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Measuring Chinese mobility behaviour during COVID-19 using geotagged social media data

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COVID-19 caused widespread disruption to normal lives and human activities. In China, the mobility behaviour response to the COVID-19 pandemic at the intra-city and population group levels is largely unknown, mainly due to a lack of individual-level publicly available mobility data. Using 210 million geotagged posts from 10 million social media users, the study quantified the changes in stay-at-home and outings across amenities and groups in China during the pandemic. The users were compared to national census data to examine their representativeness. To validate the results externally, the geotagged data was performed post-stratified correction and further comparison with commonly used data sources. The findings reveal that (i) there was between 16.8% and 57.7% decrease in visits to places of work, retail and recreation sites, parks, transit stations, grocery stores, and pharmacies within one month of the outbreak; (ii) those who are young, have a bachelor's degree or higher, and are unmarried experienced a greater decline in outings; (iii) people preferred to visit nearby locations, resulting in a 4.3% increase in visits to retail and recreational sites within a 3-kilometer radius of their homes. The data and findings could gain insight into the asymmetric impact of the pandemic on public infrastructure use and socio-demographic groups, helping design targeted policies to promote outdoor activities, stimulate economic recovery, and alleviate social inequality in vulnerable groups.

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Introduction

Human mobility describes the spatial and temporal characteristics of people's movement behaviour (Schläpfer et al. 2021). People go out for different purposes, such as commuting, shopping, and travelling (Di Clemente et al. 2018); and population groups from diverse socioeconomic backgrounds exhibit varying patterns of outdoor activities (Pullano et al. 2020; Liu et al. 2021). To better improve urban planning (Xu et al. 2018) and monitor public health (Fox et al. 2022), research into modelling human mobility has sprung up in recent years, aiming to capture people's behavioural interaction with the urban functional spaces by analysing purposes, destinations, and transportation modes of their movements (Zhu et al. 2022; Nilforoshan et al. 2023).

The outbreak of the COVID-19 pandemic caused widespread disruptions to public health system (Chirwa et al. 2023), economic system (Kartal et al. 2021b) and human mobility (Badr et al. 2020). To contain the spread of the virus, governments worldwide have implemented a wide range of non-pharmaceutical interventions to restrict travel (Chinazzi et al. 2020) and minimize physical contact (Wellenius et al. 2021). These measures shaped structural changes in human movement networks (Schlosser et al. 2020) while leaving long-term effects on people's daily routines (Lucchini et al. 2021). As observed from intra-city, normal lives and social activities were disrupted (Hunter et al. 2021), resulting in a completely different trend in public amenities use as compared to the pre-pandemic period (Kartal et al. 2021a; Sevtsuk et al. 2021). From an individual perspective, existing studies have documented striking discrepancies in mobility patterns across partisanship (Clinton et al. 2021), income (Weill et al. 2020), and demographics (Dueñas et al. 2021). Scholars have long emphasized the importance of describing human mobility within cities and across amenities (Sevtsuk et al. 2021) in understanding residents' engagement with urban spaces and adaptation to mobility restriction policies (Zhou et al. 2020). Moreover, tracking human mobility at the individual instead of population level grants us more knowledge to model disease transmission dynamics (Nouvellet et al. 2021), guide tailored public health policymaking (Bollyky et al. 2023), and evaluate socio-demographic burdens brought on by the pandemic (Mena et al. 2021).

In China, people's mobility experienced dramatic changes in the early days of the COVID-19 outbreak (Tan et al. 2021). In response to the pandemic, the government imposed city-wide lockdowns in Wuhan in early 2020 (Pan et al. 2020), nearly one-third of Chinese cities have been under strict control since then. Scholars found a substantial decline in cross-city movements since the nationwide lockdown (Lu et al. 2021) was implemented, followed by remarkable changes in population flow structure (Wei and Wang 2020) and mobility network dynamics (Tan et al. 2021). For individuals under social-distancing policies and stay-at-home orders, most of their physical contact occurred with household members during the outbreak (Zhang et al. 2021). Those findings are particularly valuable for identifying chains of pathogen transmission, modelling infectious disease dynamics, and predicting spillover risks of future epidemic outbreaks (Wu et al. 2020; Jia et al. 2020).

However, research on Chinese mobility behaviour during the COVID-19 pandemic encountered several problems concerning data sources. Globally, the Google Community Mobility Report (GCMR) provides percentage changes in place visit frequencies in six types of locations to help understand people's social activities within cities, but this dataset does not include mainland China (Hu et al. 2021). The understanding of Chinese human mobility changes during the crisis was mainly derived from city-aggregated data such as the Baidu Qianxi index (Liu et al. 2022). The publicly available mobility data accounting for intra-city movements and individual heterogeneity is still lacking (Hu et al. 2021), making it difficult to describe the interaction patterns between individuals and urban spaces. It is still unclear if population groups that exhibited more divergent behavioural patterns than usual during the pandemic have been disproportionately affected.

The study proposes a framework for analysing intra-city and group-level human mobility behaviours using massive geotagged social media data to fill current research gaps. Using over 210 million geotagged posts between 2019 and 2020 from 10 million users on Weibo, the Twitter equivalent in China, the study analysed how Chinese people changed their mobility behaviour across amenities and groups. To demonstrate the ability of geotagged data to capture large-scale human mobility behaviour (Li et al. 2021), the study examined the representativeness of users by comparing their spatial distribution and demographic structure to the entire population derived from the national census. To validate the results externally, the study corrected the geotagged data using a post-stratification method and then compared them with Baidu Qianxi data regarding city movement intensity (Huang et al. 2021). The results show that geotagged social media derived from the Weibo platform is representative and reliable to a certain extent.

In detail, the study first categorized the Point-of-Interest (POI) attached to geotagged posts into six types of places (*Residential*, *Workplaces*, *Retail & recreation*, *Parks*, *Transit stations*, and *Grocery & pharmacy*), referring to the taxonomy of GCMR (https://www.google.com/covid19/mobility/). Next, the geotagged posts were aggregated by the category of POIs to calculate the percentage change in daily check-ins in 2020 compared to the baseline in 2019. The resulting time-series metrics describe changes in the number of visits to six categories of places during the pandemic. Specifically, the study aimed to determine if distinct behaviour responses were observed in various socio-demographic groups, including age, gender, educational level, and marital status, which is lacking in GCMR. Finally, people's mobility adaptation behaviour to public health emergencies was revealed by summarizing their visit diversity and travel distance shifts to different amenities.

The results show that people dramatically reduced their visits to places of work, transit stations, and retail and recreational sites in February 2020 following the COVID-19 outbreak, ranging from 43.5% to 57.7%. When considering socio-demographic groups, younger, higher educated, and unmarried people experienced more reduction in outings. At the city level, 81.1% of cities saw an increase in visits to places of residence after the outbreak. Under the restriction policies, people have adapted their mobility behaviour by accessing fewer distinct places and visiting parks, retail, and recreational sites within shorter distances.

In summary, the study proposes a framework for analysing large-scale human mobility behaviour based on massive geotagged social media data and demonstrates its generalisability. These findings offer insight into population mobility dynamics inside the city and across population groups in China during the COVID-19 pandemic. The data could supplement the available city-level mobility metrics and fill the gap in GCMR in mainland China. With this prior knowledge, governments can formulate policies for economic recovery (Eyre et al. 2020), provide post-epidemic assistance to specific groups in need (Bonaccorsi et al. 2020), and be well-prepared for the next global emergency (Sirota et al. 2023).

