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Improving future travel demand projections: a pathway with an open science interdisciplinary approach

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Abstract

Transport accounts for 24% of global CO_2 emissions from fossil fuels. Governments face challenges in developing feasible and equitable mitigation strategies to reduce energy consumption and manage the transition to low-carbon transport systems. To meet the local and global transport emission reduction targets, policymakers need more realistic/sophisticated future projections of transport demand to better understand the speed and depth of the actions required to mitigate greenhouse gas emissions. In this paper, we argue that the lack of access to high-quality data on the current and historical travel demand and interdisciplinary research hinders transport planning and sustainable transitions toward low-carbon transport futures. We call for a greater interdisciplinary collaboration agenda across open data, data science, behaviour modelling, and policy analysis. These advancemets can reduce some of the major uncertainties and contribute to evidence-based solutions toward improving the sustainability performance of future transport systems. The paper also points to some needed efforts and directions to provide robust insights to policymakers. We provide examples of how these efforts could benefit from the International Transport Energy Modeling Open Data project and open science interdisciplinary collaborations.

1. Introduction

Transport accounts for 24% of global CO_2 emissions, of which road vehicles—cars, trucks, buses and two- and three-wheelers—account for nearly three-quarters (IEA 2020). Transport of both passengers and goods is in many ways connected to the economy (e.g. employment and welfare), socioeconomic conditions (e.g. access, congestion and sprawl), the environment (e.g. air pollution and noise), and health (e.g. safety, the spread of disease) (IPCC *et al* 2022). Long-term transport and energy system models project travel demands for the next 30–100 years to support decision-making toward future resource use and climate change impacts. Prime examples of such modelling work informing decision-makers include the IPCC Assessment Reports (IPCC *et al* 2022), IPCC's special report on *Global Warming of 1.5 °C* (IPCC 2018), and the IEA's *Net Zero by 2050 report* (IEA 2021).

The number of countries announcing pledges to achieve net-zero emissions over the coming decades has grown to over 40, including the U.S., the European Union, China and India, covering around 70% of global CO_2 emissions and gross domestic product (GDP) (IEA 2021). In this context, robust models to estimate future travel demand are essential for managing the transitions toward a low-carbon and sustainable transport future. To understand whether these pledges are feasible, it becomes crucial to examine the global mobility trends and policy options to improve transport sustainability.

Past policies that tried to drastically reduce transport emissions and energy use have largely failed, or at least not at a pace that's required to rapidly decarbonise the transport sector, due to the failure to understand travel demand drivers (Schäfer *et al* 2009, Mattioli and Adeel 2021), consumer behaviours, and the distributional impacts (Schwanen 2021). A greater understanding of the drivers of transport demand is paramount to better understanding the speed and depth of the actions required to mitigate greenhouse gas (GHG) emissions. To facilitate sustained and equitable transitions to low-carbon transport systems, researchers and policymakers need to have a much more sophisticated understanding of how travel demand will grow over time and respond to ongoing innovation and policies.

In this paper, we argue that the lack of access to high-quality data on the current and historical travel demand and interdisciplinary research hinders transport planning and sustainable transitions toward low-carbon transport futures. We first review the historical trends using data from the International Transport Energy Modeling (iTEM) Open Data project (section 2) and compare demand projections from several known models (section 3). We argue in section 4 that strong interdisciplinary collaboration involving open data, data science, behavioural modelling, and policy analysis can reduce some of the major uncertainties and contribute to evidence-based solutions toward improving the sustainability performance of future transport systems. We summarise and draw our conclusions in section 5.

2. Transport demand trends over the last 60 years

In aggregate, onroad travel distance (in passenger distance travelled, PDT, per person) and vehicle ownership strongly correlate with GDP development. This relationship holds pretty well over space and time (Schäfer *et al* 2009, Mattioli and Adeel 2021). The size of the country, population density, and spatial distribution of urban centres certainly play an essential role as well. Nevertheless, the (log-)linear relation of PDT to GDP remains clear, despite country differences concerning the above factors. Data from the iTEM Open Data & Harmonized Transport Database (Linero *et al* 2020)[12] shows that onroad PDT vs GDP per capita for all countries 1980–2018 (figure 1) exhibits a strong linear correlation of log-transformed panel data: log(onroad PDT, 1000 km per person per year) = 1.07 log(GDP per capita, 1000 USD per capita per year), implying that a 1% increase in GDP is associated with a 1.07% increase in onroad PDT. The U.S. has the highest onroad PDT per person with 20 270 km/person/year in 2017, followed by Canada and Australia. These countries have high GDP and car-dependent transport systems due to the spread of the population across large land areas and predominantly low-density urban patterns.

