Huang et al., 2020). In addition, in the United States, infection rates were found to be negatively correlated with travel distance and out-of-town travel (Tokey, 2021). However, the relationship between mobility and the COVID-19 transmission differs in the degree of urbanization (Badr and Gardner, 2021; Kishore et al., 2021b; Ramiadantsoa et al., 2021). The relationship primarily holds for more urbanized counties in the case of the United States (Kishore et al., 2021b). The relationship weakens after the early stages of the pandemic because of other interventions, such as masking (Kishore et al., 2021b; Nouvellet et al., 2021). Also, other factors, such as socioeconomic status, influence the changes in cases, along with mobility (Lamb et al., 2021).

Besides the scientific results, HMDA research provides practical recommendations for policy interventions against the COVID-19 pandemic. By analyzing human mobility data, policymakers can detect undocumented infection (Li et al., 2020), uncover locations at risk of infection (Xiao et al., 2021), and identify disease activity changes earlier than traditional epidemiological monitoring (Kogan et al., 2021). In particular, Xiao et al. (2021) used mathematical modeling (the "pedestrian-based epidemic spreading model") to identify the transmission risk of epidemics in indoor places, such as supermarkets and restaurants, during the COVID-19 pandemic and to evaluate the performance of combined non-pharmaceutical interventions of different operational levels. The results showed that a combination of non-pharmaceutical interventions could improve the performance of those interventions if their implementation was well coordinated among decision-makers.

Various researchers have quantified the effects of lockdown on human mobility in Wuhan (Kraemer et al., 2020), Tokyo (Yabe et al., 2020b), Italy (Bonaccorsi et al., 2020), and other countries (Kishore et al., 2021a; Sadowski et al., 2021). Kishore et al. (2021a) used Facebook data to analyze how human mobility changes affect the spread of COVID-19 in several countries, including India, France, Spain, Bangladesh, and the United States. They found that mobility surges several days before lockdowns, possibly due to panic buying and people moving from urban to rural areas. Their study showed that rapid implementation and public messaging are necessary to reduce social disorder and export cases from an infection epicenter after lockdown announcements. In addition, to identify the most effective activities or locations for human mobility restrictions during COVID-19, Sadowski et al. (2021) analyzed mobility in 137 countries and 50 U.S. states and found that retail and recreation areas, transit stations, and workplaces are the areas where lockdowns can most significantly reduce the number of cases. This finding shows that governments can utilize HMDA to identify activities to prioritize. Furthermore, using Facebook data, Bonaccorsi et al. (2020) evaluated the effects of a lockdown on the Italian economy and social activities during COVID-19. The two main findings of their research were that (1) mobility reduction induced by lockdown is more substantial for municipalities with higher fiscal capacities and (2) the contraction in mobility (reduction in connectivity) is higher for municipalities with lower per capita income and for those with higher inequality. They concluded that without targeted lines of intervention, lockdowns would most likely increase poverty and inequality. Thus, understanding human mobility during disasters will help policymakers support vulnerable social groups.

The COVID-19 pandemic has made public health officials realize that digital technologies related to HMDA are instrumental in predicting the spatial and temporal risks of infection. Simultaneously, the pandemic has raised ethical and legal challenges to these technologies (Kishore et al., 2020). Cattuto and Spina (2020) used a contact-tracing app for COVID-19 to assess the ethical, social, and legal challenges in institutionalizing digital public health. They argued that the current pandemic has accelerated the institutionalization of digital tools for public health and highlighted current gaps in the public governance system. Given the global nature of pandemics, it is critical to reach a consensus on creating a framework for using digital tools and global collaboration.

Challenges

Our review of 124 HMDA-focused publications shows clear promise for advancing DRR research and application. However, these emerging data sources and techniques have limitations.

