Mobility towers: Improving transportation efficiency policy by persistent evaluation of city-wide travel behaviour

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Abstract

Transportation from personal vehicles is the primary source of urban air pollution worldwide and is one of the fastest growing sources of greenhouse gas emissions (Metz et al. 2007). Coordinated deployment of Avoid-Shift-Improve policies to reduce personal vehicle usage (measured in vehicle kilometres travelled or VKT) is essential to mitigate the worsening impact of these emissions. In this paper, we describe an innovative, longitudinal method to measure key transportation behavioural metrics over time, and thus evaluate the impact of efficiency measures that aim to reduce VKT in cities. Urban planners seeking to implement new transport measures and infrastructure (roads, public transportation, bike lanes, etc.) find it difficult to quantify the ex-ante and ex-post effectiveness of such measures. In the Global South, policy makers frequently cannot measure the baseline, much less measure change. In this paper, we will show how analyzing archival (day old to years old) records from cellular tower networks that include robust safeguards for personal information, may allow measurement of key transportation metrics in a manner that can be updated constantly with low marginal cost. Thus, this method can allow quantification of the effectiveness of urban transport efficiency measures. Much of the existing literature describes progress in utilization of mobile devices for transportation data collection depending on more extensive supporting geospatial data. Our approach, which does not require such supporting data, has important implications for cities in the Global South. We propose that our cellular tower methodology is even more useful in such cities due to three factors: (1) these cities lack even basic data on the mobility behaviour of its residents, many of which can be calculated at reasonable accuracy with cellular data alone, (2) transportation behaviour is changing more rapidly, requiring more frequent measurement, and (3) mobile telephony infrastructure is at par or frequently superior to that found in the Global North.

Introduction

Transportation is the primary source of urban air pollution worldwide and is one of the fastest growing sources of greenhouse gas emissions. According to the IPCC, transportation accounted for 23 % of global greenhouse gas emissions in 2004, nearly half of which came from personal vehicles (Metz et al. 2007). The increase in transportation emissions globally is currently and will continue to be driven by the boom of personal automobiles in the developing world, primarily in China and India. Beyond greenhouse gas and urban air pollution, the explosion in personal cars has created significant social and political impact: India, for example, will be importing 85 % of its oil by 2030, and China 75 % of its oil by 2035. Road traffic accidents recently entered the World Health Organization's top 10 leading cause of death list (with 2.1 % of global deaths in 2008), and rank highest in middle income counties where car ownership has outpaced advances in transportation infrastructure design and safety practices (World Health Organization 2011).

The demand for personal vehicles is primarily due to rising incomes and cannot be easily averted through aggressive Avoid-Shift (A-S) policies because car ownership is dictated by much more than a simple desire for convenient mobility. Instead, coordinated Avoid-Shift-Improve (A-S-I) policies are required. Specifically, this means that avoiding significant growth and presence of personal vehicles in the Global North and South in the near and medium term is likely to be very difficult. Thus, policy makers and businesses must continue to work to discourage car ownership through all the methods traditionally proposed (better transit, mixed use urban design, etc.) while simultaneously addressing, managing, and reducing the impact that personal vehicles exact on their communities and the planet.

To design effective measures policymakers, academics, urban planners and civil society need excellent data from transportation in countries across the world. Unfortunately, the availability of such data—at what we have characterized as the macro and micro level—is extremely low, both in the Global North and Global South. Table 1 gives examples of this data, and characterizes the state of availability in the Global North and Global South.

We begin by reviewing the current status and recent innovations in transportation behavioural data collection, and summarize gaps and shortcomings in these methods as described by the literature. After the review, we propose and describe a new method of collecting personal transportation behavioural data, both at the macro and micro level, that relies on mining archival data from cellular networks. Our approach builds on advances in data collection from mobile devices that have developed in practice as well as the academic literature in recent years. Our method improves upon the current literature most notably in lack of reliance on supporting geospatial databases, and its ability to measure large portions of the population, and to be updated constantly at relatively low incremental cost. In addition, it offers the ability to simultaneously measure several key macro and micro transportation behaviours. We give a few examples of data collected using our approach, and explain use cases for this data that we will test in the future.