The largest share of onroad PDT comes from driving passenger cars, making it particularly important to understand the determinants of passenger car activity if one aims to understand travel demand. Per-capita driving demand is a function of vehicle ownership (a function of income), distance travelled per vehicle and the occupancy rate (Schäfer and Yeh 2020). The Gompertz curve is the most frequently used method to depict the relationship between vehicle ownership per capita versus GDP per capita (Dargay 2001, Dargay *et al* 2007, Wu *et al* 2014, Lu *et al* 2017). The Gompertz curve implies a vehicle ownership change as a GDP per capita. For each country, vehicle ownership grows slowly at low GDP per capita, then rises until it slows down due to saturation effects (as shown in figure 2 top figure). However, driving distance per vehicle is not strongly correlated to income (not shown) but a function of size, density, and spatial distribution of centres. Therefore, in cities, the driving demand is much lower despite the concentration of wealth (Davis and Boundy 2020, Kasraian *et al* 2022).

When compared against the countries' average level of per capita income, the implied income elasticity of vehicle ownership (the ratio of vehicle ownership growth to per capita income growth) declines with higher

[12] The iTEM historical dataset is composed of 15 individual datasets collected from public data sources, including the International Transport Forum (ITF-OECD), Eurostat, United Nations, International Organization of Motor Vehicle Manufacturers, etc as well as our derived new variables for checking (in)consistency between different datasets. The data are harmonised to a consistent iTEM region definition (individual countries and 17 world regions) and variables (e.g. activity, energy, emission, stock), service (freight and passenger), mode (e.g. air, rail, road, shipping), vehicle type (e.g. cars, sport utility vehicle (SUV), bus, medium-size trucks), technology (e.g. battery electric vehicles, fuel cell vehicles, internal combustion engine vehicles), and fuels (e.g. compressed natural gas, biofuels, gasoline, diesel). Though all the data come from official statistics as documented and downloadable publicly, they exhibit many data quality issues. Curating more data and addressing data quality through the open process via Github are the focus of the iTEM Open Data project, see more in the later section.