The rest of the study is organized as follows. Section 2 introduces the data sources, ways of mobility index construction, and validation methods. Section 3 presents the empirical results of

data validation and mobility behaviour patterns. Section 4 discusses the values, limitations, and policy implications of this study. Finally, Section 5 concludes.

Methods

Geotagged Weibo data. The study collected 210 million geotagged posts uploaded by 10 million Weibo users from 2019 to 2020. Weibo, the Chinese version of Twitter, is the most widely used social media platform in China, with 582 million active users in the second quarter of 2022 (41% penetration of the China population, available at http://ir.weibo.com/news-releases/news-release-details/weibo-reports-second-quarter-2022-unaudited-financial-results/). The Weibo social media platform allows users to share their geographical location by posting POIs. Specific POIs can be used to determine the detailed address and geographical coordinates of the sites visited by users. Additionally, information about users' gender, age, educational level, and marital status was collected from their self-declared profiles. All individual data used in this study were anonymized and aggregated to protect privacy.

Referring to the taxonomy of GCMR (https://support.google.com/covid19-mobility/answer/9824897?ref_topic=9822927), the POIs were then grouped into six categories (*Residential, Workplaces, Retail & recreation, Parks, Transit stations,* and *Grocery & pharmacy*) based on their social attributes. In the GCMR, places with similar characteristics are grouped into categories for social distancing guidance. Fig. 1 shows the spatial and statistical distributions of categorized geotagged posts. The spatial distribution of geotagged posts was found to be uneven, with most of them concentrated in densely populated areas. When zooming into Beijing's central area, geotagged posts were spatially clustered in the urban core area. In the statistical summary, the number of POIs decreased with the increase in their posts except for places of residence.

Weibo mobility index. Based on the geotagged data, the study calculated the percentage change in the number of visits to six categories of places as the Weibo mobility index. The geotagged posts were first aggregated to calculate the daily visits to six categories of visits between 2019 and 2020. To accommodate human activities' weekly periodicity, the study implemented a 7-day moving average for daily visits to six categories of places. Then, the study calculated the percentage change for each day by comparing it to a pre-pandemic baseline value for that same day of the week estimated over the second half of 2019. Compared to the baseline period of GCMR (from January 3 to February 6, 2020), this study's pre-defined baseline period covered longer and excluded the Spring Festival. This minimized the impacts of random swings in social media data and massive population movements on public holidays.

Data validation. Given the inherent bias of population structure in social media data (Jiang et al. 2019), the study tested whether the 10 million users from Weibo could represent the entire population in terms of geographical distribution and demographic characteristics. Taking the number of resident populations from the *China Population Census Yearbook 2020* (https://www.stats.gov.cn/sj/tjgb/rkpcgb/qgrkpcgb/202302/t20230206_1902003.html) as a benchmark, the study calculated the correlation between the proportion of residents in each province-level region to the total population and the proportion of users in each province-level region to the total users. Furthermore, the study compared the age and gender structure of Weibo users with that of the entire population retrieved from official statistics (http://www.stats.gov.cn/sj/ndsj/2021/indexch.htm).

In the next step, the study compared the Weibo mobility data with Baidu Qianxi data to cross-validate and examine whether the mobility index represents the entire population (Huang et al. 2021; Hunter et al. 2021). During the COVID-19 pandemic in China, Baidu Qianxi data was one of the most widely used open mobility data sources (Hu et al. 2021). It provides a city movement intensity (CMI) index indicating the proportion of people travelling within cities from January to April 2020. To obtain a comparable index with Baidu Qianxi CMI, the study calculated the proportion of users who had visited non-residential places (including *Workplaces, Retail & recreation, Parks, Transit stations,* and *Grocery & pharmacy*) in cities on a certain day as Weibo CMI index. Then, the study normalized these two CMI indexes and aggregated them from the city level to the provincial and national levels, weighed by the actual city residents retrieved from the *China Population Census Yearbook 2020*. Next, the study smoothed them using the 7-day moving average method and calculated percentage change by comparing them to the median value over pre-pandemic periods (January 1 to January 19, 2020). Finally, the study examined their Pearson correlation from January to April 2020. Based on the correlation analysis, the study could infer the reliability of Weibo mobility data by testing whether these two indexes followed similar temporal trends.

To understand the effects of varying sampling rates across gender and age groups on the cross-validation results, the study further employed the post-stratification method on Weibo mobility data. Post-stratification is a common technique in survey statistics for handling sampling biases. It aims to improve sample representativeness by adjusting the weights of under-sampled and oversampled population groups (Kulas et al. 2018). Following the previous method proposed by (Battaglia et al. 2009), the study denoted ω_{gr} as the post-stratification weight for group g in administrative unit r, which is computed as

$$\omega_{gr} = \sqrt{\frac{u_{gr}}{c_{gr}}} \qquad (1)$$

where μ_{gr} is the proportion of users in group g in administrative unit r, and c_{gr} is the proportion of residents in group g in administrative unit r retrieved from the *China Statistical Yearbook 2021* (https://www.stats.gov.cn/sj/ndsj/2021/indexch.htm). The square root calculation is trimming for post-stratification weight to avoid extreme weights and increasing variance. Based on the post-stratification weight ω_{gr}, the study could correct the number of users who visited place α at day i, which is calculated as

$$\widehat{N_{g\alpha i}} = \omega_{gr} N_{g\alpha i} \qquad (2)$$

where place α is in administrative unit r, N_{gai} is the number of users in group g who visited to place α at day i.

Using the corrected number of users, the study recomputed the CMI index at the province level from Weibo mobility data and performed a Pearson correlation analysis between it and the CMI index from Baidu Qianxi data. Comparing the cross-validation result derived from raw Weibo data and post-stratified Weibo data, the study examined the robustness of the cross-validation result.