The benefits of this method, which relies solely on data collected from mobile phone towers, may be much sharper in the Global South for several reasons:

- Unlike the Global North, the Global South has not sunk capital in macro-behavioural sensing technology and can avoid these costs,
- The Global South, especially India and China, has sunk significant capital into the mobile device network, and can leverage this investment for a new purpose,
- Transportation behaviour is changing much more rapidly in the Global South than the Global North, making persistent measurement with frequent updates more important.

Of course, countries in the Global South lack assets such as robust geospatial road networks, accurate census data with geospatial tagging, geospatial place categorization databases, and more which are common in the Global North and often cited in the literature as part of any transportation behavioural measurement program that leverage mobile devices. We believe that many transportation behavioural metrics can be derived *without* this supplementary data, and focus on examples that only use archival cellular data to indicate the possibility of using our method, without delay, in the Global South.

This review is timely not only to assess and improve data collection in the Global North, but because the Global South (especially Brazil, India, China and Russia) will, in the coming decade, begin to implement more assertive transportation behavioural management policies as congestion – if not pollution and climate change emissions – force the issue. Now is the time for academics and policy makers to explore innovative, more actionable methods to collect such data as a means towards better transportation policy.

Background and Literature Review

TRADITIONAL APPROACHES FOR TRANSPORTATION BEHAVIOURAL DATA COLLECTION

In this paper, we define and categorize different types of transportation behaviour as "macro" and "micro." For the purposes of this paper, transportation behaviour only refers to personal transportation (no freight or commercial transportation). Our categorization follows a general framework, outlined in Table 2.

Macro Behavioural Data Collection Practices

The minimal macro-behavioral transport data needed to make effective national transportation energy/climate change impact management are given from the IPCC as fuel sold and vehicle kilometers travelled (Waldron et al. 2006). We derived a more comprehensive list from the major federal data collection ef-

Table 1. Characterization of Transportation Behavioural Data at the Macro and Micro Level in the Global North and Global South

	Examples	Status in Global North	Status in Global South
Macro Transportation Behavioral Data	Total VKT, VKT by state/city, average vehicle efficiency	Largely available, accurate, and updated annually, published by regional and national governments.	Sometimes available at national level, disputed accuracy
Micro Transportation Behavioral Data	Traffic count/speed by road segment and time of day, VKT breakdown by demographic and trip purpose, response to interventions	Available only on major roads, derived from survey data with disputed accuracy, updated every five-to-ten years.	Largely unavailable. Speed data on major roads may leapfrog other micro data due to spread of navigation apps/devices.

Sources: (Ramachandra and Shwetmala 2009).

Table 2. Framework for Categorizing Transportation Behaviour as "Macro" or "Micro".

	Macro	Micro
Whom it measures	Populations (e.g. car owners in India)	Sub-populations, and individuals (e.g. lower-income women who have children in Cincinnati)
Geographic scope	Large areas (e.g. region, province, city)	Smaller portions of cities/infrastructure (e.g. a road segment or intersection)
Time scale	Large (e.g. annual)	Small (e.g. morning vs. afternoon, winter vs. summer)

forts for the United States (S. C. Davis, Diegel, and Boundy 2011). They are:

- Total vehicle kilometres travelled (VKT) and VKT per capita.
- Consumption of fuel by transportation end use sector (commercial trucks vs. personal cars vs. rail, etc.) and by fuel (alternative vs. petroleum).
- Domestic vs. imported fuel.
- GIS database of roads and road characteristics (speed limit, pavement, road class etc.).
- Vehicle ownership per 1,000 people.
- Vehicle sales by vehicle class and energy efficiency.
- Fuel and vehicle prices.
- Emissions (GHG as well as air pollutant) per mile for different vehicle and fuel types.

The traditional approach to macro-behavioral transport data collection in the Global North follows two approaches: standardized government collection of indicators and/or intensive installed hardware. For example: The U.S. Federal Highway Administration (FHWA) publishes a monthly report on total VKT in the U.S. This is accomplished by requiring all states to submit traffic count data from over 4,000 permanently installed sensors on major highways on a monthly bases. The FHWA then extrapolates national VKT from the 4,000 indicator stations using a model (Federal Highway Administration 2011). This data service – critical for both transportation energy management as well as providing a key economic activity indicator for many government and private groups – typifies the use of government standardization as well as the use of installed hardware.