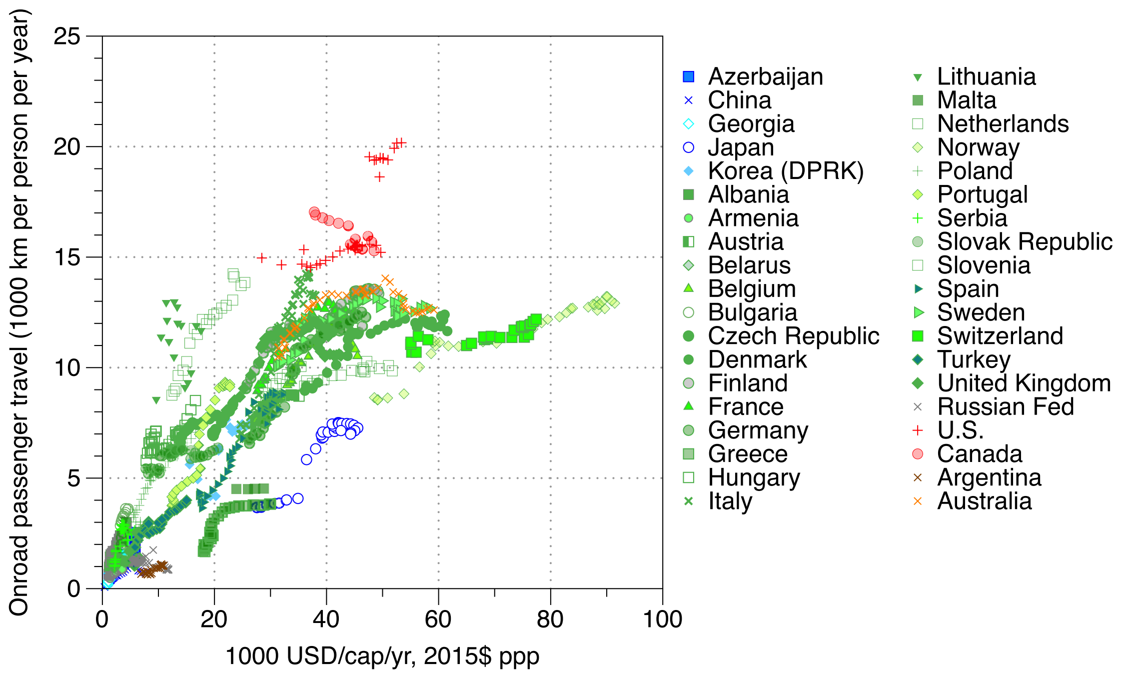

Figure 1. Onroad passenger travel distance and GDP (in 2015 dollars based on purchasing power parity (PPP)) per capita by country, 1980–2018. The colour of the countries is roughly organised by continent. Data source: Linero *et al* (2020).

GDP (figure 2, bottom). The saturation level of vehicle ownership can depend on population density and urbanisation levels, as well as on income inequality and the availability of alternative mobility options (such as walking, cycling, and public transport) to car travel. Dargay *et al* (2007) project, for example, a lower saturation rate of 683 vehicles per 1000 people for India compared with 807 vehicles for China, given that China's population density is only one-third of India's (dividing population by habitable land area). The historical and geographical context and country-specific considerations greatly affect vehicle adoption rates and saturation levels, which pose challenges for global transport demand projection models.

3. The long-term challenges

Long-term transport and energy system models project future travel demand by extrapolating historical trends (such as total PDT and the number of vehicles in use) combined with exogenous assumptions of future GDP and population and technology characteristics (e.g. efficiency improvement, costs of private car travel). The models project transport mode, vehicle type, technology, and fuel choices using econometric, market equilibrium, cost-minimisation or expert judgement (Edelenbosch *et al* 2017, Yeh *et al* 2017). Figure 3 shows the projections from several global energy/transport systems models that contribute to the iTEM intercomparison exercise (see appendix). Global vehicle stock is estimated to exceed 2 billion vehicles by 2040, doubling from one billion cars in 2015 (Sperling and Gordon 2009), reaching 2.5–3.6 billion vehicles by 2050. China's estimated number of cars is 88–560 million (65–450 vehicles per 1000 people) in 2050 across a wide range of scenarios, changing from 160 to 180 cars per 1000 people in 2020. The uncertainties are increasing over time, from 2020 to 2050.

The significant variations observed in the projections shown in figure 3 are driven by models calibrating to different sources of historical data; various methods of estimating demands by mode (e.g. aggregating demand based on the number of vehicles (bottom-up) vs disaggregating based on economy-wide energy used (top-down), Yeh *et al* 2017); differences in the assumptions regarding the future elasticity of new car sales to income (particularly with regards to China (Linn and Shen 2021)), occupancy rate (for which very poor quality data exist), vehicle kilometres travelled per vehicle, policy scenarios and the ambition level toward meeting the temperature targets, etc.

4. An interdisciplinary approach to improve the policy relevance of future projections

Global energy system models and integrated assessment models still face significant challenges in representing the behavioural aspects of travel demand regarding mode choice, technology adoption and demand response to policies (Creutzig 2016, Schwanen 2021, IPCC *et al* 2022). Though the existing literature