Empirical results

Weibo mobility index. Figure 2a–f shows percentage changes in the number of visits across six categories in 2020 compared to the 2019 baseline. In the month following the government's announcement of human-to-human transmission of COVID-19 on January 20, 2020, there was a decrease in visits to places of non-residence compared to the 2019 baseline. Specifically, there was a 45.5% reduction in visits to workplaces, a 57.7% reduction
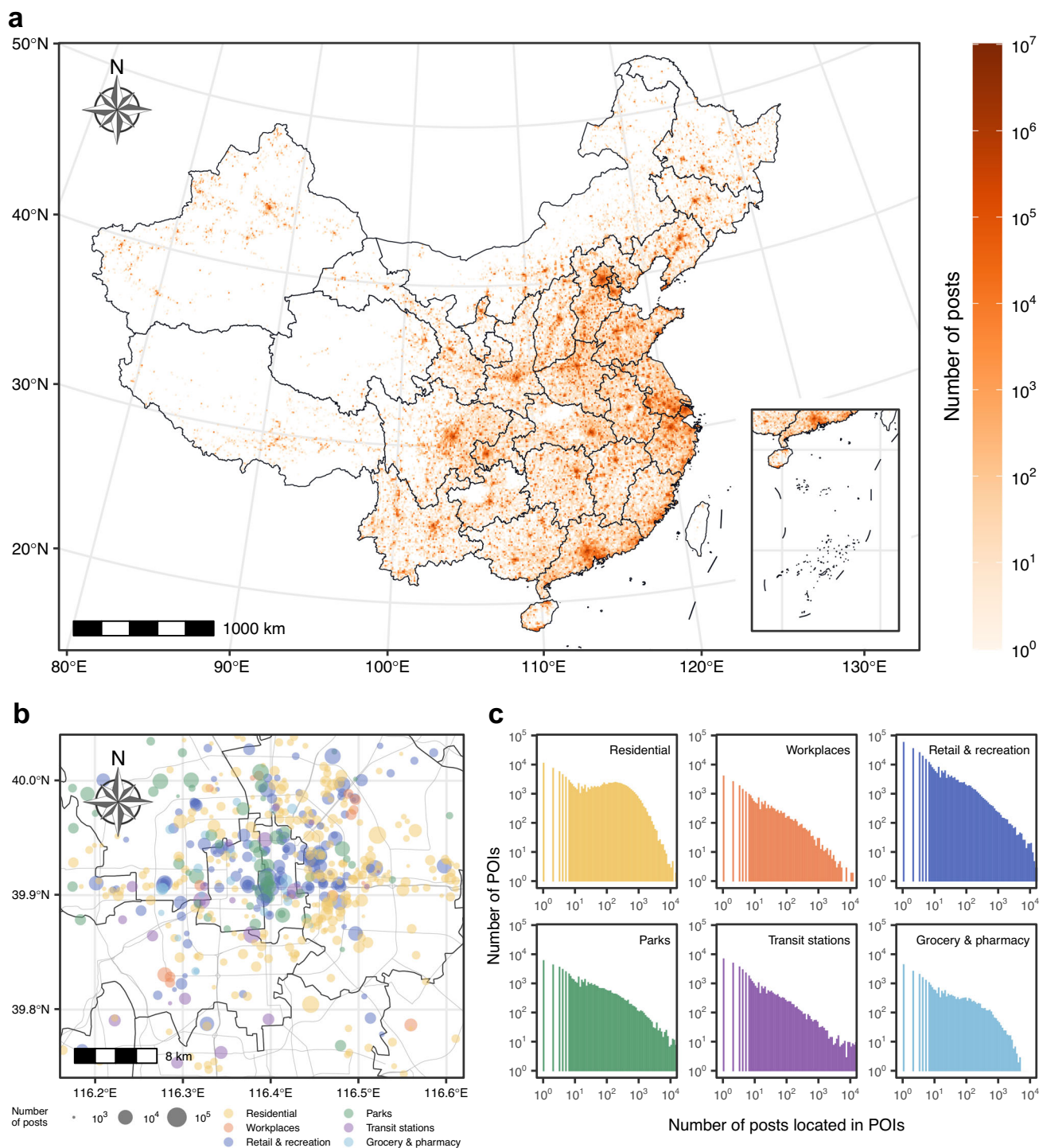
Fig. 1 Description of geotagged Weibo data from 2019 to 2020. a The spatial distribution of geotagged posts in China. **b** The spatial distribution of categorized geotagged posts in Beijing. **c** The number of posts located in POIs against the number of POIs.

in visits to retail and recreational sites, a 38.7% reduction in visits to parks, a 43.5% reduction in visits to transit stations, and a 16.8% reduction in visits to grocery stores and pharmacies. In contrast, visits to places of residence increased by 10.7% during the same period. The stay-at-home requirement and social distancing policies partly explained the opposing changes in visits to the residence versus other venues. As the pandemic continued, visits to workplaces, retail and recreational sites, grocery stores and pharmacies returned to baseline quickly in the second quarter of 2020. However, visits to parks and transit stations did

not return to normal until the end of 2020. It is noteworthy that public holidays encouraged outings to retail and recreational sites, parks, and transit stations but discouraged work outside the home.