The Global North has spent tens of billions of dollars for on-road sensors and such data collection infrastructure for transportation (US Department of Transportation 2006). Current hardware approaches are very expensive. In the US, each traffic monitoring device to be used on a single intersection costs between $2,000 (for a simple loop traffic counter) and $24,000 (for machine vision), plus installation costs and $2,000–$4,000/year for maintenance (US Department of Transportation 2012). These costs do not include the installation and maintenance of a data management system.

In the Global South, collection is much more fragmented or unavailable for these metrics. The IPCC noted difficulty in collecting reliable VKT and fuel sold from nations in the Global South (Waldron et al. 2006). For example, in China, already the world's largest market for personal vehicles, no national office has the ability (or the authority) to report either national fuel consumption data or VKT. Instead, regional offices may collect partial VKT data through surveys, manual (eye ball) counts at certain intersections, and commercial/government vehicle records. Energy use projections and related policy work rely on these expensive, infrequent and often non-representative sources (Huo et al. 2012).

Micro Transportation Behavioural Data Collection Practices

We inferred a list of key micro behavioral transportation metrics from common elements in many National and Regional transportation behavioral surveys in the U.S. and U.K (Oak Ridge National Laboratory 2010) (Economic and Social Data Service Government 2012). These metrics are widely considered to be part of a strong transportation energy policy:

- Near-real-time speed and travel time.
- Number of vehicles per household, drivers per household, and workers per vehicle.
- Daily person trips and vehicle trips, as well as length of trips (leading to personal kilometres and vehicle kilometres travelled).
- Trips and kilometres-travelled cut and cross-cut by:
  - Trip purpose.
  - Major demographic category (income, gender, age, race).
  - City, city size, and urban/rural home location.
  - Travel mode.

In the Global North, this data is overwhelmingly collected by survey, and the survey methodology is most frequently some form of travel diary, supplemented by in person, phone, or online questionnaires (Violland 2011). Household travel surveys vary in frequency from every five to ten years in the U.S. to annually in the U.K. and some parts of Australia to new rolling census in some major urban areas in Europe. Very few countries in the Global South conduct travel surveys due to the high cost and effort involved. Table 3, below, notes which of these metrics can best be assessed with cellular data alone (e.g. data available in the Global South).

Gaps in Traditional Transportation Behavioural Data Collection

Consensus exists around following gaps:

- **Inaccuracy of travel diaries:** participants tend to under-report the trips they take. Certain categories of trips are more often under-reported than others, notably short trips, non-work trips, and trips that do not originate or end at home ((Hu 2004), (Bohte and Maat 2009)(P. R. Stopher and Greaves 2007)). This leads to non-optimal policy decisions.

- **Expense of data collection:** Surveys require lots of time and money, mainly for consultants to conduct and analyse survey data. This limits the frequency with which surveys are done. Costs for surveys have been rising in the past decade (Hartgen 2009).
- **Lack of capture of full days' routes or tours:** Surveys struggle in representing a full series of linked (chained) or a day's worth of trips. While most surveys do include trip purpose and to and from tags for trips, ways of analysing and presenting this data to make it actionable for policy have lagged (P. R. Stopher and Greaves 2007).
- **Sporadic nature of data collection:** Even though some countries, as mentioned above, have moved to annual collection of survey data, this level of sporadic sampling cannot fully capture travellers' responses to events ranging from weather to new developments to policy interventions, as pointed out in several studies (e.g. Ortúzar et al. 2011).

RECENT INNOVATIONS IN TRANSPORTATION BEHAVIOURAL DATA COLLECTION

Several innovative methods have emerged in recent years for transportation behavioural data collection. They fall into three main categories:

- Use of vehicle-probe data for real-time speed conditions,
- Use of GPS devices to displace or enhance travel diaries, and
- Use of cellular data or installed censors measure zone-to-zone transfers of the population.

In this section we briefly describe the literature related to each of these three new methodologies, as well as its benefits and shortcomings.

Real Time Speed Conditions

The use of mobile devices with GPS as "probes" that measure real-time speed data is almost ubiquitous in the United States and other nations in the Global North. Their use has been well-covered in the academic literature (e.g. Herrera et al. 2010) and applied by commercial concerns such as Google Maps and INRIX (Barth 2009).

Real time speed conditions have several benefits and enablers that are worth listing, as they provide a model for future transportation behavioural measurement from mobile devices:

- Real time and constantly updated at a low incremental cost,
- Leverage existing, distributed devices, thereby reducing costs.