Extrapolation of specific case studies and models

Many HMDA studies have been based on particular disasters in specific locations, such as Hurricane Sandy in New York (Rahimi-Golkhandan et al., 2021), the Great East Japan Earthquake in Japan (Song et al., 2014), and Hurricane Maria in Haiti (Bengtsson et al., 2011; Lu et al., 2012), among others. These methodologies have been well developed to understand and simulate human mobility in specific cases, but it is also necessary to develop a means of extrapolating human mobility models for use in different disasters, hazards, and locations (Song et al., 2014). For instance, many researchers using mobile phones to collect mobility data collect as much data as they can. However, a model or method generated using lots of data may be less reliable in areas in which mobile phone use, mobile tower density, or mobile radio coverage are lower (Bengtsson et al., 2011).

User representativeness and demographic context

Although HMDA studies can estimate human mobility quantitatively, human mobility data sources can be biased. First, mobile phone and social media users may not represent the entire population in a study area (Karami et al., 2021; Rahimi-Golkhandan et al., 2021). For instance, data from SafeGraph, a company that collects anonymized location data, were collected from approximately 10% of all smartphones in the United States (Yabe et al., 2021b). In addition, mobile phone usage is lower in certain populations such as children, the elderly, the poor, and women (Bengtsson et al., 2011). Mobile phone users, especially those utilizing GPS services and social media, tend to be younger (Bengtsson et al., 2011; Song et al., 2016). During extreme heat events in Phoenix, Arizona, Longo et al. (2017) found that homeless research participants who did not have access to digital devices responded to the heat event differently than those with access to such devices. Therefore, when underrepresented groups exhibit mobility patterns distinct from those of mobile phone users, research results relying solely on mobile phone data are biased (Bengtsson et al., 2011; Liu et al., 2021).

Second, HMDA is applied spatiotemporally to reveal urban dynamics, yet it is limited in understanding the demographic context (Ilieva and McPhearson, 2018). Methodological challenges also exist in estimating the demographic information of social media users. For example, although the demographic information of Twitter users is unavailable, human mobility by age cohort was estimated after Hurricane Maria using Twitter data (Martín et al., 2020b). DRR-related laws and initiatives have identified vulnerable social groups to prioritize their protection. DRR planning must be conducted considering the differences among vulnerable groups attributed to various disparities, such as gender, income, and social isolation. To address these limitations, other data sources such as population-based studies are needed (Bengtsson et al., 2011).

Privacy

Because location data contain sensitive private information, their use for DDR may raise concerns about privacy issues (Kounadi et al., 2018), particularly in developing countries (Taylor, 2016), introducing issues for research reproducibility and replicability (Tullis and Kar, 2021). Several anonymization technologies have been developed for location data. For social media data, for example, a novel model outlining the relationships between privacy and security threats in the smart city context was proposed to protect social media users (Moustaka et al., 2019). For trajectory data, Zhao et al. (2020) proposed a method that can reduce the risk of personal privacy violations using multiple trajectory data histories from one user.

Preparation is vital to ensure the rapid implementation of human mobility analysis in response to future mega-disasters while ensuring privacy. To do so, building a partnership with mobile phone companies before a disaster occurs is recommended (Bengtsson et al., 2011; Ramiadantsoa et al., 2021). Similarly, probe car data must be collected and published through collaboration among automobile companies and car navigation system manufacturers (Hada et al., 2009). One of the challenges in handling probe car data is developing a standard data format that can be used by each company. To address this challenge, a new data format developed by Google, called general transit feed specification, has been applied extensively to public transportation location data (Prommaharaj et al., 2020).

Limited temporal and spatial scales

The limited temporal and spatial scales of human mobility data are additional potential sources of uncertainty in HMDA research. Several scholars have highlighted the significance of increasing the temporal and spatial resolutions of data. For instance, Lu et al. (2012) noted a limitation in terms of the frequency of data updates, stating that their dataset was updated daily for one location. Later, Wang and Taylor (2018) argued that the diverse geographic scales of different hazards may lead to different effects on sentiment levels and human mobility patterns. To estimate the differences in population distribution between daytime and nighttime, the availability of finer-scale commuting data would reduce uncertainties in the daytime scenario (Freire and Aubrecht, 2012). Data for analyzing human mobility in weekly and seasonal cycles are also required because these cycles affect population distributions in urban areas (Freire and Aubrecht, 2012).