To understand how people balanced their outdoor activities and stay-at-home choices, the study aggregated five non-residential categories into one category and calculated the corresponding percentage change in the number of visits. Figure 2g shows that people's visits to non-residential places sharply decreased after the announcement of COVID-19 human-to-human transmission,
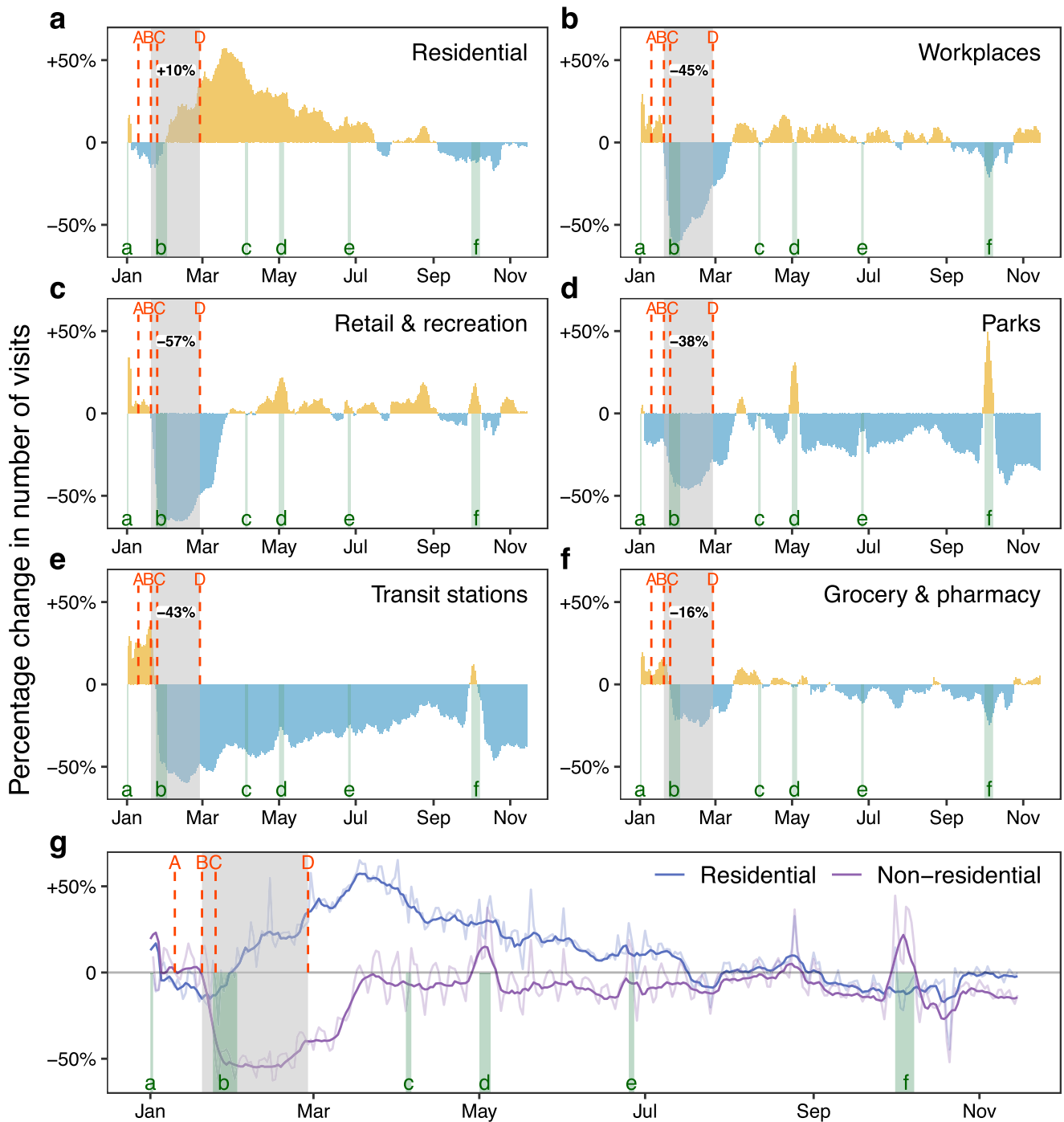
Fig. 2 Percentage change in the number of visits during 2020 in China. a–f Percentage change in visits across six categories of places. **g** Percentage change in visits to residential and non-residential places. Non-residential places include workplaces, retail and recreational sites, parks, transit stations, grocery stores and pharmacies. The temporal trend is the percentage change in visits compared to the baseline. The baseline represents a normal value for that day of the week and is the median value throughout the second half of 2019. The shaded area in grey highlights the one month after the national announcement of COVID-19 human-to-human transmission. Increases and decreases in percentage change are coloured in orange and blue, respectively. The red dotted line notes the announcements related to public health. The green-shaded area highlights public holidays.
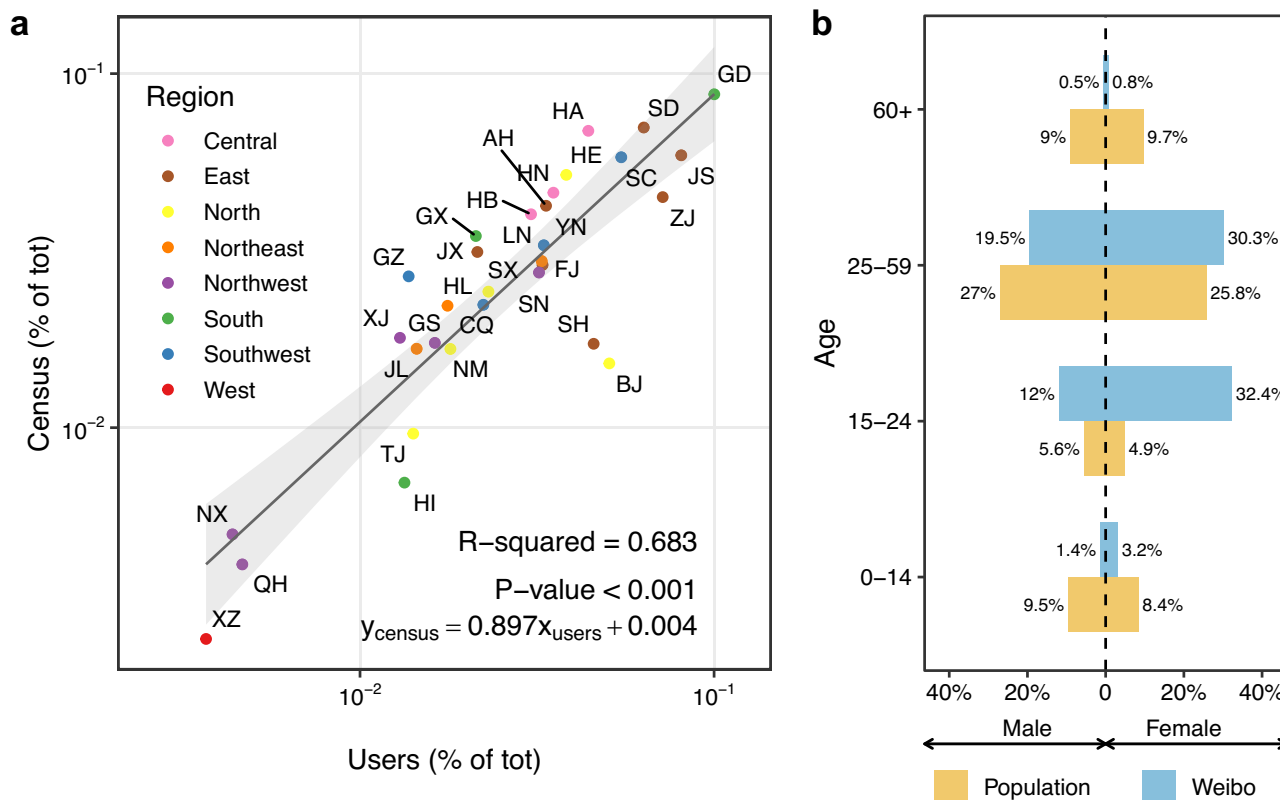
Fig. 3 Test the representativeness of users. a Linear correlation analysis between users and the local population in province-level regions in mainland China. As a fraction of the total, the number of users assigned to each province-level region is against that of the local population. The colour code corresponds to China's eight regions. **b** Age and gender structure of users and the entire population. Notes: AH Anhui, BJ Beijing, CQ Chongqing, FJ Fujian, GD Guangdong, GS Gansu, GX Guangxi, GZ Guizhou, HA Henan, HB Hubei, HE Hebei, HI Hainan, HL Heilongjiang, HN Hunan, JL Jilin, JS Jiangsu, JX Jiangxi, LN Liaoning, NM Inner Mongolia, NX Ningxia, QH Qinghai, SC Sichuan, SD Shandong, SH Shanghai, SN Shaanxi, SX Shanxi, TJ Tianjin, XJ Xinjiang, XZ Tibet, YN Yunnan, ZJ Zhejiang.

reaching a trough of 55.0% below the baseline on February 9, 2020, then gradually recovered in April 2020, which indicates that residents avoid visiting urban amenities in the early stages of interventions. On the contrary, the number of check-ins at residences substantially increased after nationwide emergency responses. It exceeded the baseline starting in February 2020 and lasted until September 2020, which was likely caused by strict stay-at-home orders and the public threat of a virus outbreak.

Data validation. Scholars usually have concerns about how well the social media data are representative of the entire population (Huang et al. 2022). To relieve this concern, the study examined the users' geographical distribution and demographic structure. Fig. 3a shows the correlation between the proportion of users with respect to total users and the proportion of the population with respect to the total population in each province-level region in 2020. The linear regression coefficient of 0.897 ($P < 0.001$) indicated a strong positive association between the number of users and the population in province-level regions. Figure 3b depicts the age and gender structure of users and the entire population in China. It revealed unequally more females than males in the Weibo mobility data. In terms of age groups, populations aged less than 14 or more than 60 are largely underrepresented, while groups aged 15 to 24 are over-represented. The study acknowledged the issue of sampling biases and then implemented a post-stratification experiment to investigate the effects of this gender and age bias on the mobility index.

The study further compared the CMI index derived from Weibo mobility data and Baidu Qianxi data. Fig. 4 shows the CMI index from two data sources and their Pearson correlation for 31 province-level regions in mainland China. There were 21 province-level regions whose Pearson's $_r$ coefficient was greater than 0.8 ($P < 0.001$), indicating that the percentage change in two indices over time in most province-level regions has similar temporal trends.