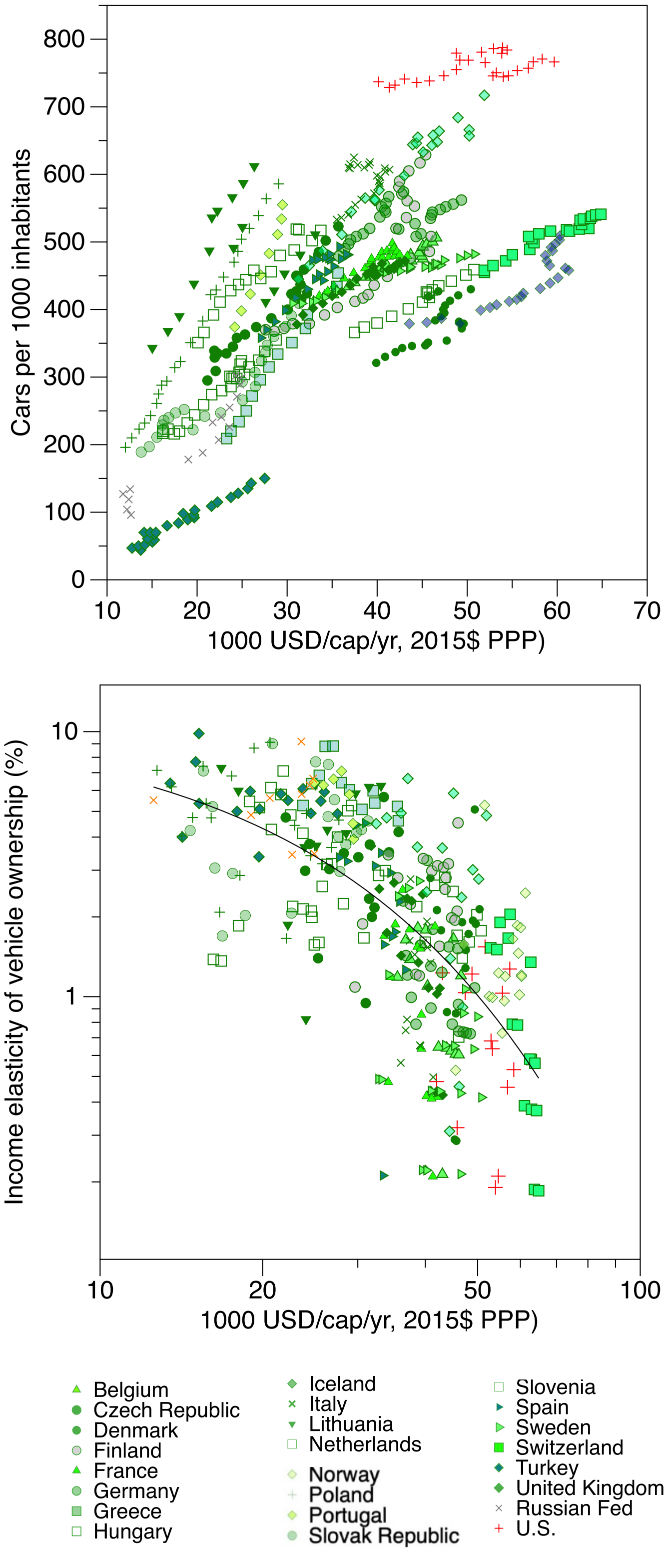

Figure 2. Passenger car ownership per 1000 inhabitants, 1960–2018 (top); and implied income elasticity of vehicle ownership, 1993–2018 (bottom), as a function of GDP (in 2015 dollars based on purchasing power parity (PPP)). Data source: Linero *et al* (2020) (25 countries, 1993–2018, $N = 527$, primarily European countries plus the U.S. and Canada). Not all countries have data for all the years within this range.

has already built models connecting mobility data at various scales (ITF/OECD 2020, Muratori *et al* 2021), significant advances in modelling global, long-term mobility projections require greater integration with interdisciplinary transportation research. We lay out such a framework in figure 4 involving open data (section 4.1), data science (section 4.2), behavioural modelling (section 4.3) and policy analysis (section 4.4) from different disciplines. We provide concrete examples in an open data platform, novel and synthetic data,