Furthermore, the analysis of human mobility during normal times, such as when estimating a primary residence (e.g., schools, offices, and homes), would enhance the predictability of human mobility during disasters. During disasters, people tend to travel to locations where they have social ties and bonds (Lu et al., 2012; Yabe et al., 2021b). For example, Lu et al. (2012) found that the destinations of people that moved from the epicenter after the Haiti earthquake in 2012 were highly correlated with their mobility patterns during normal times, specifically with the locations where people had significant social bonds. This means that the analysis of people's movement during normal times would improve the predictability of movement during disasters (e.g., social bonds can be detected by the analysis of movement during holiday seasons).

Lack of evidence-based planning and framing for long-term planning

Few studies have examined how to utilize HMDA research for DRR policy and planning. Digital transformation of human mobility data has the potential to revolutionize DRR research and practice in at least three ways through its effects on real-time management, evidence-based planning, and long-term planning (Engin et al., 2020). Whereas real-time monitoring and management are relatively well studied for various types of hazards and temporal and spatial scales (see the section Limited Temporal and Spatial Scales), studies on decision-making based on evidence from HMDA and framing for long-term planning are still lacking. Furthermore, among the four DRR phases (discussed in the sections Combatting Infectious Diseases and the COVID-19 Pandemic and Mitigation and Prevention Phase), the mitigation and prevention phase is still under-explored by HMDA scholars. For example, future research can address how human mobility prediction can be used to store emergency goods and maintain backup plans for lifelines in preparation for disasters.

Robustness of urban infrastructure

The robustness of urban telecommunication infrastructure affects the quality of HMDA research. In general, mobile phone networks are more resilient to disasters than other lifeline systems (Bengtsson et al., 2011). However, large-scale disasters may interrupt the power supply and destroy mobile towers, resulting in a complete loss of functionality of mobile phone networks (Bengtsson et al., 2011). Limited access to mobile phones may also cause data bias (Bengtsson et al., 2011). As advanced urban infrastructure is interconnected and dependent on electricity grids (Haraguchi and Kim, 2016; Haraguchi et al., 2016), the robustness of telecommunication networks also depends on electricity grids and other lifeline infrastructure.

Future directions

Our review of 122 HMDA-related studies shows that scholars in emerging HMDA research are in accord. Advances in methodology and data collection are crucial for overcoming the current limitations of HMDA. Although it is important to understand existing HMDA research techniques and develop new ones, the potential of HMDA should not be overestimated. Nevertheless, there are significant opportunities to utilize HMDA in DRR planning and practice to increase urban resilience. Considerable work remains to be conducted to address the existing challenges that face HMDA and to make the emerging field more accessible to a wide range of research needs (see Table 4 for future research questions). This review indicates that the use of HMDA for DRR in cities is still largely limited to the fields of computer science, civil engineering, and information technology. The fields of urban planning and policymaking have yet to embrace the potential of HMDA. Therefore, we suggest the following future directions for HMDA research on DRR.

Vulnerability analysis

In existing studies, human mobility analysis has been combined with hazard analysis, such as that of earthquakes (Freire and Aubrecht, 2012) and floods (Yabe et al., 2018), resulting in measurement of the exposure of human mobility to natural hazards. However, the relationship between human mobility and vulnerability to disasters remains to be investigated thoroughly. Understanding human mobility among vulnerable populations is an additional area in which HMDA can provide innovative and vital opportunities. As pioneers, Yabe and Ukkusuri (2020) studied income inequality in evacuation behavior during Hurricane Irma in Florida, whereas Yabe et al. (2021b) explored the links between physical infrastructure (as an exposure factor) and socioeconomic systems (as a vulnerability factor). Deng et al. (2021) used high-resolution human mobility data to reveal racial and wealth disparities during Hurricane Harvey. Further research can build on these studies to analyze other socioeconomic characteristics (e.g., ethnicity, age, disability status, and immigration status) for other DRR phases. DRR researchers and practitioners have attempted to reduce the effects of disasters on vulnerable populations and to incorporate vulnerability aspects fully into

Table 4. Future research questions related to big data and human mobility during disasters.