A post-stratification study was then conducted to examine the robustness of cross-validation. The study corrected the uneven sampling of population groups by employing the post-stratification technique and recalculated the CMI index. Figure 4 shows identical temporal trends between the Weibo CMI index derived from the original and post-stratified data, together with their Pearson correlation with the CMI index from Baidu data. Sixteen province-level regions saw an increase in Pearson's r_c coefficient (ranging from 0.01 to 0.09) after post-stratification compared to that from the original data. Moreover, the results show that Pearson's r_c coefficient increased only slightly on a national scale. Those patterns indicate that sampling bias had a minimal impact on cross-validation results, and the mobility index calculated in this study sufficiently represented the entire population.

Heterogeneity across population groups. Several studies have shown that people's responses to the COVID-19 pandemic varied depending on socioeconomic and demographic factors (Weill et al. 2020; Jay et al. 2020). However, few explored those
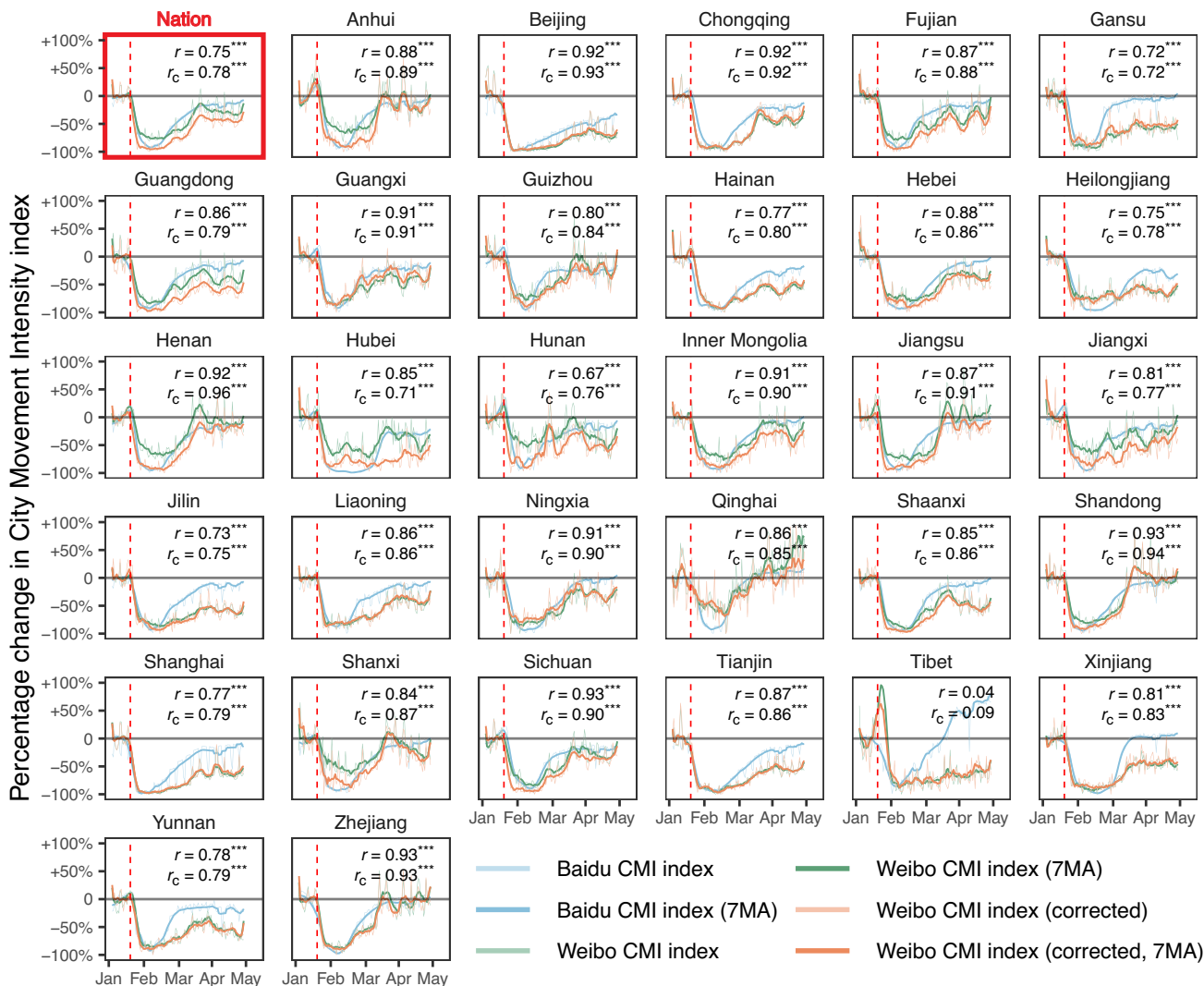
Fig. 4 Pearson correlation analysis between the percentage change in the city movement intensity (CMI) index derived from Weibo mobility data and Baidu Qianxi data. Lines with high transparency depict the original percentage change value, while lines with low transparency depict the smoothed value with a 7-day moving average method. The red vertical dashed line indicates January 20, 2020 (the national announcement of COVID-19 human-to-human transmission). The percentage change is calculated by comparing it to baseline days. The baseline days represent a normal value for that day of the week and are given as the median value over pre-pandemic periods (January 1 to January 19, 2020). r represents the Pearson's correlation coefficient for the percentage change in the CMI index derived from Weibo mobility data and Baidu Qianxi data, while r_c derived from Weibo mobility data corrected by the post-stratification method. ***represents the significance level of $P < 0.001$.

discrepancies in China. Here, the study took advantage of individual profile data to calculate the change in outings and home-dwelling among different population groups. Specifically, the study first categorized users into different groups based on their gender, age, education levels, and marital status, then calculated visits to places of residence and non-residence for each group. Finally, the study computed the percentage change in the number of visits by comparing visits during the pandemic outbreak (the month following January 20, 2020) against visits during the baseline period (the second half of 2019).

Figure 5 illustrates the percentage change in visits among population groups. There are some similarities between males and females in mobility response, while there are more significant differences between other groups. The male and female groups experienced an increase of 13.6% and 9.3% in residential visits and a decrease of 50.9% and 60.4% in non-residential visits compared to the second half of 2019. For the five age groups, the older the age, the fewer reductions in visits to places of non-residence, ranging from 64.6% of the 18–22 age group to 30.6% of

the 36–40 age group. In terms of places of residence, most age groups saw increased visits ranging from 27.4% to 39.2%, except for the 23–25 and 26–30 age groups. For educational levels, those with a bachelor's or higher degree had more visits to places of residence by 12%, while those with a high school diploma decreased by 4.2%. Marital status also affects people's mobility response. Compared with married individuals, single individuals experienced more reductions in visits to places of residence (14.5%) and non-residence (62.7%) after the pandemic outbreak.