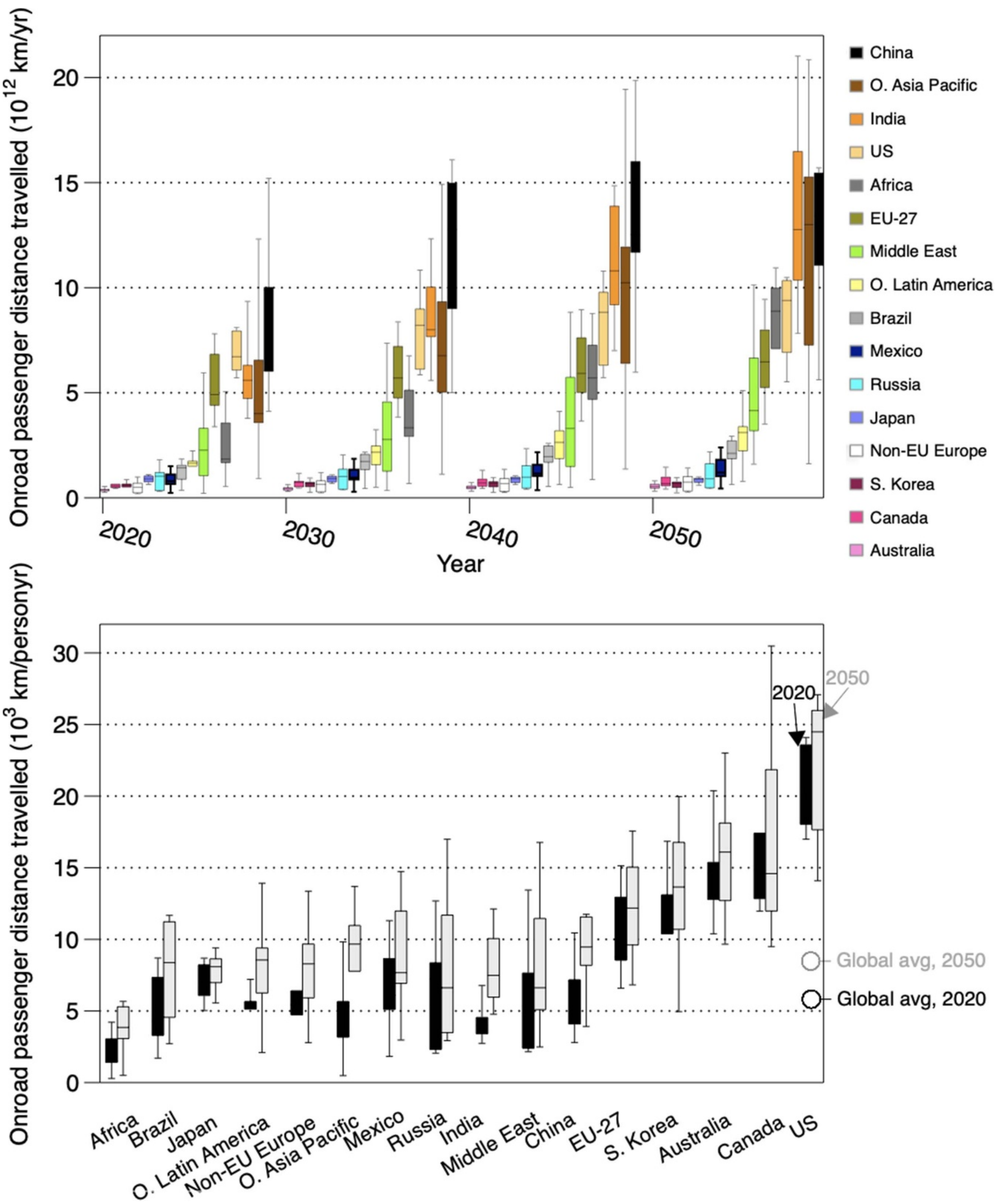

Figure 3. Scenarios of annual onroad passenger distance travelled, 2020–2050 (top), and onroad passenger distance travelled per person per year in 2020 and 2050 (bottom) for 16 world regions. The box plots show the interquartile ranges between the first and third quartile based on 11 scenarios (6 models) listed in appendix. The whiskers are drawn to the smallest/largest non-outlier.

and the mobility research informing policies during the COVID crisis to shed light on potential paths forward.

