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COVID-19 effects on urban driving, walking, and transit usage trends: Evidence from Indian metropolitan cities

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ABSTRACT

The outbreak of the COVID-19 pandemic disrupted all walks of life, including the transportation sector. Fear of the contagion coupled with government regulations to restrict mobility altered the travel behavior of the public. This study proposes integrating freely accessible aggregate mobility datasets published by tech giants Apple and Google, which opens a broader avenue for mobility research in the light of difficult data collection circumstances. A comparative analysis of the changes in usage of different mobility modes during the national lockdown and unlock policy periods across 6 Indian cities (Bangalore, Chennai, Delhi, Hyderabad, Mumbai, and Pune) explain the spatio-temporal differences in mode usages. The study shows a preference for individual travel modes (walking and driving) over public transit. Comparisons with pre-pandemic mode shares present evidence of inertia in the choice of travel modes. Association investigations through generalized linear mixed-effects models identify income, vehicle registrations, and employment rates at the city level to significantly impact the community mobility trends. The methods and interpretations from this study benefit government, planners, and researchers to boost informed policymaking and implementation during a future emergency demanding mobility regulations in the high-density urban conglomerations.

1. Introduction

The unprecedented spread of the COVID-19 pandemic triggered a monumental shift in lifestyle. Universal mask policy, social distancing protocols, closure of educational and other business institutions, constrained attendance policies in offices, work from home culture, online shopping, and travel restrictions became a part of the 'new normal' (WHO, 2020; Wilder-Smith & Freedman, 2020). The transportation sector also endured substantial disruptions due to the changes induced by non-pharmaceutical interventions to break the chain of spread (Liu & Stern, 2021; Parr et al., 2021). The percussions of the pandemic on transportation systems are long-term, with effects on the transport infrastructure, operations, mode choice, and overall user behavior (Tirachini & Cats, 2020). The global community adapted well to the new environment out of fear of the wide-spreading contagion resulting in an overall reduction of travel demand. Parady et al. (2020) indicated a willingness to reduce essential and recreational trips among urban communities. Sense of own safety and social commitment coupled with stringent enforcements resulted in travel reductions exceeding 70% in the USA, Europe, India, and other parts of the world immediately after the announcement of stay-at-home orders (Aloi et al., 2020; De Vos, 2020; Politis et al., 2021). An expert survey by the WCTRS COVID-19 task force evaluated contingency plans for disaster response, pandemic thwarting measures adopted, and the public response on a global scale (Zhang, Hayashi, & Frank, 2021). The survey highlighted the modal inclination away from public transport to private modes, including cars, bicycles, and walking. A study by Eisenmann et al. (2021) backed this sense of confidence in individual modes through analyses of intra-individual variation in mode preferences during the strictest phase of lockdown in Germany. Case studies from Manila (Hasselwander et al., 2021) and Istanbul (Shakibaei et al., 2021) reported a paradigm shift in community travel behavior with a higher post-pandemic recovery rate of car mobility. Active modes of transport like walking and cycling also witnessed a revival of choice due to less congested and safer environments when compared to mass transit services (Nurse & Dunning, 2020).

India enforced one of the strictest lockdowns to curb the spread (Hale et al., 2021). The timelines of policy interventions (including unlocking stages) and their highlights are presented in Table 1 (Ministry of Health and Family Welfare, 2020). There were revolutionary travel reductions in response to lockdowns, with a significant reduction in all modes of

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Table 1
Highlights and timeline of national lock and unlock policy interventions in year 2020.

Policy	Dates	Policy highlights
Janata curfew	22 March	One day national lockdown of all activities except essential services
Lockdown 1 (L1)	25 March–14 April	Strict curb on all travel, social gatherings, night curfews, closure of all institutions except for essentials
Lockdown 2 (L2)	15 April–3 May 3	Continuation of national lockdown with relaxations on agricultural, industrial, medical, and maintenance activities.
Lockdown 3 (L3)	4 May–17 May	Classified regions into red, orange and green zones depending on COVID-19 cases to implement relaxations, reinstating public buses and trains with limited occupancy, Shramik special train services started.
Lockdown 4 (L4)	18 May–31 May	Extension of national lockdown for 2 more weeks with more relaxations in green zones, Resumption of international flights (Vande Bharat Mission), Inter-state travel permitted for freight and emergencies.
Unlock 1 (U1)	1 June–30 June	Lockdown limited to containment zones, reopening of hotels, shops, and economic activities with strict guidelines.
Unlock 2 (U2)	1 July–31 July	States are given the freedom to frame and implement policies. Limited inter-state travel permitted. Relaxations on social gatherings, limited domestic air travel permitted.
Unlock 3 (U3)	1 August–31 August	Removal of night curfews, reopening of gymnasiums, yoga centers, parks for exercises, more metro, and public transit services, relaxations on inter-state travel.
Unlock 4 (U4)	1 Sept–31 Sept	More relaxations on gatherings and public events, religious, entertainment, political sports, research, and higher educational institutions allowed to function with limited attendance

travel. Bhaduri et al. (2020) explored the mode-specific trip frequencies in India through multiple discrete choice models, considering the several socioeconomic factors that alter the utility of modes. 95% of the respondents reported a reduction in daily commute and discretionary travel. Aaditya and Rahul (2021) revealed a higher willingness of people to minimize leisure and essential trips when compared to work trips in India. Prolonged lockdowns and economic stress advanced the willingness of the community for a trade-off between risk and travel for work-related trips (Dev & Sengupta, 2020). Although the fear and uncertainty resulted in panic and excessive buying of essential commodities, the fear of infection and the lockdown restriction resulted in the reduced frequency of trips to buy essential commodities (Patil et al., 2021).

The associations of transportation networks with the diffusion of diseases have been well investigated in the past (Cartenì et al., 2020; Gensini et al., 2004; Kraemer et al., 2020). Studies by Peak et al. (2018) during the Ebola epidemic revealed the importance of understanding natural travel behavior and modal preferences of communities under unplanned emergencies. In contrast to the previous pandemics, digital traces from the contemporary smartphone dominant societies tracked by various location sharing services boost research with invaluable mobility datasets. Google Maps, Apple Maps, Facebook, and Twitter are examples of such services that aggregate de-identified communities' travel patterns and make them publicly available. Mbunge et al. (2021) and Huang et al. (2021) underline the importance of using these emerging technologies for comprehensive monitoring, tracking, mapping, simulations, and predictions to reinforce medical research, urban land use planning, transport planning, and bolstering preparedness to deal with future instances causing disruptions of similar or aggravated scales. Mobility datasets aggregated from social media and other web services during the pandemic has been used efficiently to explore the contrasting spatio-temporal patterns of population movement in different parts of the world (Beria & Lunkar, 2021; Cacciapaglia et al., 2020; Pullano et al., 2020; Saha et al., 2020; Tamagusko & Ferreira, 2020). Visualizations reveal heterogeneity in trends across different geographical units. Association analyses, peak predictions, curve fitting with change in mobility, and various pharmaceutical parameters linked to the viral spread constitute a growing body of research (Kissler et al., 2020; Leung et al., 2020; Nouvellet et al., 2021; Padmakumar, Patil, & Gadiya, 2022; Sulyok & Walker, 2020). Integration of mobility datasets from multiple sources improves the assessment and provides more reliable results (Buckee et al., 2020; Huang et al., 2021).

Urban centers, which constitute 55% of the world population and 80% of the global economic activities, experienced the highest slump in mobility under the pandemic influence (Hasselwander et al., 2021). Uncertainty and lack of awareness loomed around policy formulation and execution during the first pandemic wave. Blanket restrictions on mobility, enforced by several countries, lacked an understanding of people's responsiveness to travel restrictions considering regional demography, socio-economics, changing safety conceptions, and choice of modes. Outlining evidence-based policy recommendations to bolster preparedness and mitigate the impact of a future emergency demanding lockdown on the urban transport sector is critical. The hypotheses in the study involve:

1. Recuperation of urban travel to pre-covid levels marks an increased preference for individual travel modes such as driving and walking over shared public transit services.
2. The changes in urban driving, walking, and transit usage trends under mobility restrictions depend on regional socio-economics and pre-pandemic mode shares.

This paper explores the hypotheses through a comparative study of changing driving, walking, and transit usage trends during the different stages of national-level risk aversion protocols across 6 metropolitan cities in India (Bangalore, Chennai, Delhi, Hyderabad, Mumbai, and Pune), hinging on openly accessible Google and Apple mobility reports. The study advances the growing body of literature advocating the potential of the big and openly-accessible mobility datasets from Google and Apple by identifying correlations between them and proposing a standardization method for efficient comparisons. The methods of the study also propose the flexible Generalized Linear Mixed-Effects (GLME) models to explore the interactions between socio-economic parameters of cities and the corresponding mobility matrices. The spatio-temporal variations in mobility are captured by the fixed and random effects components of the GLME model. The high-density agglomerations in the study portray mobility characteristics different from the richer and car-dominant societies in Northern America, Europe, and Australia, forming the bulk of mobility literature during the pandemic. Evidence of changing mobility trends from the developing Indian cities is expected to support decision-making in developing global cities with comparable socio-economic characteristics and pre-covid mode shares.