Temporal changes in visiting behaviour. People have adapted their mobility behaviour in response to the pandemic outbreak in terms of amenities visits (Sevtsuk et al. 2021), daily movements (Lucchini et al. 2021), and interaction with recreational sites (Yoon et al. 2022). Taking advantage of the precise locations people visited extracted from large-scale check-in data, the study quantified the change in visiting behaviour in response to the COVID-19 outbreak in China.
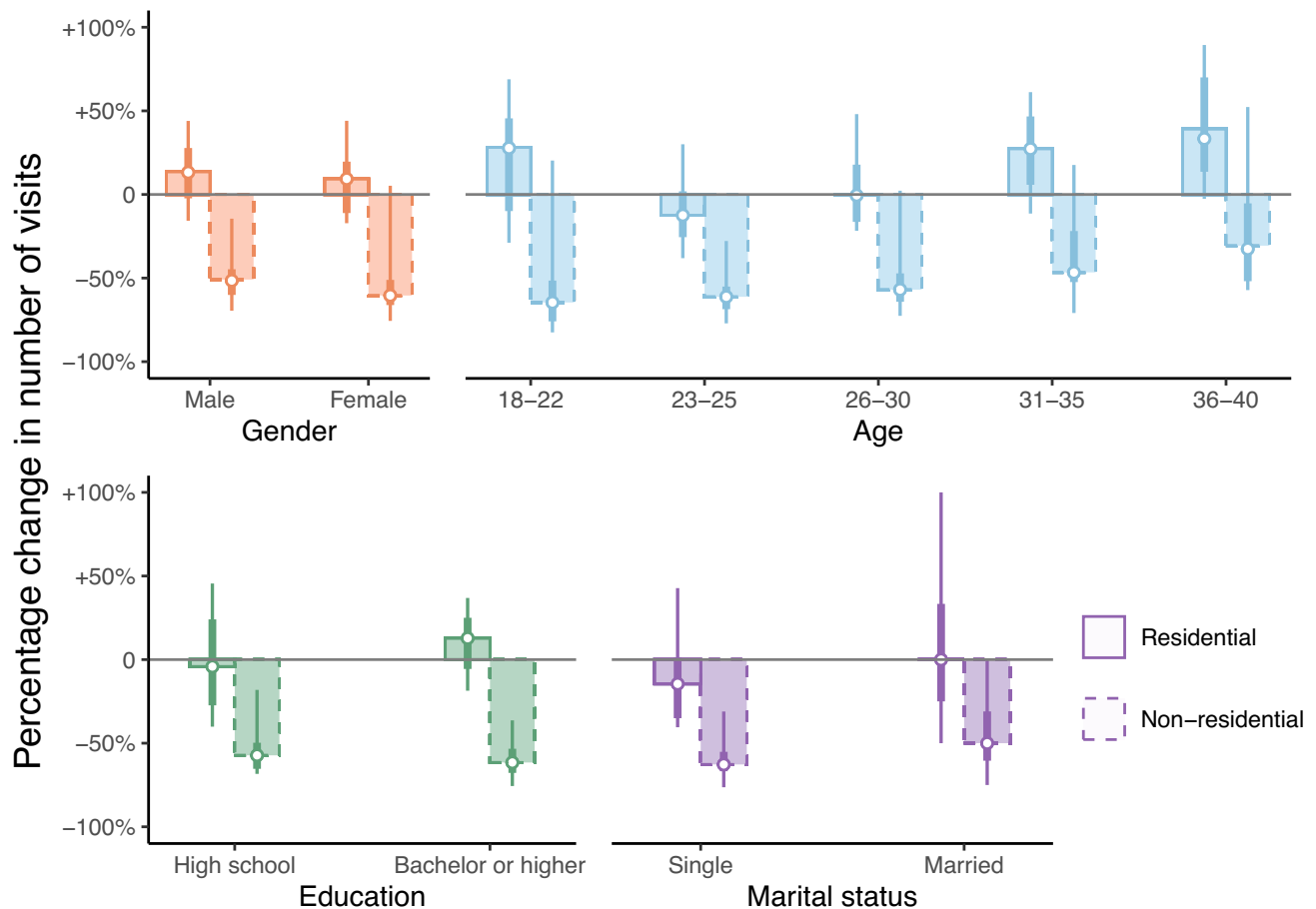
Fig. 5 Percentage change in the number of visits to places of residence and non-residence across population groups. The percentage change in visits is calculated by comparing visits during the pandemic outbreak (the month following January 20, 2020) against visits during the baseline period (the second half of 2019). Line styles indicate places of residence and non-residence, and different groups are represented by colours in bars.

Inspired by the different trends in visits to various amenities (Fig. 2), the study seeks to discover the disparities in mobility change across cities in response to the COVID-19 outbreak in 2020 in China. Here, the study calculated the proportion change in the number of visits to six categories of places between the pandemic outbreak period (the month following January 20, 2020) and the baseline period (the second half of 2019) for each city. The plot displayed in the left panel of Fig. 6a reveals that the median proportion of visits to places of residence across cities increased by 48.0% following the pandemic outbreak. However, all other categories of places experienced a visitation decline. In descending order, the study found the median proportion change in visits to grocery stores and pharmacies decreased by 4.5%, places of work decreased by 15.6%, transit stations decreased by 33.3%, parks decreased by 34.3%, and retail and recreational sites decreased by 52.0%. Most cities (81.1%) saw an increase in the proportion of visits to places of residence during the pandemic outbreak. However, only 4.9% of cities experienced an increase in retail and recreation sites, 9.8% experienced an increase in transit stations, and 15.2% experienced an increase in parks. The right panel of Fig. 6a shows the number of visits across six categories after the pandemic outbreak. It was determined that there is no correlation relationship between the number of visits and the proportional change in visits.

Moreover, to understand the diversity of places people visited during the pandemic, the study calculated the number of distinct POIs visited by users in each city, and then compared it to the baseline period to compute the percentage change. As shown in

Fig. 6b, the median number of non-residential POIs and residential POIs declined from early 2020, with the lowest value in February 2020 (8.9% of non-residential and 4.3% of residential). Since then, the number of residential POIs gradually returned to baseline and maintained a comparable amount as in the pre-pandemic period. However, the number of non-residential POIs did not return to baseline until the end of 2020, and its overall level in 2020 was 3.4% lower than baseline. Notably, the variance in percentage change in POIs among cities in 2020 was more significant than the baseline in 2019.