4.1. Providing open access to high-quality data

There are several publicly available transportation data sets, but the datasets are often incomplete and inconsistent across sources due to differences in data collection and data processing methods used. The incompleteness and inconsistencies create difficulties for researchers to interpret and analyse the data. Modellers typically spend a lot of time and resources to collect, clean and harmonise these data individually and repeat this process every year. Although a few institutions provide detailed datasets, their cost is prohibitively high for research institutions and non-governmental organisations. These data barriers pose challenges for researchers to fully understand today's transportation systems and create useful knowledge for the transition to sustainable and low-carbon mobility. A direct consequence of this problem is the lack of

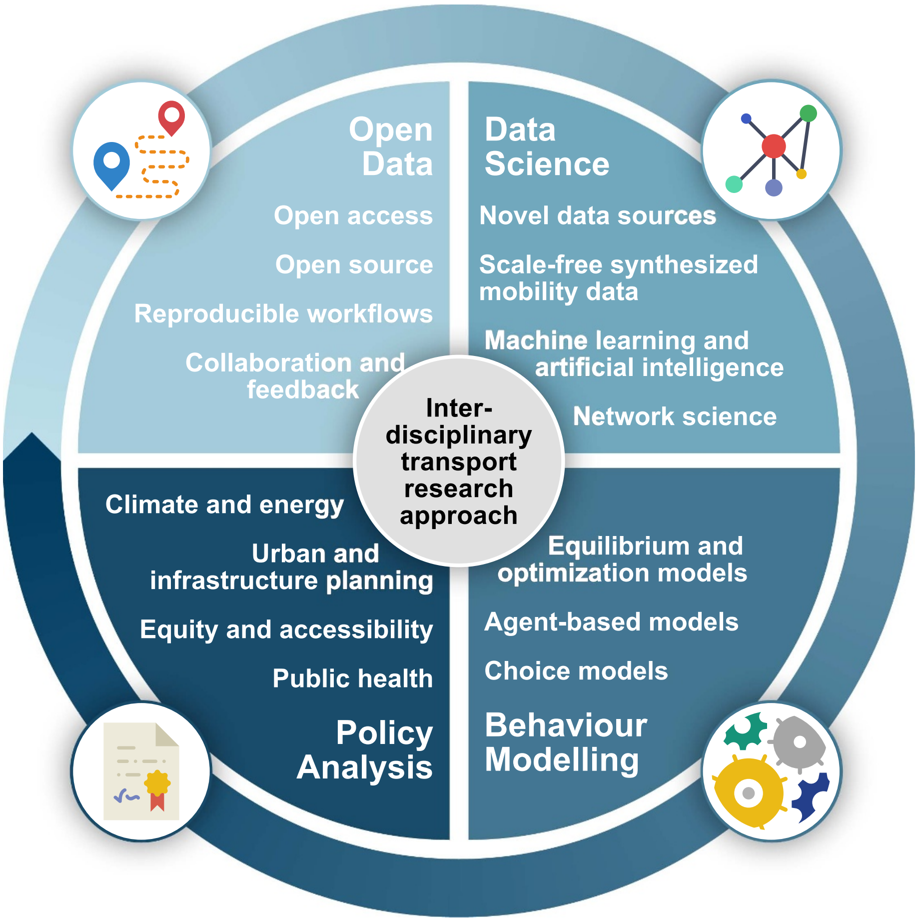

Figure 4. An illustration of an open science interdisciplinary research agenda in data, methods, models, and analyses to advance knowledge in transport demand projections. We explain each quadrant in sections 4.1–4.4.

consistent historical values in each model, adding another layer of uncertainty for making future projections.

The recently established iTEM Open Data project (iTEM 2022a, 2022b) is a community process to produce open transport data: high-quality, transparent, frequently updated and improved, and free to access. As articulated in related disciplines (Hörsch *et al* 2018, Arnold and Bowler *et al* 2019, DeCarolis *et al* 2021), the project implements the principles of FAIR Data (findable, accessible, interoperable, reusable) to produce valid data using reproducible, interoperable, reusable code and builds on existing standards for handling statistical (meta)data. The harmonised transport database aims to create transparency through two key features:

- Open access: a comprehensive collection of publicly-available transportation data that are harmonised, cleaned, cross-checked and cross-validated.
- Open source: all source codes used for cleaning and modifying the original datasets are publicly accessible from GitHub and documented. All codes are available for modification and extension.