2. State-of-the-art literature

The hypotheses in the study have been explored by researchers across the world through several methods, constituting a growing body of mobility literature during the pandemic. Limited opportunities for traditional data collection methods posed new challenges to the global research community. Abdullah et al. (2021) employed a binary logistic regression to compare the likelihood of choosing public and individual travel modes during covid-induced travel restrictions in Lahore, using data from a questionnaire survey. Results demarcate a preference of solo modes such as private vehicles, walking, and cycling. Socio-economic factors including vehicle ownership, income levels, and educational qualifications were identified to influence the choice of modes, with the upper stratum showing reluctance in shared modes. Several other online questionnaire-based surveys also reveal a never before noted trend in the modal preferences during the pandemic (Aaditya & Rahul, 2021; Das et al., 2021; Thombre & Agarwal, 2021). Although health, hygiene, and safety are important parameters affecting the mode choices and willingness to travel in the short term, the implications of the pandemic on travel behavior have long-term effects. A gradual mode shift is apparent post the first wave of pandemic owing to fear of shared spaces. 45% of the survey respondents in the study by Paul and Sarkar (2020) considered buying a car. Households that entirely relied on public transportation were the most affected and contributed significantly to the shift to active modes like cycling and walking for short trips. Patil et al. (2021) reported the reduced frequency of travel among consumers in India to buy essentials during the lockdown. The behavioral changes analyzed through survey data from 730 Indian households revealed the reluctance to travel long distances to buy essentials and evidenced panic buying. Results from 1945 survey respondents from India in Pawar et al. (2021) point to contradictory results among the economically weaker section. Findings indicate travel reductions above 40% due to safety concerns. However, among the 75% who reported public transit as unsafe, only 5% showed interest in shifting to private modes due to financial constraints.

Advanced ICT technologies generate big data, which throws light on the actual supply and demand of transportation systems. Integration of big data from sources including mobile phones, GPS, smart cards, and points of interest with traditional data helps improve the efficiency of classical transportation models. Improved transportation system models aid long-term decision-making by enhancing the capacity of planners to analyze, predict and plan commuter mobility in a context of limited information. Croce et al. (2021) demonstrated the same through a framework integrating traditional and floating car data (using vehicles with embedded GPS) in Calabria, Italy. Pullano et al. (2020) employed mobile phone data in 10 French cities during 3 stages of travel restrictions to bring out the spatio-temporal heterogeneity in mobility patterns. Smart card data from Mass Transit System Corporation in Hong Kong revealed a 42% decrement in overall daily commute (Zhang, Jia, et al., 2021). Comparison of urban travel behavioral changes for different age groups revealed travel reductions of 73%, 86%, and 48% respectively among student, children, and senior citizen cardholders. Urban mobility in Santander, Spain, recorded 93% less usage of public transport services during the early pandemic stages. Data from public transport ticket counters, position data from GPS installed in buses, metros, and taxis, and information from 45 traffic control cameras installed in different parts of the city, indicate reduced demand for publicly shared travel modes. Congestion levels dropped lowest during peak hours (Aloi et al., 2020). Analyses of aggregated mobility trends using the 'Facebook data for good' (Facebook, 2020) at administrative units in France, Italy, and the UK, revealed the influence of urban conglomerations in the context of behavioral changes in transportation (Galeazzi et al., 2020).

Mobility datasets aggregated from social media and other web services during the pandemic reflect daily variations in travel patterns across multiple categories. These datasets, which are spatio-temporal and easily accessible, serve as a great resource due to challenging data collection circumstances during the first pandemic outbreak. Several studies explore the potential of such mobility reports to observe the contrasting spatio-temporal population movement patterns under lockdowns. Wen et al. (2021) examined the impact of alert levels announced by New Zealand authorities on overall mobility and mode choices using Apple and Google mobility reports. Budapest witnessed a 50% to 60% reduction in overall community mobility between March and April 2020, with public transport services enduring a slump of 80% in demand (Bucsky, 2020). Visualizations of varying patterns of public transportation across 12 countries by Tirachini and Cats (2020), using Google mobility reports, illustrate deviations exceeding 70% from normalcy in Italy, the UK, and India between April and June 2020. Exploratory data analyses of mobility trends during lockdowns in India (Saha et al., 2020), Portugal (Tamagusko & Ferreira, 2020), Latin America (Zhu et al., 2020), and Australia (Munawar et al., 2021) summarize the travel adaptations. Common observations involve reductions in travel demand for non-essential activities, loss of confidence in public transportation systems, and surge in the use of active transport modes such as walking and cycling as the immediate effect of pandemic restrictions on transport supply and demand. The community mobility datasets published by tech giants Google and Apple have been identified as reliable and valuable data sources, backed by international literature. However, both the data sources compound fluctuations in mobility matrices since the pandemic outbreak, the computation methods and categories tabulated are different. Most of the available research employs the data individually and fails to notice the correlations between them to explore the comparability of trends across multiple categories. Comprehending their close association and devising a methodology to standardize multi-source mobility data to a common base timeline widens the opportunities for comparative analyses.

Developing pandemic resilient cities demand structured and flexible transportation planning. Public transport is pivotal to local mobility in cities and deserves attention to incorporate fresh challenges (Abou-Korin, Han, & Mahran, 2021; Gascon et al., 2020). Reduced ridership on account of safety concerns in public transport modes caused the service providers to alter the number of trips and timetables in a bid to minimize financial burdens (Gkiotsalitis, 2021). Studies portraying shared transport services as a potential virus spreader aggravated the uncertainty (Martínez & Short, 2021; Park & Kim, 2021). Hence evidence-based decision-making to support public transport planning at operational, strategic, and tactical levels are essential leading into the post-covid era (Gkiotsalitis & Cats, 2020). Reshaping the transportation management systems through the use of real-time information to keep the users posted about location, occupancy, expected arrival, and travel times aids in better crowd management systems (Darsena et al., 2021). Introduction of contactless technologies for ticketing inside public services further boost the confidence of users (Parashar & Cheriyan, 2021). Planning at the operational level involves identifying the changing patterns of demands along the service route to plan stops and schedules and to optimize fleet management. Sustainable urban mobility is one of the dominant challenges in smart city development. Comprehending the pandemic effects on urban mobility is of strategic importance to urban planners to catapult the virus-induced momentum to revive sustainable and resilient transport modes (Nikitas et al., 2021). Integration of multi-dimensional transport plans involves decisions on public transits, non-motorized transport, mobility management, modal integrations, and strategic investments (Russo & Rindone, 2021). Long-term objectives have to be accomplished through short-term actions with adequate quantifiable targets. Reviewing the modifications to the built environment and computing the changing user perceptions over a target horizon can bolster urban transport planning decisions (Cirianni et al., 2017). Improving the attractiveness of active modes, including walking and cycling, requires informed investments in the infrastructural development front (Hadjidemetriou et al., 2020). In addition to exploring the changing trends in urban driving, walking, and transit usage trends, it would be prudent to investigate the association of regional parameters to evaluate the public response to policies. Blanket restrictions on all travel-related activities during the first pandemic wave involve tremendous social and economic costs. Interpretations considering pre-pandemic modal preferences and socio-economic characteristics of the province under consideration, aids to develop contingency plans best suited for a region. Devising targeted strategies for regions with respect to planning of transit services and for promotion of sustainable active modes, requires association of regional socio-economic variables with the mobility fluctuations through a flexible modelling approach. Applicability of the versatile GLME model to capture the spatio-temporal mobility matrices through its fixed and random effects components is covered in limited studies (Garnier et al., 2021; Gupta et al., 2021).

Technological advancements propel high expectations for knowledge-based strategies to support comprehensive policymaking. In comparison to the previous health emergencies, the explosion of the internet era and smartphone dominant societies have provided massive mobility datasets through activity tracing such as Google and Apple reports, which provide opportunities for researchers to study travel behavior on account of an unprecedented global crisis. The ongoing pandemic is believed to induce monumental changes in the attitude of the population towards travel on the whole. Pledging safety paramount importance, shifting to work from home culture, reducing travel for non-essential activities, and reduced preference of shared modes are believed to present planners, governments, and academicians with questions of long-term sustainability. A majority of the available research focuses on developed cities in Northern America, Europe, and Australia, where the population characteristics and traditional mode choices differ from that of developing cities such as the metropolitan cities in India. Exploring the hypotheses proposed in the introduction in the context of developing cities are essential to capitalize on the virus-induced momentum to support sustainable policy recommendations. Apart from the hypotheses, the study also advances the existing body of literature through the methods used. Methodological contribution includes suggesting the use of big and freely accessible mobility data derived from smartphone services under challenging data collection circumstances, a framework to integrate multi-source mobility datasets identifying the correlations between them, and advocating the use of the adaptable GLME models for association analyses with regional socio-economic parameters. The research questions in the study are expanded, following the survey of literature to include:

1. How are the categories in Apple and Google community mobility reports correlated?
2. How did the national-level lockdowns and unlocks affect the magnitudes and rate of mobility change under the driving, walking, and transit categories in India?
3. How did income, vehicle registrations, and worker population share of a region affect the choice between driving, walking, and transit during the pandemic?
4. Do the changing mode usages indicate the inertia of pre-pandemic mode choices?