Several states within the U.S. have found that the costs of using vehicle probes (dedicated vehicles, usually commercial, with installed speed monitoring equipment) are about one-fifth to one-fourth that of dedicated hardware. However, the probe vehicle technique has not been easily ported for behavioural measurement beyond speed where one or two examples can stand for the speed of the whole road segment. While some groups have tried to infer traffic count from GPS-probe speed data, results have not been extremely accurate, especially on non-highways (Lomax 2011).

Use of GPS Devices as Supplements/Replacements for Household Travel Surveys

Across the Global North, many groups have been exploring and improving upon the use of GPS devices as a means of supplanting or supplementing travel diaries. GPS-enabled surveys have the benefit of being automatic, recording exact trip distances, endpoints, and times (e.g. (P. R. Stopher and Greaves 2007) (Jean Wolf, Guensler, and Bachman 2001) However, most GPS-enabled surveys thus far still also require supplemental diary data from the participants (e.g. (Bohte and Maat 2009) (J. Wolf et al. 2004)(Caltrans 2012)).

While the GPS enabled surveys can enhance richness and accuracy of results, as found in the literature cited above, much work remains before GPS without participant interaction can totally displace surveys. For example, several researchers found they had trouble correctly inferring trip purpose because of a lack of available geospatial data about land use (e.g. P. Stopher, FitzGerald, and Xu 2007). In addition, current GPS approaches tend towards the use of a specialized GPS recorder in the participants' vehicle, necessitating a lengthy recruitment and provisioning process for each survey. This raises the costs of perpetual data collection.

Use of Archival Cellular Data to Measure Large Scale Travel

Literature has emerged in the last several years, pointing to the applicability of using cellular archival data for large-scale transportation analyses, notably to create the Origin-Destination matrices on which most regions transportation demand forecast models rely (e.g. (Zhang et al. 2010) (Caceres, Wideberg, and Benitez 2007)). Several companies have emerged to apply this technique as consultants for regional governments, such as the Southern Alabama Regional Planning Commission (Harrison 2012) or California (Milam, Stanek, and Jackson 2012). Beyond this use case, not much exploration has occurred in applying this type of data to transportation problems, with the exception of some discussion of cellular data use for VMT taxes (B. Davis and Donath 2012).

Specifically, we use the term "cellular archival data" to refer to locational data collected from cellular tower networks (i.e. not GPS networks). Most probable locations for any device at a point in time (usually a set of locations in a circular or ovulate shape) are determined based on the signal strength(s) of the most proximate towers to a cell phone at any given time. Accuracy is usually at the 200 m to 500 m level. The number of such points a cell phone makes each day varies widely based on tower technology, phone technology, and phone use habits of the users. Before the data is delivered "outside" the cellular network, it is usually aggregated in some way, such as – in our case – collected into 1 km grids.

Of course, to activate this benefit it must be possible to access the data. Availability and accessibility of this data varies country to country. In the U.S., as indicated by the studies cited above, such data has been available for aggregate analysis by researchers and engineering firms for several years. All wireless carriers collect and store individual archival locational data (for their own network optimization as well as to meet the requirements of the E-911 legislation to help police locate missing persons via cell phones). The data protection requirements for this data are comparable to any other moderately sensitive data because there are no individual records shared, and no "personally identifiable data" (a regulated category of data that contains name, phone number, address, etc) (Baker and Matyjaszewski 2010). In other words, it is less sensitive than most health or other personal behavioural surveys done by social scientists, and also less sensitive than the GPS-travel behavioural tracking studies referenced throughout this paper. For most major U.S. carriers, cellular subscribers are automatically opted-in to this type of anonymous, aggregate analytic use of their data, though all customers may opt out (e.g. Verizon Wireless 2013). Regulations in Europe around privacy are more stringent than the U.S. in general, though aggregate cellular data is still used in the manner described in this paper to support transportation and urban design.