Initial iterations of the iTEM project incorporate upstream data from more than 15 sources, including the International Transport Forum (ITF-OECD), Eurostat, United Nations bodies, the World Bank, and the International Organisation of Motor Vehicle Manufacturers. Current poject efforts focus on harmonising, cleaning, cross-checking and cross-validating the input data and creating graphs to visualise the data. The code that handles these data is free, open-source, continuously tested, and developed in the open using established reproducible and collaborative workflows and feedback from a global user community. For instance, GitHub users have identified data errors in countries including China, US, India, Iceland and Canada for specific variables and years. These community-led activities have improved the overall data quality of the iTEM database and corrected the errors contained in the original datasets provided by the international organizations or the statistical agencies of the corresponding countries.

The iTEM Open Data process offers a venue for this work—and the resulting data—to be shared: instead of regularly repeating data-searching and data-cleaning by individual teams, researchers invest their efforts in connecting new data sets, identifying and patching erroneous data points, or improving methods for harmonisation. The project's data processing pipeline extends from retrieval and cleaning of input data sources, harmonisation, and (flexible) (dis-)aggregation, to derivation of new measures, infilling, and output/dissemination of the harmonised data set. The results include the historical data series of key transportation measures in figures 1 and 2. In other disciplines, including climate science and high energy physics, open data and community processes have lowered barriers for collaboration and improved the validity of scientific results and usefulness of insights. Similar practices in transport—albeit more limited within the full scope of open data—have also gained momentum (ADB 2022). The broader agenda we lay out here offers advances within the transport data community and thus their usability and uptake by decision-makers.

4.2. Data science grounded in novel data sources and methods

Trip-based data from conventional data sources, such as travel surveys, are one of the most detailed and vital data sources on individuals' mobility trajectories used to study the flows of the population travelling between different locations/regions. However, travel surveys are challenging to obtain and are often only available for a few selected cities/countries and a few years. How can we understand the travel demand of countries, their future growth, and the policy options to reduce transport emissions if we only have old, outdated survey data from only a few cities? Big data has significantly advanced travel and traffic data collection and analysis. Big data can come from cell phone Global Positioning System (GPS), bus and metro cards, social media such as Facebook, Twitter, Instagram, or traffic sensors.

Mobility research utilising big data includes collecting and processing unprecedented amounts of data that reflect spatial-temporal dynamics about people, their movement, and activities (Romanillos *et al* 2015, Ermagun and Levinson 2018, Welch and Widita 2019). It presents new opportunities for planners, engineers, researchers, and citizens to understand and solve our transport problems at a very detailed level. Its broad spatial and fine temporal coverage allow us to measure large-scale human mobility flows at a lower cost. However, their application in characterising the overall mobility is still limited because of the known issues associated with big data, such as sampling biases (e.g. only specific subgroups of the population use the apps) and behaviour distortions (e.g. users interact with apps only at certain hours). Additionally, unconventional data sources do not contain socioeconomic information, which minimises the risks of violating privacy and makes them difficult to generalise.

More research is still needed to understand the various aspects of mobility patterns, including temporal, spatial and behavioural aspects. Rigorous testing and systematic identification of the strengths and weaknesses of different data sources are needed. Integrating multiple data sources might address the deficiencies identified in individual sources. Notably, such work will need to be based on a solid theoretical foundation, showing how and why triangulating multiple specific data sources is critical to capture spatial and behavioural aspects of mobility and to account for biases known to exist in most unconventional data sources. New skill sets and knowledge are still needed to reliably apply these new data and modelling techniques globally.

Data fusion and model integration have the potential to address the limitations of novel data and broaden their uses. For example, synthetic data offers statistically accurate representations of a populations in aggregate but not at the individual level. Synthetic data also has the advantage of addressing errors and gaps in the empirical data and avoiding privacy issues affecting the availability of commercial-in-confidence data. Statistical, probabilistic, machine learning, and artificial intelligence data fusion methods have been applied broadly (Anda *et al* 2021, Venkatramanan *et al* 2021).

4.3. Modelling behavioural heterogeneity

Travel demand is the aggregate of human mobility at various spatial and temporal scales (figure 5). Human mobility plays a central role in society, including urban planning, infrastructure investments, emergency planning and response, social science research (e.g. social interactions and migration), energy and climate (e.g. fuel use demand and the GHG emissions), and public health (e.g. the diseases spread).