3. Methodology and mobility data

3.1. Methodology

Fig. 1 portrays the graphical schema of the methodology adopted. Google community mobility reports serve as the data source for usage patterns in transit stations. Mobility variations in transit stations, including bus, train, and subway stations, are assumed synonymous with usage. Apple mobility trend reports provide information about driving and walking categories. The freely accessible mobility datasets are smoothly unified to a common base timeline for spatio-temporal comparisons between driving, walking, and transit categories across 6 metropolitan cities in India characterized by million-plus populations (refer to Fig. 2). Visualizations, statistical summaries, and piecewise linear trend fits of mobility patterns provide insights into the pandemic affected mobility variations and changing modal preferences. Data across the 6 cities are analyzed during the period between 25 March 2020 and 30 September 2020, comprising of lockdowns L1-L4 and unlock phases U1-U4 (refer to Table 1). The methods of the study also involve investigating the association of regional socio-economics on the changing modal usage trends, using the Generalized Linear Mixed-Effects model.

3.2. Mobility data

Mobility trend reports published by Apple (Apple, 2020) chart the travel behavior of the population across over 100 countries at national and sub-national scales, under the influence of the COVID-19 pandemic.

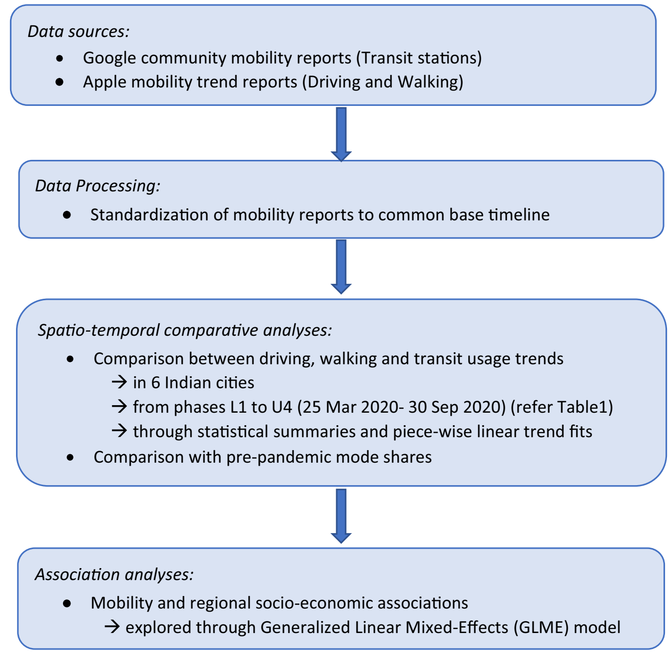

Fig. 1. Graphical schema of methodology.

The data is aggregated based on the number of navigation requests sent to Apple maps in driving, walking, and transit categories, by its users for direction. Navigation requests are considered a proxy to mobility patterns and are documented with adherence to strict privacy protocols. Change in mode-wise usage is tabulated as percentage change with respect to a pre-pandemic normal day, i.e., 13 January 2020, which is considered as 100%. Apple mobility trends are freely accessible for India at the country level and for cities like Bangalore, Chennai, Delhi, Mumbai, Hyderabad, and Pune. However, the categories available for India are limited to driving and walking.

The study resorts to Google data (Google, 2020), which captures the variation in community travel patterns through transit stations, to consider the movement trends in public transit. Data in the transit station category records mobility based on access frequencies and time spent by users in public transport stations, including railway stations, bus stops, and metro stations, and is assumed to represent public transport travel. Unlike Apple reports, Google considers the baseline as the median value over the 5 weeks between 3 January and 6 February 2020. The estimation method is based on trajectory tracking and estimation of time spent at activity centers from users opting to share locations. The differences between both datasets are summarized in Table 2.

3.3. Comparison and standardization of mobility datasets: national level

A comparative analysis using different datasets advocates comprehensive exploration of data behavior and standardization of the data to a common base timeline. Snoeijer et al. (2021) observed the direct and analogous effects of non-pharmaceutical interventions on mobility data published by both Apple and Google. Huang et al., 2021 proved the close association between Apple and Google datasets in a similar analysis at the county level in the USA. Extending the research for India, Fig. 3 illustrates the similarity in travel response to mobility curtailing policies in India at the country level, using both datasets. The trends in transit, driving and walking categories of Google and Apple reports, respectively, graph 'U-shaped' curves with a sharp slump in mobility change below the pre-pandemic value, on account of strict enforcement of social distancing norms from the third week of March 2020. The recuperation of activities corresponds to phase-wise easing off of policies. A strong

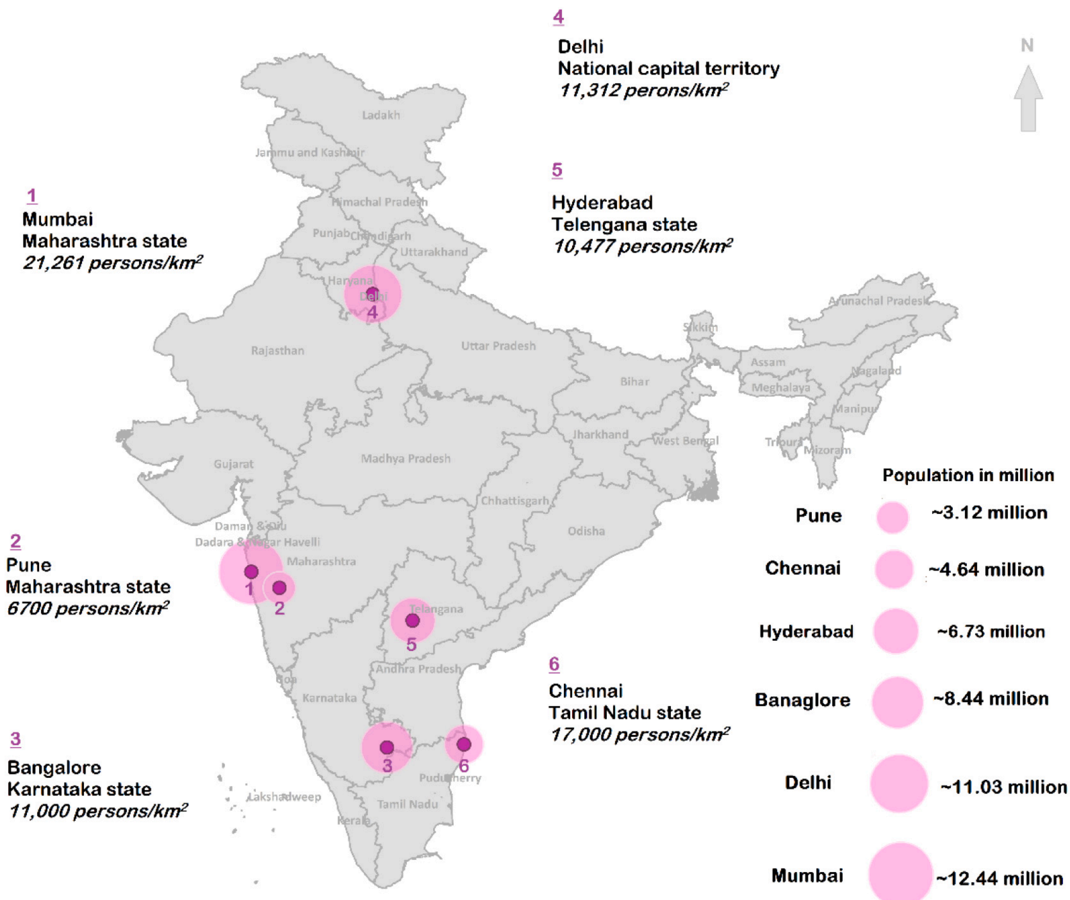

Fig. 2. Metropolitan cities considered in the study of the mobility of different modes.

Table 2
Characteristics of Apple and Google mobility reports.

	Apple reports	Google reports
Base timeline	13 January 2020 (Assumed as 100%)	Median value over the 5 weeks between 3 January and 6 February 2020 (Assumed as 0%)
Method of estimation	Number of navigation requests in Apple maps	Monitoring of access frequency and time spend at activity centers
Categories	Driving, walking, transit	Retail and recreation Grocery and pharmacy Parks Transit stations Workplaces Residences

correlation (r = 0.92) exists between data from both sources for India (refer to Fig. 4), reflecting similar trends.

A crucial aspect of coalescing the Apple and Google mobility trends is determining a common base timeline for meaningful comparative reasoning (Jeffrey et al., 2020). The base timeline should represent a period of normalcy, where the effect of the ongoing pandemic is minimal on the travel patterns. After translating the Google report values by +100 to match with the Apple data, the mobility change in each category is averaged over a two-week pre-pandemic period in India, when both the datasets are available, i.e., between 15 February 2020 and 29 February 2020, to construct a common reference value. Daily fluctuations in travel by each mode are computed as percentage changes compared to the newly derived base timeline. For instance, a mobility change of +10% corresponds to a 10% increase compared to the average between 15 February 2020 and 29 February 2020. Standardized trends from both reports for India (see Fig. 5) illustrate comparable changes in the usage of transit, driving, and walking as mobility modes, concerning magnitude and timeline.