In the Global South, privacy regulations are non-existent or more lax, enabling potential access to more raw, individualized, and hence sensitive data streams. For example, in India, privacy regulation has just started to emerge with a Do Not Call registry and data protection guidelines for the banking industry. In addition, researchers have found that individual preferences about privacy will be more open in India's more collectivist culture. However, in just the past 12 months, a spate of articles in population news outlets have echoed American-style articles "outing" the use of private data for individual advertising targeting, indicating a potential shift in concepts of individual privacy (Kumaraguru and Sachdeva 2012). In a country that issued formal government identification numbers just a few years ago, concepts of PII are still evolving, but it is reasonable to expect that data regulation will be similar to that in Europe within a decade or two. In the mean time, the hurdles to available in the Global South, unlike the Global North, are more tactical: developing relationships with wireless companies who collect this data and may not have aggregated and shared it before in this manner. Wireless firms in the Global South have already started to enable location-based individual advertising (i.e., sending a coupon for a store when a user is near the store) indicating technical capacity will not be a major barrier.

The overwhelming benefit of the cellular approach is that it has a drastically higher sample size than GPS or Survey methods. In addition, since the data is archival and anonymous, this large population can be analysed and re-analyzed at times in the future at very low incremental cost per person. This improves the comprehensiveness and statistical representation of the data compared to the alternatives.

However, cellular data as used thus far has three significant drawbacks. First, its geospatial accuracy is poor (~0.25 to 0.5 km) compared to GPS. Second, data is collected less frequently that with a dedicated GPS device. These factors limit cellular data's applicability to very precise measurements, such as turning ratios and lane switching behaviour, especially in spatially dense urban environments. In addition, because the data is anonymous, all information about users' demographics must be inferred from area demographics.

Summary

To summarize above: real-time speed probes have done an excellent job leveraging the dispersal of GPS-enabled, connected, pre-existing mobile devices to create a complex, persistent, and evolving source of useful data for transportation in the Global North. However, this data is targeted and useful only for its primary metric: speed. The example and strengths can and should be a blueprint for those interested in measuring other transportation behaviours – both macro and micro – with the same persistence and efficiency.

Historically, cellular data has offered this high sample size, but costs, convention, and lack of spatial accuracy have slowed cellular data use for transportation analysis beyond O/D and a few Home/Destination tables. We believe that developing approaches that use the same sources of data described in the "Cellular Data" section above, but applying analytic techniques closer to those described in the "GPS Travel Diary" and "Real Time Travel Speed" sections above, can yield very useful, low-cost approaches to measuring key transportation behaviours over time and thus, the change in behaviour in reaction to interventions such as new policy measures. This is discussed in more depth in the conclusion section.

Figure 1 shows the Friday trip origin for neighbourhood location in Alameda before and during a new civic event (a monthly art festival), demonstrating the power of this data to measure impact over time and events/interventions.

Potential in the Global South

We propose that archival cellular data can displace the need for expensive and often inaccurate surveys, as well as expensive sensing equipment to deliver persistent, accurate, low-cost measurement of some (but not all) of the key macro and micro transportation behaviours. Building on the literature review and background research, we analysed which sources of data are necessary to measure the key transportation metrics necessary for effective greenhouse gas management discussed above. Table 3 contains the results.

Conclusions: Next Steps and Application to the Global South

In this paper, we proposed a method to collect certain key transportation behavioural metrics solely from analysis of archival, anonymous mobile device (cellular) data. We build on a robust literature of experimentation in transportation behavioural measurement using mobile devices. Mobile devices offer the possibility of improved accuracy and richness of data, at lower costs leading to more persistent measurements. However, while most of the existing work pushes towards the integration of more supplementary geo-data for more robust and rich results, we focused on what results can be obtained through single source data feeds (cellular alone) and simplified analysis. We chose this focus to demonstrate that the applicability of some of the advanced work done in the Global North on mobile device data collection can apply and be of great benefit to certain countries with high mobile device penetration – but little availability of supplementary geo-data – in the Global South. Not only can transportation behavioural metrics be done using mobile device data in the Global South, the extremely low availability of any metrics, the lack of sunk costs in on-road sensing technology (and the existence of sunk costs in the mobile tower network) and rapidly shifting population and transportation behaviour indicate that our using mobile device data may be both more valuable and more cost effective in the Global South.