Mobility distances. In addition to detecting the locations where people visit and the change in visiting frequency, it is important to understand how far people go for outings (Santana et al. 2023). Travel distance is a critical description of human movement (Kraemer et al. 2020), a key component in studying mobility laws (Simini et al. 2021), and a key parameter in modelling infectious disease transmission (Kraemer et al. 2021). Data-driven studies have revealed global human movement characteristics regarding travel distance at the country or regional level (Kraemer et al. 2020). However, it remains unclear how people changed their travel distance to different amenities under lockdown policies. Here, the study calculated the travel distance for visiting six categories of places at the individual level before and after the pandemic outbreak. The study first filtered the most frequently visited residential POIs for users to determine their home location, then computed the haversine distance for each outing using
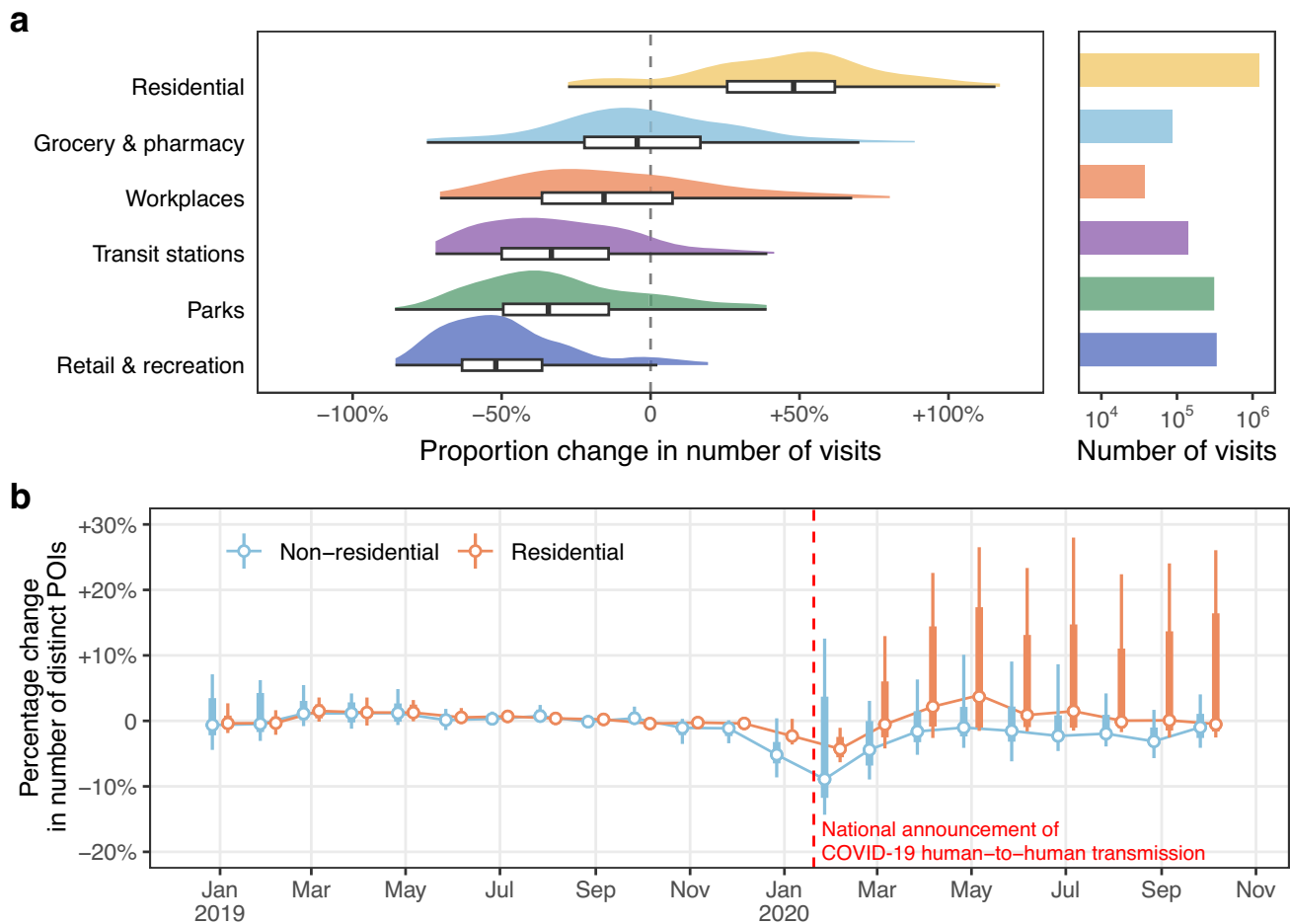
Fig. 6 Temporal change in visiting behaviour. a Proportion change in the number of visits across six categories. The left panel describes the distribution of proportion change in visits during the pandemic outbreak period (the month following January 20, 2020) against the baseline period (the second half of 2019) for cities in China. The right panel describes the number of visits during the pandemic outbreak period. **b** Percentage change in the number of distinct POIs compared to the baseline period. Representative cities with sufficient user samples are displayed.

home and destination coordinates. Moreover, the study calculated the median distance for an individual to visit specific categories of destinations during the baseline and pandemic outbreak period. Finally, the study plotted the density distribution of travel distance for individuals before and after the pandemic outbreak.

Figure 7 partitions the travel range into four segments: under 1.5 km (walkable), 1.5–3 km (nearby), 3–15 km (far), and over 15 km (distant). Most people travelled short distances to all categories of destinations, with around 80% travelling less than 15 kilometres. Overall, people usually took walkable or nearby distances to places of residence (other than home location), grocery stores, and pharmacies. After the COVID-19 outbreak, there was no obvious deviation in the distribution of distance to places of work, grocery stores, and pharmacies for individuals, but 3.0% more people chose to travel within 3 km to places of residence, 4.3% more for retail and recreational sites, and 3.8% more for parks. At the same time, fewer people chose to travel far distances to these places (4.1% fewer for places of residence, 4.5% for retail and recreational sites, and 1.5% for parks). This evidence suggests that people tended to visit places of residence, retail and recreational sites, and parks close to their homes after the outbreak.

Discussion and implications

The COVID-19 pandemic caused widespread disruption to human activities, especially in mobility routines (Lucchini et al.

2021) and the use of public services (Sevtsuk et al. 2021). Utilizing large-scale, aggregated geotagged data collected from Weibo, the study examined how mobility changes in China during the pandemic varied by cities, amenities, and population groups. The data-driven approach revealed that people had 57.7% fewer visits to retail and recreational sites, 45.5% fewer visits to places of work, and 43.5% fewer visits to transit stations, but 10.7% more visits to places of residence compared to the baseline period. By the end of 2020, the number of visits to all categories of places had gradually returned to the baseline except for parks and transit stations. Females, younger, bachelor's or higher degree holders, and unmarried people experienced a greater reduction in visits to places of non-residence following the outbreak. At the city level, 81.1% of cities saw an increase in the proportion of visits to places of residence during the pandemic outbreak. In contrast, over 90% of cities experienced a decline in visits to retail and recreation sites and transit stations. The study also revealed that the total number of distinct non-residential locations people visited in 2020 was 3.4% lower than the baseline. Additionally, people tended to visit nearby places under mobility restriction policies. Trips to retail and recreational sites within 3 km of home increased by 4.3%, and trips to parks increased by 3.8% during the pandemic compared to the baseline.