Trend plots adjusted to the common reference line (0% assumed as the mean of mobility change between 15 February 2020 and 29 February 2020) chart 'U-shaped' curves for each mobility mode with minimum mobility during the initial phases of national lockdown (see Fig. 5). Policy interventions to curtail the spread of the virus triggered sharp slumps in mode-wise mobility trends across the cities considered, following the national level trends (see Fig. 6). The revival of travel, post lockdown relaxations, during the stepwise reopening (starting from 1 June) marked a gradual rise in usage of all mobility modes across all cities. Although localized infection clusters and resource scarcity contributed to the contrasting behavioral response, the visualizations portray similar overall trends from an aggregate scale.

4. Mobility of driving, walking, and transit modes

4.1. Piecewise linear trend fits

Policy interventions regulating mobility realize contrasting effects depending on the spatial and temporal aspects. Comprehending the speed of the effect is as important as understanding the magnitude of change in usage of different mobility modes under norms. Segmented or piecewise trend fitting is an appropriate method to analyze the rate of variation in mobility during different phases of policy implementations (Garnier et al., 2021; Jeffrey et al., 2020; Snoeijer et al., 2021). Models summarize a linear trend during each phase of the pan India lockdown/unlock from L1 to U4, with breakpoints coinciding with its timeline. The

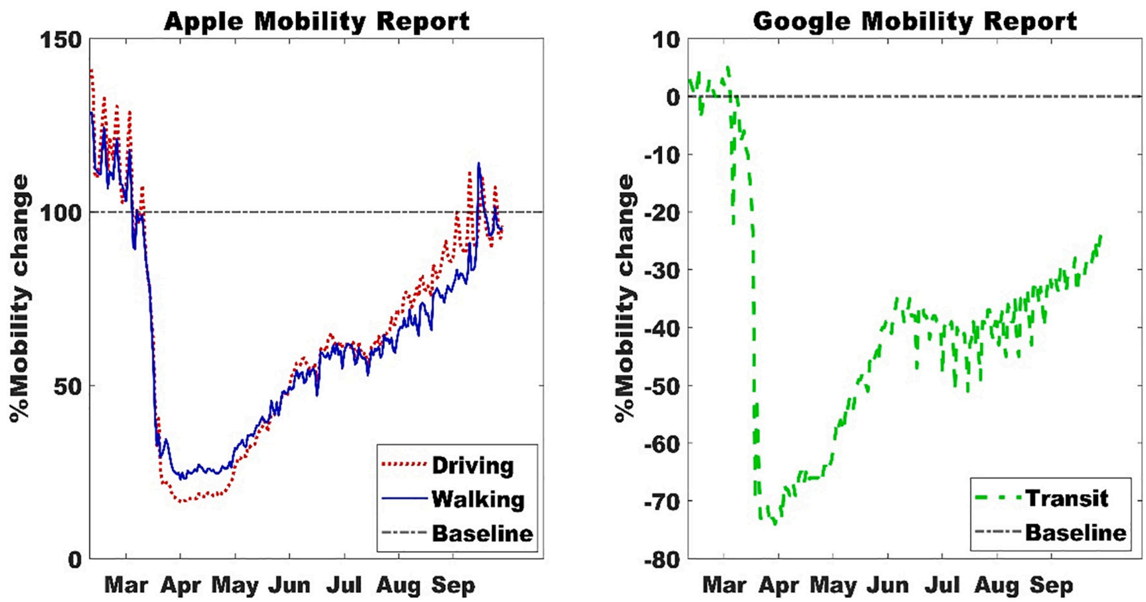

Fig. 3. Mobility trends for India.

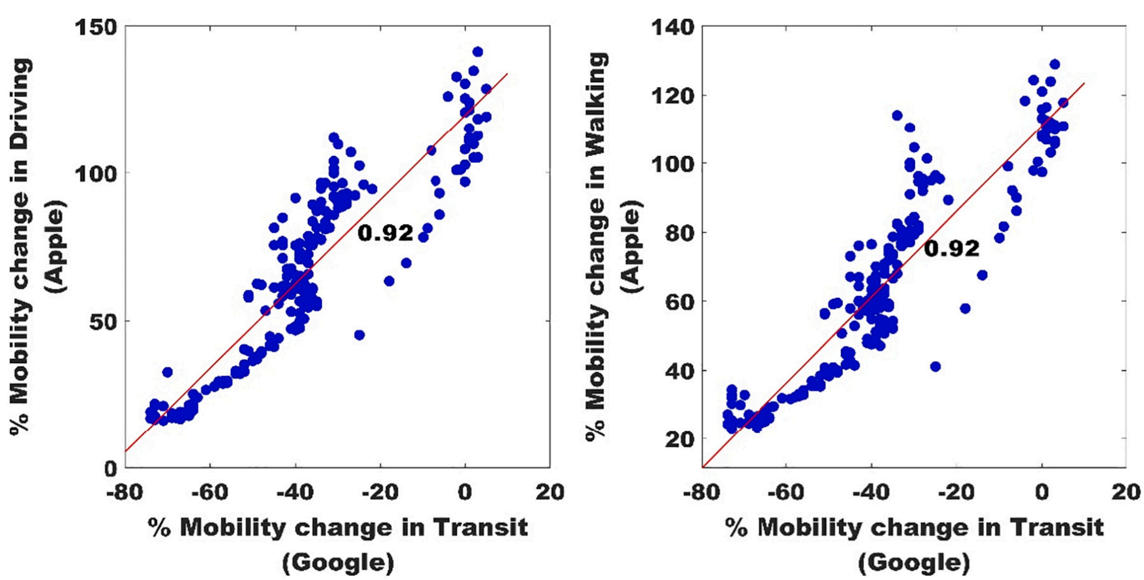

Fig. 4. Correlation between Apple and Google datasets for India.

slope of each trendline corresponds to the rate of increase or decrease of mobility during the period considered. Fig. 7 illustrates the piecewise linear trend fits for the city of Bangalore from L1 to U4. Slopes of the trendlines representing the mobility change rates (%/day) are tabulated for Bangalore in column 3 of Table 3. Similar values for Chennai, Delhi, Hyderabad, Mumbai, and Pune, are also estimated and tabulated in Tables 4, 5, 6, 7, and 8.

4.2. Summary of mobility trends

The summary of mobility changes during the different phases of pan India risk aversion protocols under transit, driving, and walking modes, are tabulated for Bangalore (refer to Table 3), Chennai (refer to Table 4), Delhi (refer to Table 5), Hyderabad (refer to Table 6), Mumbai (refer to Table 7) and Pune (refer to Table 8). The comparative analysis does not concentrate on the spontaneous change in mobility due to new infection clusters or localized policies; instead, the focus is on unraveling the heterogeneity in the change in the attitude of the community towards different travel modes under the same national lockdown policies. Summaries include the means of daily mobility change for the period considered (in %) in column 1 while corresponding standard deviations (in %) are in column 2. Column 3 portrays the rate of mobility change (in %/day) indicated by the slope of trendlines and column 4 averages out the value for the rate of mobility change (in %/day) during the lockdown (L1-L4) and unlock phases (U1-U4).

4.3. Discussion on mobility trends

The results summarizing the public travel behavior of India's urban community point to the fear-induced reduction in the overall travel demand. Cities that are the engines of economic activities witnessed immediate mobility reductions exceeding 80% from normalcy following the announcement of lockdown (refer from Table 3 to Table 8). Illustrations of public response in the 6 cities suggest regional heterogeneity

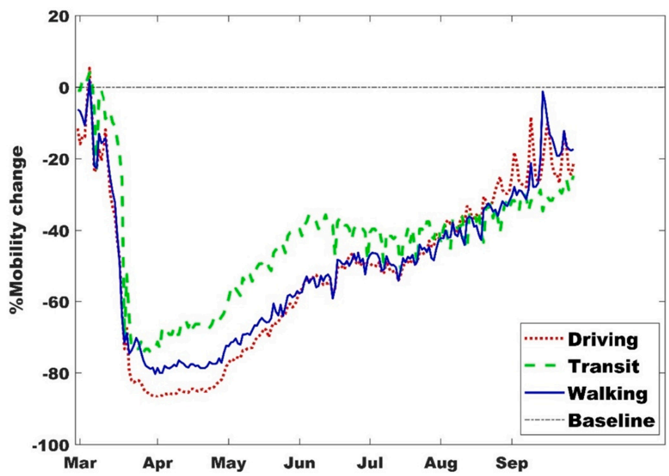

Fig. 5. Standardized mobility trends in transit, driving, and walking categories along with the constructed base timeline for India.