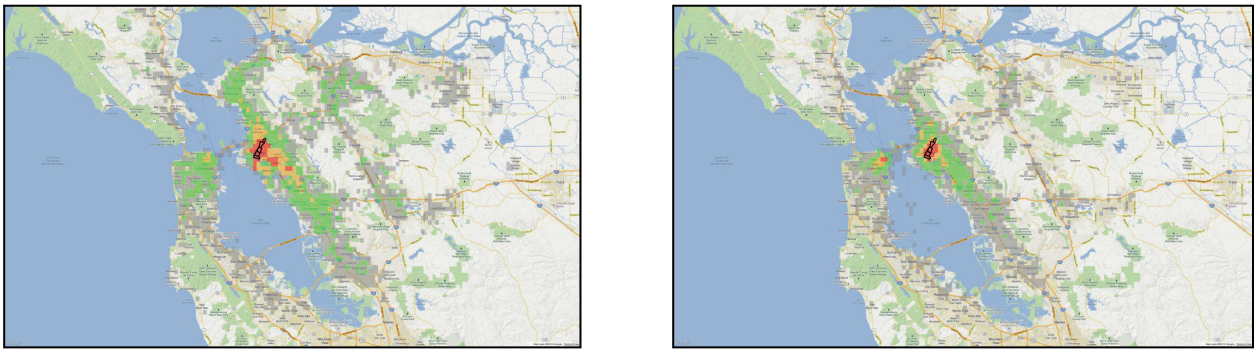

Figure 1. Home locations of visitors to Broadway in downtown Oakland on a typical Friday before the First Friday Art Walk, and After the First Friday Walk. Red squares show high concentration of visitors from this area, followed by orange, and then green and grey. This graphic shows that cellular data has the potential to measure transportation behavioral change over time, and to measure the impact of policy interventions or other changes (such as, in this case, a popular new event).

Table 3. Key metrics for managing transportation impact on emissions, and which data sources are necessary to measure them (if they are not to be measured by survey).

Metric	Cellular data?	Road network?	GPS device data?	Geospatial Household Census?	Geospatial directory?	Feasible in GS?
Total vehicle kilometres travelled (VKT) and VKT per capita						✓
Consumption of fuel by transportation end use sector (commercial trucks vs. personal cars vs. rail, etc.) and by fuel (alternative vs. petroleum)						✓
Domestic vs. imported fuel						
GIS database of roads and road characteristics (speed limit, pavement, road class etc.)						
Vehicle ownership per 1000 people						
Vehicle sales by vehicle class and energy efficiency						
Fuel and vehicle prices						
Emissions (GHG as well as air pollutant) per mile for different vehicle and fuel types						
Near-real-time speed and travel time						
Number of vehicles per household, drivers per household, and workers per vehicle						
Daily person trips and vehicle trips, as well as length of trips (leading to personal kilometres and vehicle kilometres travelled)						✓
Trips and kilometres-travelled cut and cross-cut by:						
Trip purpose						
Major demographic category (income, gender, age, race)						
City, city size, and urban/rural home location						
Travel mode						

Dark means data is a requirement, lighter colour means data can improve or supplement the metric. Metrics that are only in dark colour for cellular data could be measured cost-effectively in the Global South in a near time frame, as indicated by a check mark in the Feasible for GS column.

Of course, certain limitations will exist: lack of basic census data (with geospatial tagging) paired with uneven mobile device data will limit the accuracy of the results, due to difficulty in statistical normalization in the Global South. Some survey work by researchers can provide can supplement cellular data analysis to provide these normalization coefficients if necessary/feasible. In addition, lack of census and other types of geospatial data restrict the number of metrics available with a single-source method, as shown in Table 3. Finally, the lack of accurate geospatial road network data limits the ability of analysts to extrapolate precise routes and analyse small road segments in dense road environments, thus inhibiting certain use cases for these metrics in traffic management and modelling.

However, as countries such as India, China, and Brazil grow economically, these data resources will become available and the limitations will be mitigated. In the mean time, growing nations in the Global South can take advantage of their successful implementation of mobile telephony to leapfrog data collection for transportation, with sinking the billions of dollars into in-road sensing and survey like their counterparts in the Global North. Immediate applications include better forecasting of petroleum needs from better understanding of VMT trends, improved congestion management plans and transit route designs from O/D matrices, and better insight into health, safety, and even commercial development implications of a society with a rapidly changing relationship to the automobile and transportation. Such analyses can begin immediately and be updated constantly, which are the critical factors for transportation data collection in countries where burgeoning demand for mobility threatens health and quality of life.

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