Previous studies suggested that the population flow at the city level experienced a dramatic change in China during the early stage of the COVID-19 pandemic with backflow variation modes
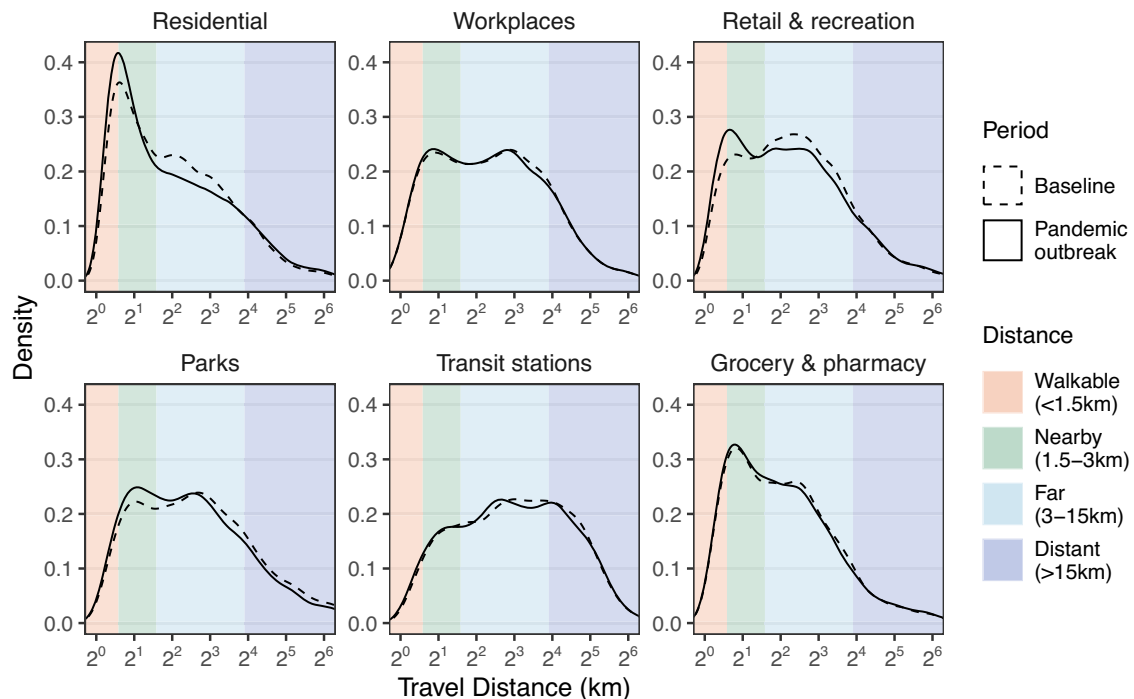
Fig. 7 The distribution of travel distance across six categories of destinations at the individual level. Specifically, the residential category represents residential places other than the user's home. The solid line indicates the baseline period (the second half of 2019), and the dotted line indicates the pandemic outbreak period (the month following January 20, 2020). The background colours indicate different distance partitions.

(Tan et al. 2021) and hierarchical structure generation (Wei and Wang 2020). The results in this study add to this typical evidence by providing quantitative estimates of mobility changes across public amenities. The new detailed mobility patterns uncovered by this study, such as fewer visits to specific non-residential places and shorter distances to retail and recreational sites and parks during the pandemic, extend the existing knowledge of people's mobility behaviour in China. Due to the limited public fine-grained mobility data in China (Hu et al. 2021), the study presents an effective way to monitor and depict mobility changes at intra-city and population group levels from an individual-level perspective. Moreover, the percentage change in the number of visits across six categories of places, calculated at the same steps as the GCMR, could fill the data gap for the Google mobility index in mainland China.

There is evidence from previous influential studies that socioeconomic factors (Liu et al. 2021), demographic factors (Zhang et al. 2023), and other characteristics of populations were associated with their mobility changes during the COVID-19 pandemic. The study highlighted the asymmetric impact of the pandemic on population mobility changes according to socio-demographic factors, providing evidence that the pandemic has exacerbated social inequalities in China. During the past decades of rapid urbanization, China has seen uneven regional development and a dramatic change in its demographic and economic structure (Zhang et al. 2016). The findings uncover the difference in mobility response between regions, which could probably be attributed to factors like the urban environment (Wang et al. 2018), policy stringency (Chirwa et al. 2023), and weather conditions (Liu et al. 2023).

As a result of the COVID-19 pandemic, people's mobility behaviour in China has changed significantly (Tan et al. 2021). This paper analysed how mobility changed in categories of places at the intra-city and population group levels, providing a comprehensive view of mobility behaviour in China during the COVID-19 pandemic. Monitoring how people interact with public amenities and urban space could help governments design policies to promote outgoing activities for economic recovery (Spelta et al. 2020). The study also raised concerns about social inequality related to socio-demographic disparities. The negative financial impact of the pandemic adds to living costs (Depren et al. 2021). Significant effort is needed to sustain vulnerable groups in the post-pandemic period (Yu et al. 2023). Although the pandemic has passed, its impact on human mobility may be long-lasting (Kellermann et al. 2022). Future studies should employ long-term data to track mobility changes in the post-pandemic era.

Conclusion
The COVID-19 pandemic disrupted human mobility behaviour, resulting in significant social (Bonaccorsi et al. 2020), economic (Kartal et al. 2022), and public health (Badr et al. 2020) consequences. There is a limitation in the public individual-level mobility data in China (Hu et al. 2021), leaving key questions unanswered about how people responded to the COVID-19 outbreak at intra-city and population group levels. Here, using 210 geotagged posts from over 10 million social media users, the study quantified changes in visiting across functional amenities and socio-demographic groups. The data-driven approach shows that the pandemic has substantially impacted people's mobility behaviour at nationwide and city scales across all amenities — there was a significant decline in visits to workplaces, retail and recreation sites, parks, transit stations, grocery stores, and pharmacies between 16.8% and 57.7%. Moreover, its impacts vary across genders, ages, educational levels, and marital statuses. The number of visits to places of residence increased in 81.1% of cities following the outbreak. Under strict restrictions, people have adapted their visiting diversity and travel distances. This is probably the first study depicting the diverse mobility response in China during the pandemic from the perspective of amenities, population groups, and cities. These findings could help promote targeted pandemic-exiting policies (Sharma et al. 2021), identify

vulnerable population groups (Bollyky et al. 2023), and guide policy decisions for future global emergencies (Sirota et al. 2023).

Future research should consider using long-term geotagged data spanning from 2019 to 2023 to monitor Chinese mobility behaviour changes before, during, and after the COVID-19 pandemic. Previous research has indicated that the recovery of population mobility behaviour is a slow and fluctuant process (Tang et al. 2023; Liu et al. 2023), tracking this process can provide insight into the recovery status of social activities, commercial consumption, and industrial economies (Eyre et al. 2020; Zhao et al. 2023). In addition, future research could examine mobility behaviour within cities in conjunction with factors such as public health, policy intervention, and socioeconomic conditions. This would explore the correlation or even causal relationship between mobility behaviour and external factors (Pullano et al. 2020; Xing et al. 2021), guiding targeted policies for strengthening mobility resilience and preparing for the next global emergency.

Some limitations remain to be addressed in future research. First, systematic bias in individual factors such as gender and age still exist in mobility data. Geotagged data is limited to users who opted to share their location when posting. They may not be a random selection of the entire population. This problem was recognized, and a post-stratification technique was applied to examine the effects of sampling biases on the results, but other unobserved biases may not have been captured. Second, geotagged posts are unevenly distributed across space and time. Although the geotagged data has been compared with other reliable data sources to evaluate its performance, more techniques should be employed in future studies to minimize this data sparsity issue. Third, some less populated cities or regions may be underrepresented by insufficient check-ins due to uneven spatial distribution of social media users. This can introduce bias in analyses from a national perspective. Other forms of data, such as mobile phone positioning or cellular signalling data (Pandit et al. 2022), should be considered to supplement geotagged social media data in the future.

Data availability

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Author contributions

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Competing interests

The authors declare no competing interests.

Ethical approval

This article does not contain any studies with human participants performed by any of the authors.

Informed consent

This article does not contain any studies with human participants performed by any of the authors.

Additional information

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