in the extent and rate of change of mobility trends in transit, driving, and walking categories, under national lockdown policies. The initial phases L1, L2, and L3 witnessed mobility changes in all the 6 cities to the order of approximately −70% to −90% owing to stringent lockdown policies. Common observations across cities include recuperation of activities by all modes and increasing standard deviations towards the unlock phases, indicating relaxations in curbs. The recovery in transit usage charted sluggish trends compared to driving and walking as mobility modes. Flatter mobility change rates in the transit category under unlocks, maybe a combined effect of service capacity constraints and elevated safety skepticism. The average reduction in transit usage over driving and walking in unlocks U3 and U4 (see Table 9) reinforces the visible inclination (as in Fig. 6) to individual travel modes over shared public transit services in all 6 cities considered. Values in Table 9 are the averages of difference between % mobility change in transit and driving and between transit and walking in U3 and U4, i.e., average (% mobility change in transit – % mobility change in driving/walking in U3, U4). Sharp mobility growth rates under the walk category signify the increasing prevalence of active modes among the urban inhabitants following the first pandemic incidence. Mumbai dwellers contributed to the maximum overall reduction of mobility during the first pandemic wave (>85%). The average mobility change rates defined as the slopes of linear trend lines were also observed to be least in Mumbai, i.e., transit (0.07%/day), driving (0.09%/day), and walk categories (−0.03%/day) during the initial stages of the lockdown. The findings of the study correlate with the results of several international studies

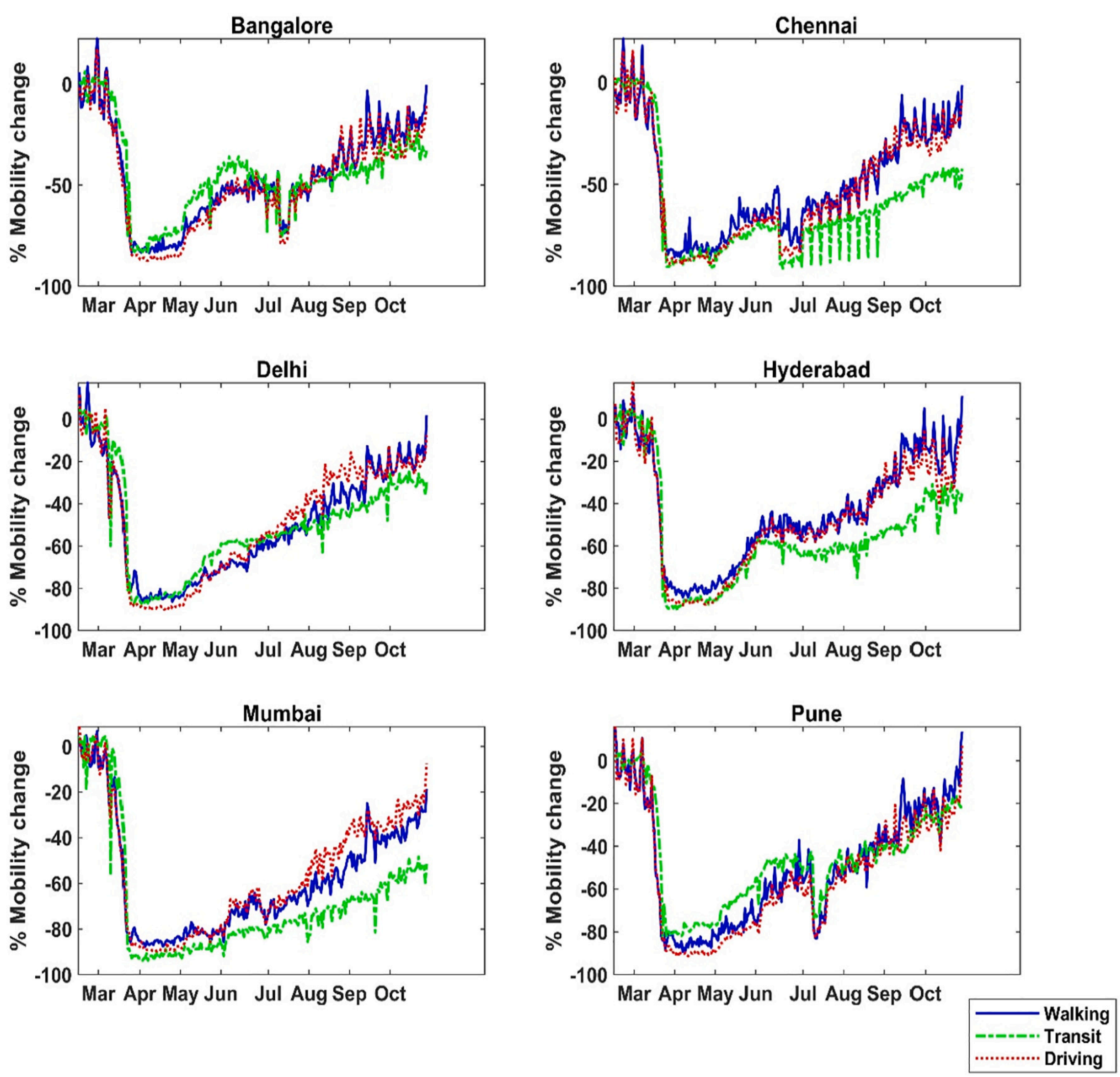

Fig. 6. Standardized mobility trends across 6 cities in India.

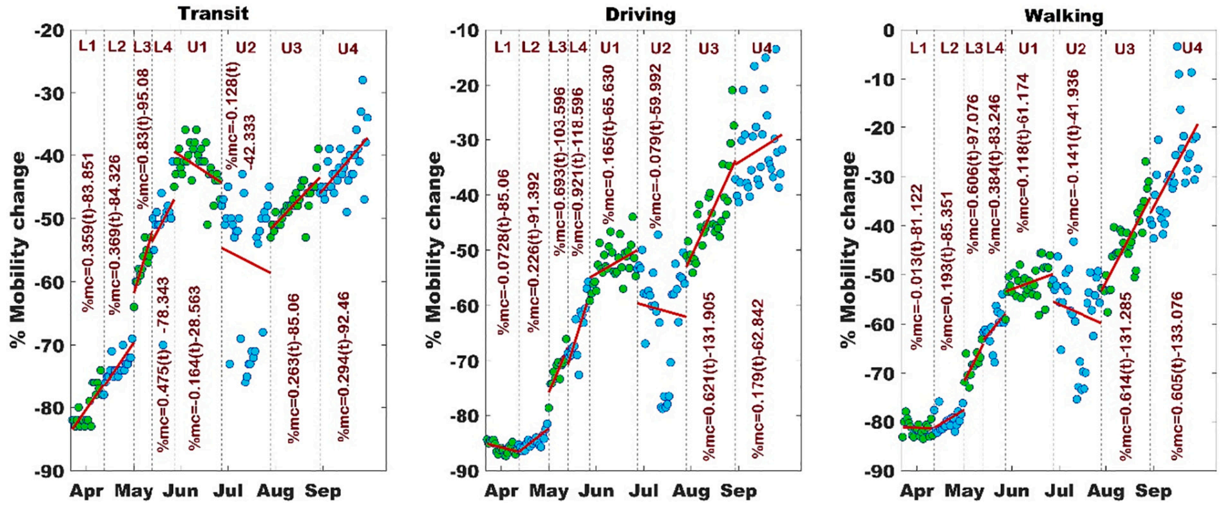

Fig. 7. Piecewise or segmented linear trends based on national phases of policy implementation for Bangalore.

Table 3
Statistical summary of mobility data for Bangalore.

Policy	Transit				Driving				Walking			
	Mean (%) (1)	Standard deviation (%) (2)	Mobility change rate (%/day) (3)	Avg of (3) (%/day) (4)	Mean (%) (1)	Standard deviation (%) (2)	Mobility change rate (%/day) (3)	Avg of (3) (%/day) (4)	Mean (%) (1)	Standard deviation (%) (2)	Mobility change rate (%/day) (3)	Avg of (3) (%/day) (4)
L1	−79.89	2.92	0.36	0.51	−85.86	0.97	−0.07	0.44	−81.27	1.7	−0.01	0.3
L2	−72.82	2.82	0.37		−84.45	1.87	0.23		−79.54	2.58	0.19	
L3	−56.22	3.08	0.83		−71.1	2.42	0.69		−67.47	3.15	0.64	
L4	−50.32	6.54	0.48		−63.94	5.15	0.92		−60.5	3.71	0.38	
U1	−41.76	3.5	−0.16	0.07	−52.24	3.24	0.17	0.22	−51.38	3.1	0.12	0.3
U2	−56.91	11.01	−0.13		−61.05	9.63	−0.08		−57.85	8.87	−0.14	
U3	−47.38	3.04	0.26		−43.15	7.47	0.62		−43.5	7.08	0.61	
U4	−41.49	4.53	0.29		−31.62	7.73	0.18		−28.04	9.66	0.61	

Table 4
Statistical summary of mobility data for Chennai.