Research topics	Future research questions	Sources
Vulnerability analysis and impact assessment	- How can vulnerability aspects be investigated in HMDA studies? - What are the relationships between business performance and customer visits after disasters?	Yabe et al. (2020c)
SNS data and analytical techniques	- How can tweets in languages other than English be analyzed? - How can a disaster-specific lexicon generated using social media be developed to classify tweets based on disaster psychology?	Wang and Taylor (2018)
Analytical techniques	- How can a model developed for a specific population, place, or disaster event be extrapolated to predict human mobility in a different case?	Song et al. (2014)
Data integration	- How can different types of data, such as mobile phone and survey data, be coupled? - How can bias in population estimation be removed?	Yabe et al. (2020c); Song et al. (2016); Rahimi-Golkhandan et al. (2021)
Smooth connection with decision-making, evidence-based planning, and long-term city design	- How can HMDA be used to make city disaster planning more evidence-based? - How can HMDA be utilized to fill in the gaps between resource supply and demand during disasters? - In which fields is HMDA most valuable for city planners to formulate long-term city designs?	The authors referring to Engin et al. (2020)

emergency response, planning, and long-term policymaking. Despite their efforts to conduct post-disaster surveys, fully accounting for the impacts on fragile populations and vulnerability reduction has been hampered by the shortage of temporarily and spatially comprehensive data on the mobility of vulnerable populations. Studies on the relationship between human mobility and vulnerability will enhance the quality of data-driven DRR (Freire and Aubrecht, 2012).

Mitigation and prevention phase

More research on HMDA is required for the mitigation and prevention phase of the disaster management cycle. As discussed in the section Combatting Infectious Diseases and the COVID-19 Pandemic and presented in Figure 3, many HMDA studies have been conducted on the preparation, response, and recovery phases. However, effective HMDA research and practice are lacking in the mitigation and prevention stage, which is partly because of the lack of partnership between HMDA researchers and stakeholders.

In practice, the HMDA research results can be linked to the implementation of risk mitigation and disaster prevention. For instance, based on the results of HMDA research on temporal changes in human mobility (e.g., seasonally or hourly), urban planners can make multiple evacuation plans, store backup generators, or maintain emergency preparedness stockpiles for stranded commuters.

One example is the mitigation of potential damage by developing a simulator using heterogeneous sensors to evaluate the efficiency of mitigation and prevention planning. Higashino et al. (2017) developed a mobile wireless network simulator called MobiREAL that enables real-time crowd control by reproducing the movement of pedestrians at large stations, shopping malls, and underground malls. Cumbane and Gidófalvi (2021) developed a method of estimating the spatial distribution of displaced people by using mobile phone data. As not all displaced people will be in shelters when a disaster strikes, this approach can help governments and humanitarian agencies plan for the optimal allocation of resources, eventually mitigating the potential impacts on vulnerable populations.

Development of analytical techniques for evidence-based DRR planning

Although HMDA is not necessarily a silver bullet for filling gaps in DRR, it has considerable potential to make DRR more evidence-based. To advance solutions to the challenges raised in existing HMDA research, scholars must develop analytical methods to couple human mobility data from mobile devices with other data sources in future studies and bring HMDA into wider use in DRR. Further, the use of HMDA for evidence-based DRR planning and policymaking must be investigated. The research tactics and techniques in these areas will solve long-standing problems in DRR planning, such as gaps between resources and needs during disasters, as well as evidenced-based, dynamic disaster planning that differentiates between times (e.g., seasons, times of day, and days of the week) and locations. For example, developing a technique to analyze the content and sentiment of social media in the specific context of disasters and pandemics is vital. This technique has the potential to fill gaps in the needs of evacuees during the response phase. In addition, identifying patterns from multiple disasters is common in the literature; however, extrapolation of discovered patterns to other hazards or geographical locations remains to be studied. Another simulation technique to combine with HMDA research is the digital twin city. A digital twin city is a digital representation of a city, enabling comprehensive data exchange and containing models, simulations, and algorithms describing features and behaviors, including mobility, in the real world city (Papyshev and Yarime, 2021; Dembski et al., 2020). How to relate HMDA research with a digital twin city has not yet been explored.