Policy	Transit				Driving				Walking			
	Mean (%) (1)	Standard deviation (%) (2)	Mobility change rate (%/day) (3)	Avg of (3) (%/day) (4)	Mean (%) (1)	Standard deviation (%) (2)	Mobility change rate (%/day) (3)	Avg of (3) (%/day) (4)	Mean (%) (1)	Standard deviation (%) (2)	Mobility change rate (%/day) (3)	Avg of (3) (%/day) (4)
L1	−87.48	2.02	0.26	0.27	−87.45	0.97	0.03	0.30	−82.03	4.28	0.19	0.30
L2	−85.60	3.02	−0.08		−85.98	1.78	0.01		−81.65	2.05	−0.10	
L3	−79.32	2.85	0.69		−78.42	2.49	0.65		−73.82	4.79	0.91	
L4	−74.66	1.73	0.23		−70.97	2.54	0.53		−65.82	4.23	0.19	
U1	−77.72	8.82	−0.79	0.05	−73.45	8.28	−0.73	0.24	−66.24	7.64	−0.39	0.33
U2	−75.07	7.85	0.48		−66.40	7.68	0.67		−62.41	7.07	0.48	
U3	−68.57	8.29	0.11		−50.32	8.49	0.69		−50.11	8.03	0.52	
U4	−55.41	3.71	0.40		−29.72	5.83	0.35		−28.77	9.15	0.71	

marking a similar paradigm shift in modal preferences during the crisis (Dingil & Esztergár-Kiss, 2021; Molloy et al., 2021). A WCTRS COVID-19 task force survey covering a diverse group of individuals from over 60 countries reported modal shifts towards private vehicles, walking, and cycling (Zhang, Hayashi, & Frank, 2021). Similarly, findings from studies of Hasselwander et al. (2021) from Manila and Shakibaei et al. (2021) from Istanbul re-iterate the quicker recovery rate of car usage to normalcy as opposed to public transit following the pandemic. Comparable results from international studies utilizing different data sources reveal that the methodology proposed in the study to standardize and compare driving and walking trends from Apple reports and transit usage trends from Google reports is reliable to justify the hypotheses in the study.

Although aggregate datasets do not give hardcore evidence about the mode-wise behavioral inertia or newly added users of each mode, an interpretation considering the pre-pandemic preferences cannot be overlooked entirely (refer to Fig. 8 for pre-pandemic mode shares in Indian cities). An interesting observation from the Indian context is that although the growth of transit usage is slower than driving and walking, the revival is much quicker than in the car dominating societies in Europe and the USA (refer to Christidis et al., 2021; Lee et al., 2021; Lou et al., 2020). Pune and Bangalore, cities with lesser historical public transit, recorded the least reductions in transit mobility among the 6 cities. Similarly, cities with higher individual mode share (motorized

Table 5
Summary statistics of mobility data for Delhi.

Policy	Transit				Driving				Walking			
	Mean (%) (1)	Standard deviation (%) (2)	Mobility change rate (%/day) (3)	Avg of (3) (%/day) (4)	Mean (%) (1)	Standard deviation (%) (2)	Mobility change rate (%/day) (3)	Avg of (3) (%/day) (4)	Mean (%) (1)	Standard deviation (%) (2)	Mobility change rate (%/day) (3)	Avg of (3) (%/day) (4)
L1	−85.73	1.22	0.09	0.34	−88.79	0.84	−0.07	0.18	−82.22	4.21	−0.43	0.01
L2	−82.70	1.11	0.14		−88.70	0.86	0.07		−83.76	1.32	0.01	
L3	−74.61	2.19	0.62		−82.16	1.52	0.44		−78.08	1.09	0.27	
L4	−64.85	2.53	0.49		−73.38	1.41	0.27		−72.92	1.49	0.16	
U1	−58.18	1.14	0.04	0.23	−63.95	4.18	0.40	0.37	−67.00	3.30	0.26	0.43
U2	−53.74	2.33	0.23		−49.58	4.67	0.47		−55.46	3.69	0.33	
U3	−48.38	4.51	0.25		−32.01	7.08	0.64		−42.34	6.62	0.56	
U4	−40.24	3.71	0.36		−24.85	3.73	−0.05		−28.81	7.48	0.54	

Table 6
Summary statistics for mobility data for Hyderabad.

Policy	Transit				Driving				Walking			
	Mean (%) (1)	Standard deviation (%) (2)	Mobility change rate (%/day) (3)	Avg of (3) (%/day) (4)	Mean (%) (1)	Standard deviation (%) (2)	Mobility change rate (%/day) (3)	Avg of (3) (%/day) (4)	Mean (%) (1)	Standard deviation (%) (2)	Mobility change rate (%/day) (3)	Avg of (3) (%/day) (4)
L1	−87.76	1.60	0.21	0.36	−86.07	1.86	−0.15	0.38	−80.77	2.21	−0.21	0.35
L2	−85.56	1.22	0.03		−85.88	1.35	0.10		−79.65	2.17	0.15	
L3	−79.70	2.00	0.44		−78.40	2.38	0.57		−74.39	2.59	0.45	
L4	−69.45	3.80	0.77		−66.78	4.48	1.02		−63.70	4.88	1.02	
U1	−59.34	2.23	−0.08	0.13	−53.55	2.92	0.15	0.29	−50.84	4.11	0.14	0.41
U2	−63.15	2.10	0.08		−53.60	2.70	0.16		−50.96	3.75	0.21	
U3	−60.25	4.47	0.19		−42.80	5.17	0.40		−41.95	6.58	0.45	
U4	−50.10	3.99	0.35		−25.40	6.63	0.46		−21.09	9.42	0.83	

Table 7
Summary statistics for mobility data for Mumbai.

Policy	Transit				Driving				Walking			
	Mean (%) (1)	Standard deviation (%) (2)	Mobility change rate (%/day) (3)	Avg of (3) (%/day) (4)	Mean (%) (1)	Standard deviation (%) (2)	Mobility change rate (%/day) (3)	Avg of (3) (%/day) (4)	Mean (%) (1)	Standard deviation (%) (2)	Mobility change rate (%/day) (3)	Avg of (3) (%/day) (4)
L1	−92.18	1.01	0.02	0.07	−88.24	1.38	−0.18	0.09	−84.96	2.16	−0.22	−0.03
L2	−90.97	1.23	0.04		−88.36	1.09	0.10		−84.92	1.58	0.18	
L3	−88.46	1.31	0.11		−82.34	1.57	0.41		−80.63	1.88	−0.05	
L4	−87.75	1.56	0.10		−81.94	1.44	0.02		−82.05	1.50	−0.03	
U1	−82.20	2.91	0.18	0.23	−69.96	5.50	0.50	0.38	−72.63	5.08	0.46	0.39
U2	−78.67	2.66	0.24		−67.69	4.69	0.45		−69.68	3.76	0.29	
U3	−73.87	4.24	0.26		−50.13	5.81	0.47		−60.19	4.13	0.28	
U4	−66.19	3.97	0.24		−35.29	3.43	0.11		−44.30	7.39	0.51	

Table 8
Summary statistics for mobility data for Pune.

Policy	Transit				Driving				Walking			
	Mean (%) (1)	Standard deviation (%) (2)	Mobility change rate (%/day) (3)	Avg of (3) (%/day) (4)	Mean (%) (1)	Standard deviation (%) (2)	Mobility change rate (%/day) (3)	Avg of (3) (%/day) (4)	Mean (%) (1)	Standard deviation (%) (2)	Mobility change rate (%/day) (3)	Avg of (3) (%/day) (4)
L1	−79.79	1.72	0.16	0.32	−89.49	1.25	−0.12	0.21	−84.93	2.61	−0.20	0.17
L2	−76.55	0.69	0.03		−89.42	0.97	0.08		−83.94	2.45	0.20	
L3	−67.39	1.84	0.60		−82.74	1.84	0.51		−78.06	2.48	0.01	
L4	−61.37	2.22	0.50		−78.98	1.90	0.38		−73.89	4.07	0.65	
U1	−49.13	4.62	0.36	0.17	−64.45	7.01	0.72	0.29	−60.34	7.13	0.64	0.36
U2	−54.82	9.97	−0.23		−65.20	9.63	−0.17		−60.32	12.61	−0.26	
U3	−45.08	3.95	0.21		−47.77	5.49	0.39		−46.20	6.29	0.47	
U4	−38.19	4.67	0.35		−34.11	6.08	0.22		−29.70	9.03	0.59	

Table 9
Average difference in % mobility change in U3 and U4.

Cities	(transit – driving)	(transit – walking)
Bangalore	−7	−11
Chennai	- 22	−23
Delhi	−16	−8
Hyderabad	−21	−23
Mumbai	−28	−18
Pune	−1	−4

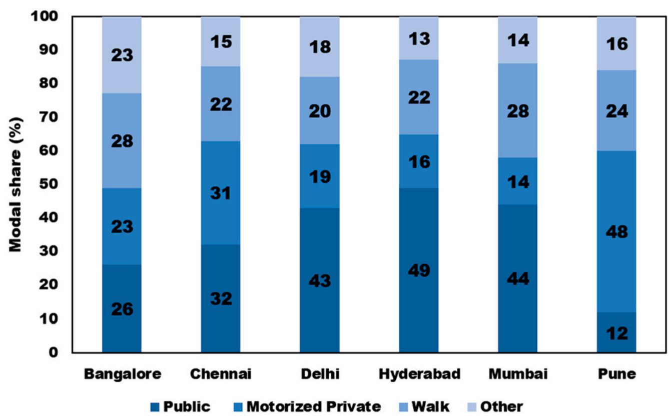

Fig. 8. Pre-pandemic mode shares in Indian cities (Ministry of Urban Development, 2019).

vehicle and walk), such as Pune, Bangalore, and Chennai, marked reductions in driving and walking during early lockdown stages. These cities witnessed higher growth rates in driving under unlocks. Hyderabad, Mumbai, and Delhi, which constitute a higher share of public modes, sketched sluggish growth rates in driving under enforcement relaxations. Evidence of prevalence of pre-pandemic inertia of mode choice in the post-pandemic mobility recovery stage from Indian cities necessitates similar investigations from global cities with traditionally different modal preferences. A policy issue identified from the Indian urban setting is that although cities represent a traditionally high share (around 20%) of walking as a mobility mode (see Fig. 8), the road conditions are unfavorable for non-motorized travel in a majority of areas and requires attention as more people move to active modes post the pandemic. Similarly, an understanding of the changing mode usage trends in association with traditional mode shares across world cities aids the authorities to capitalize on the virus-induced momentum to make informed and sustainable investment decisions. Experiments concerning pop-up cycle lanes and adaptable walkways in studies by Fuller et al. (2021) and Paydar and Fard (2021) are examples of driving mitigative strategies in urban areas.

5. Mobility and regional socioeconomic factors

5.1. General

Socioeconomic characteristics of the population have a significant role in decision-making, risk assessment, and travel mode preferences. The attractiveness of a travel mode for an individual depends on multiple factors, including quality of service, the income of the individual, trip purpose, time of day, and mode characteristics (Chakrabarti, 2017). Understanding utility functions of modes demand mobility data of finer resolution. However, at an aggregate level, this study attempts to shed light on the relationship between the socioeconomic attributes of a city and the change in mode usage.

The regional socioeconomic attributes used to relate the changing mobility patterns across the 6 metropolitan cities during the phases of national lockdown and unlock include per capita GDP (in 100,000 rupees), registered motor vehicles (per 1000 individuals), and worker population rate (per 1000 individuals). These attributes correspond to regional scales and not individual levels. Variables used in the study are easily accessible from government and other public websites. Links to data sources are provided in the appendix.

5.2. Mobility model framework

The generalized linear mixed-effects (GLME) model by virtue of its inherent flexibility in dealing with unobserved heterogeneity within clusters or groups, serves as an ideal model for panel data analysis (Boisjoly et al., 2018; Mannering et al., 2016). GLME models have been methodically applied for association investigations of mobility variation with regional socioeconomic attributes in studies by Garnier et al. (2021) and Gupta et al. (2021), utilizing the model structure efficiently to explain spatio-temporal trends. Mixed-effects include fixed and random effect components. Fixed effects relate the response variable to predictors, like a standard regression model assuming a normal distribution of errors. The group effect is dealt with by the random effects component, which models the variation as per a suitable distribution and link function relating mean μ with other independent variables. GLME models adapt better to data exhibiting variance within groups, than linear regression models which create heteroskedasticity problems for such data. The basic structure of a GLME model used in this study is described as:

$$Y_{i\,t} = X_i.\beta + Z_t.\gamma + \varepsilon$$

The response variable Y_{it} represents the average percentage mobility change for a particular mode during the different phases of national-level policy implementations. The average percentage change in mobility values for the 6 cities under transit, driving, and walking categories are tabulated in column 1 of Tables 3, 4, 5, 6, 7, and 8. Regional parameter matrix X_i is modeled as fixed effects with coefficients β. Phases of policy implementation are modeled as normally distributed random effects with mean 0 and standard deviation σ. Z_t denotes the random effect coefficient matrix, while ε is the normally distributed residuals.

5.3. Model estimation

Linear mixed-effects models are developed for transit, driving, and walk categories, considering regional parameters as fixed effects and normally distributed random effects applied on intercepts through an identity link function, with levels of policy implementation as the grouping variable. In mode-wise LME models with better R^2 and statistically significant predictors as shown in Table 10, per capita GDP (in INR 100,000), registered motor vehicles (per 1000 individuals), and worker population rate (per 1000 individuals) were identified as significant socioeconomic indicators with logically apt signs. Results in Fig. 9 portray the fixed effect coefficients of income levels, motor vehicle ownership, and employment participation rates among city dwellers with the change in mobility under transit, driving, and walking categories. A positive interaction indicates that an increase in that parameter causes a positive change in mobility. Random effects causing temporal changes on the model intercept do not explain the interaction of socioeconomic parameters with mobility data and are hence overlooked in

Table 10
Model statistics of LME models for transit, driving, and walk category.

	Transit	Driving	Walking
R^2	0.833	0.951	0.953
Adjusted R^2	0.832	0.948	0.950
Log-likelihood	50.066	59.941	65.700
Random effects σ	0.114	0.190	0.168

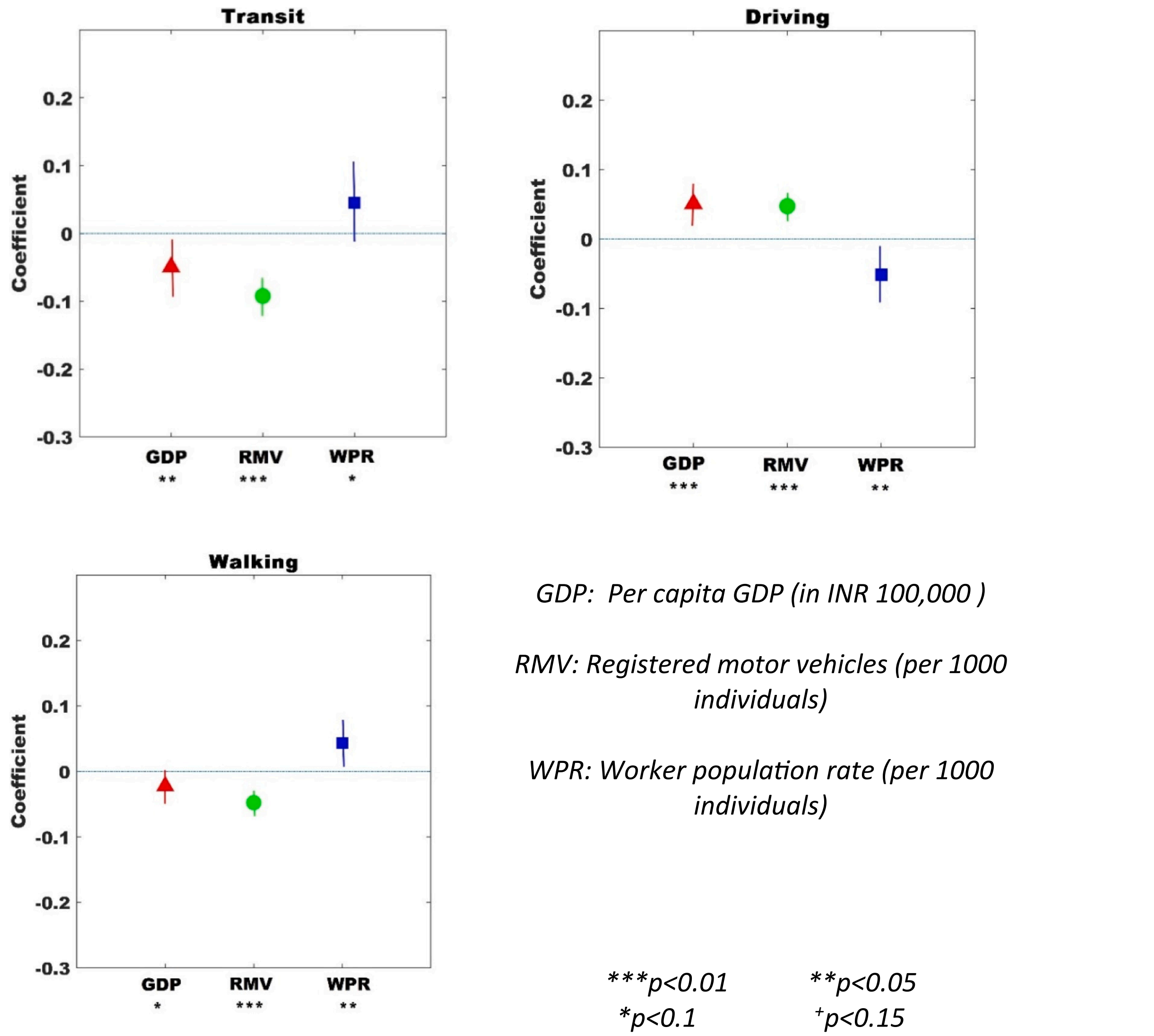

Fig. 9. Fixed effect coefficients of GLME models for transit, driving, and walking mobility modes. Marker denotes mean values while bars represent 95% confidence intervals.

this article.