Integration of multiple data sources

One of the strategies for addressing the HMDA challenges suggested in the current literature is to integrate various sources of human mobility data and combine HMDA with conventional research methods and data, such as surveys, focus groups, or action research methods (Yabe et al., 2020c). Li et al. (2021b) demonstrated the potential of their developed data platform to integrate various types of big data related to human mobility. In addition, Lwin and Sekimoto (2020) utilized trip survey data to validate results using CDR data, whereas others have employed other data sources to validate results or improve analysis. This trend could be reinforced. By using diverse sources of data from mobile devices, biases among estimated populations can be minimized (Song et al., 2016), and new insights into vulnerability, such as residential status, can be revealed (Martín et al., 2020a). In this sense, different data types must be integrated into analyses to increase the representativeness of human mobility estimates. Flexibly designing a tool and method to include additional data, such as detailed transportation and weather data, would provide another advantage to users (Ilbeigi, 2019; Wang et al., 2017).

Associations with decision-making and long-term planning

This review reveals that few scholars have developed decision-making frameworks that use HMDA for evidence-based urban planning and DRR. Although some researchers have explored resilient transportation planning using HMDA (e.g., Rahimi-Golkhandan et al., 2021) and developed a GIS-based tool with CDR data for end-users (e.g., Lwin et al., 2018a), HMDA remains a relatively unfamiliar area in urban planning and disaster planning. As an exception, Yabe et al. (2021a) discovered that information from non-public-agency accounts had more substantial effects than that from public-agency accounts on the decision-making of affected people during Hurricane Sandy, concluding that government agencies must develop better communication strategies to make long-term plans. They associated HMDA research results with the long-term communication strategies of public agencies during emergencies. Developing such a decision-making framework with HMDA is vital for urban planners to formulate disaster preparedness plans and to develop city infrastructures in the long term.

Gaps in the connections between HMDA and practices (e.g., policymaking and DRR planning) can be filled by conducting transdisciplinary research. The foundation of transdisciplinary research is the mutual learning of scientists and individuals in society, including policymakers and other societal stakeholders (Scholz and Steiner, 2015a, 2015b). One type of transdisciplinary research, defined as “Mode 2,” has the objective of creating sustainable knowledge and action for system transition (Rigolot, 2020; Scholz and Steiner, 2015b). When transdisciplinary research emphasizes the creation of knowledge, it is sometimes called knowledge co-production (Caniglia et al., 2021; Chambers et al., 2021; Mach et al., 2020). Through knowledge co-production and transdisciplinary research processes, scholars work together with diverse stakeholders to create transformative changes toward shared goals (Caniglia et al., 2021). In the field of sustainability, co-production and transdisciplinarity have been increasingly practiced and examined (Chambers et al., 2021). Similarly, in the field of urban resilience, future scholars should perform transdisciplinary research by collaborating with stakeholders to use HMDA to transform urban systems into more resilient ones.

Conclusions

The promise of HMDA in addressing complex urban resilience challenges is compelling. This paper presented a systematic review of human mobility research with the objective of providing a holistic view of the ever-increasing number of research studies in the field of HMDA. The opportunities and challenges provided by new sources of human mobility data and analytical techniques are only beginning to be explored. The potential areas of application are wide-ranging, from real-time emergency response, effective impact and risk assessment, and data-driven scenario making to transdisciplinary collaboration between researchers and practitioners. However, the occurrence of catastrophic disaster events and the complexity of new data and urban systems foil attempts to conduct systematic HMDA research. This review revealed that HMDA has the potential to transform DRR to increase urban resilience. In particular, if demographic contexts are analyzed in HMDA research, the understanding of vulnerable populations during disasters will be enhanced. In addition, this paper recommends that the results of HMDA research should be more closely linked to practices, particularly in the mitigation and prevention phase, using transdisciplinary and knowledge co-production approaches. By doing so, with HMDA, practitioners can incorporate human behavior into real-time emergency response, achieve evidence-based policymaking, and design long-term plans to increase urban resilience.

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Supplemental material

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