5.4. Model discussion

As proposed in the Introduction section, a GLME model is successfully employed to reveal the interaction of regional parameters, including income levels, vehicle ownership, and employment rates, with changes in mode usage under restrictions (refer to Fig. 9). The fixed and random effects components of the model capture the spatial and temporal aspects which foster heterogeneity in the evolution of mobility trends since the initial incidence of the pandemic. Random effects are fitted on levels of policy implementation and not on spatial parameters, as the focus is on elucidating the interactions of regional differences with mobility under each phase. Mixed-effects consider grouping effects, and hence such models are preferred over a pooled OLS regression. Advocating the applicability of the GLME model to elucidate the mobility associations with regional parameters in similar spatio-temporal data is a methodological contribution of the study. Although the current study has implemented random effects on the intercepts alone, a wider avenue is opened to the research community to explore more about the variables and their probability distributions to be considered in random effects.

Regional differences in population characteristics foster heterogeneous responses to uniform mobility restraining policies at a larger regional scale. For instance, a 50% capacity constraint on public transit services announced nationwide during the L3 phase of lockdown (refer to Table 1) did not ensure uniform changes in mobility across all geographical units in India. Blanket restrictions to alleviate mobility by a certain percentage across all regions may not have the intended impact owing to the regional disparity. Hence, comprehension of the socio-economics of the mobility recovery following the first pandemic wave is critical in devising targeted interventions best suited for a region. Findings from the Indian cities reveal that higher per capita GDP and registered motor vehicles (per 1000 population) propel quicker revival of driving over transit and walk, which are negatively correlated. Worker population rate (per 1000 population) relates positively with transit and walk while driving category is inversely affected. Cities with lower per capita GDP and registered vehicles resort to cheaper modes like public transport or walk for essential activities or work trips. Higher employment rates in a community are expected to promote more travel by all modes for work-related trips. However, the driving category shows contradictory trends, unlike walk and public transit. A possible reason could be the affordance of the new work-from-home culture among the richer car-owning spectrum of the employed society. Although it is not possible to confirm the implications without individual mobility data, findings from several global studies align with the hypotheses. Higher income levels and ownership of mobility tools were identified to propel more driving in European countries (Christidis et al., 2021; Lee et al., 2021) and counties in the US (Lou et al., 2020). Similar reports in Abdullah et al. (2021) from Lahore also back the results. During the mobility recovery phase of the pandemic, the financially constrained and informal worker population category showed more willingness to utilize transit services risking safety in Bogota (Dueñas et al., 2021). Pawar et al. (2021), through a survey of 1945 respondents, reported less interest among the lower economic stratum to shift to private vehicles. The outcomes of association analyses from the densely populated Indian cities, in conjunction with the other studies, prove that in developing cities, although the attractiveness of public transit services has taken a hit during the pandemic wave, the recovery to normalcy would be quick and demands strategic investments to serve people cost-effectively and sustainably. The active transport modes such as walking and cycling are bound to be benefitted more in India than the car-dominant societies in Europe, Australia, and Northern America, owing to the socio-economic differences.

6. Conclusion

COVID-19 is an unforeseen global phenomenon inflicting profound impacts on all human-oriented systems. The transformation of travel demands post challenges to transportation systems, especially in the high-density urban agglomerations, post the first pandemic wave. Although health, hygiene, and safety were the user priorities in the short-term, virtual meetings replacing business and educational trips, the digital revolution in service sectors comprising of finance, entertainment, shopping, and ticket purchasing may have a significant long-term effect on the travel patterns, mode preferences, and trip characteristics. Social distancing norms and viral contraction risk guaranteed limited opportunities for comprehensive travel data collection. Under these circumstances, the hypotheses explored in the study involve, (1) Recuperation of urban travel to pre-covid levels marks an increased preference for individual travel modes such as driving and walking over shared public transit services, and (2) The changes in urban driving, walking, and transit usage trends under mobility restrictions depend on regional socio-economics and pre-pandemic mode shares. Following the survey of the globally growing body of mobility research during the pandemic, exploring the various data sources and methods used, the research questions in the study were expanded to (1) How are the categories in Apple and Google community mobility reports correlated? (2) How did the national-level lockdowns and unlocks affect the magnitudes and rate of mobility change under the driving, walking, and transit categories in India? (3) How did income, vehicle registrations, and worker population share of a region affect the choice between driving, walking, and transit during the pandemic? (4) Do the changing mode usages indicate the inertia of pre-pandemic mode choices? Introspecting these questions, in the context of developing cities in India is essential to capitalize on the virus-induced momentum to support sustainable policy recommendations. Apart from the hypotheses, the existing body of literature is advanced through the methods used.

The study explores the close association between publicly available Google and Apple mobility trends for India. It highlights the power of efficiently integrated mobility datasets to elucidate the extent and rate of variation of travel patterns concerning transit, driving, and walking as mobility modes during the phases of pan-India safety norms. Results and visualizations from a comparative study in 6 metropolitan cities of India point to higher affection of individual modes like driving and walking over public transit. Chennai, Hyderabad, and Mumbai experienced over 20% less usage of public modes relative to private modes during unlocks U3 and U4. Active modes also witnessed a revolutionary rise in attractiveness during the later lockdown phases marking increased confidence in walking among the urban inhabitants. Relating the change in mode-wise mobilities with pre-pandemic mode shares gave evidence of the prevalence of inertia in the choice of travel modes. With high traditional car share, cities including Bangalore and Pune marked a quicker resurgence of mobility under the driving category. The socioeconomics of a region significantly impacts regional heterogeneity in response. Generalized linear mixed-effects models are employed to reveal the interaction of regional parameters such as income levels, vehicle ownership, and employment rates with change in mode usage under restrictions. Findings reveal that a city with higher per capita GDP and the number of registered motor vehicles (per 1000 population) propels a quicker revival of driving than transit and walk, which are negatively correlated. Worker population rate (per 1000 population) relates positively with transit and walk while driving category is inversely affected. Interpreting these associations in combination suggests increased use of public and walk modes by regions with low income and vehicle ownership over driving to accomplish essential and work-related trips.

Implementing lockdowns is associated with substantial economic and social costs. During the first pandemic phase, the strategies lacked awareness about how cities that are the engines of economic activities would respond. Transforming urban transportation globally to adapt to the changing world, plagued with potential pandemic threats, necessitates knowledge of behavioral response derived from efficiently integrated multi-source mobility datasets, which aid authorities in developing sustainable contingency mobility plans. Revamping travel in cities by prioritizing public transportation and active travel modes motoring on the observed pandemic travel trends deserves attention. Strategic planning to redesign public services involves rescheduling trips and routes to meet the revised spatio-temporal demand patterns. Prioritizing investment decisions on contactless technologies, frequent sanitizations, and crowd management strategies in city buses, metros, and trains at the expense of non-essential comfort can serve as a short-term solution to rekindle lost confidence. From a long-term perspective, channeling investments to develop shared transportation infrastructure and to redesign public spaces to include safe pedestrian walkways and infrastructural support to integrate active mobility with public transport services is a big step towards sustainable and resilient global cities. Although Indian cities traditionally indicate higher shares of public transit and walk, the automobile-dominated Indian urban setting poses practical complexities for non-motorized travel. 4 out of the 6 cities considered in the analyses fall under the 21 most congested cities in the world (Tom Tom, 2021). An increased preference for driving among the Indian urban community post-pandemic can cause chaos on Indian roads in the future if left unattended. The concepts of transit-oriented development and walkable cities demand elevated contemplation in the developing cities in India. The lower economic stratum prefers public or active modes for travel. Governmental interventions targeting the communities at a disadvantage promote social equity during the crisis. Public participation has to be vouched for a sustainable future as governmental investments post the pandemic on transportation facilities may be significantly affected by the global economic crisis.

The hypothesis, methods, and circumstantial knowledge from the study can be extended to any geographical unit and are expected to leverage the utilization of massive datasets of public mobility that are freely accessible and spatio-temporal. Mobility data based on optional location sharing and map requests on smartphone services may not accurately portray actual intentions to travel and has limited penetration among the complete spectrum of the population. Investigating multiple mobility data sources and extending the proposed standardization methods to them, reduce bias in data, increase categories for analyses, and widen the scope of mobility research. The current study focusses on changes under broader categories such as driving, walking, and transit. However, the categories can be further narrowed down to include the sub-categories such as car, two-wheeler, cycles, bus, taxi, metro, train, walk, and IPT services in future studies along the same lines. The results of the study shall not be interpreted from individuals' points of view as the focus is at an aggregate scale. However, as a direction of future research, incorporation of individual travel patterns and their socio-economics to the framework could also be attempted.

The association of changing mobility trends with viral counts or any other pharmaceutical parameter was beyond the scope of this study. An atmosphere of mutual learning and information sharing among the different disciplines and world countries is the need of the hour to break the chain of spread.

CRediT authorship contribution statement

P. Athul: Conceptualization, Methodology, Formal analysis, Writing – original draft. **Gopal R. Patil:** Conceptualization, Methodology, Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Sources of data

Table A1
Sources of data.

Data	Source link
Google community mobility reports	https://www.google.com/covid19/mobility/
Apple mobility trend report	https://covid19.apple.com/mobility/
Socioeconomic data	Handbook of Urban Statistics 2019 http://mohua.gov.in/ India Census official websites https://censusindia.gov.in/ India stat website https://www.indiastat.com/

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