In the broader transport literature, methods of projecting human mobility vary across different temporal scales, spatial coverage, the level of aggregation, and the research questions at hand. For example, gravity-, radiation- or activity-based models have been applied to study and compare the mobility patterns at the level of individuals (Yang *et al* 2014), within cities (Noulas *et al* 2012), and in countries (Hawelka *et al* 2014). These studies offer insights into human mobility in various topics, including physics, social networks, urban development, migration, complex systems and infectious disease (Barbosa *et al* 2018). Given the rich insights from mobility research of different scales, these mobility models are more suited to model mechanisms

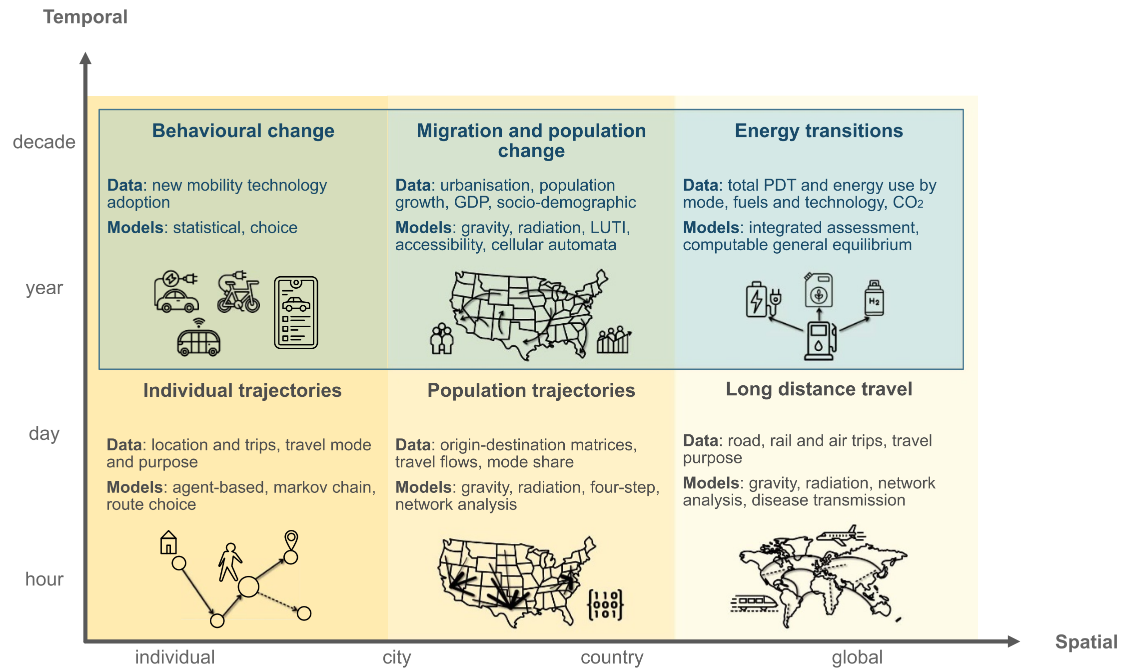

Figure 5. Illustrative framework for the types of personal travel activity estimates (data and models), the phenomena studied (headings), and the nested nature of how these different activity levels interact across different temporal and spatial scales, as illustrated in yellow and blue boxes. PDT: personal distance travelled. While the data and models on the bottom row (time resolution of hours, days, or years) tend to be descriptive, the models on the top row (time resolution years to decades) can be descriptive or normative. Blue boxes highlight the scales relevant to normative energy transition scenarios aimed at influencing long-term changes.

driving mobility and better understand and test hypotheses of how individuals react and adapt to socioeconomic, demographic, technology, and policy changes.

Similarly, agent-based modelling (ABM) with Big Data analytics and large-scale optimisation techniques has gained popularity in studying the transformative changes in mobility (González *et al* 2008). ABMs often rely on synthetic population data that is a statistically accurate representation of a population in aggregate but not at the individual level. The individuals are synthesised so that (a) they do not violate any individual's privacy and (b) they can be modified to create alternative scenarios (Barrett *et al* 2018, Waldrop 2018). The latter feature makes synthetic populations an ideal technique for analysis and planning for future scenarios involving drastic behavioural changes (Martinez *et al* 2015).

Finally, accessibility modelling measures potentials and attractions that influence human mobility. These models are ideal for studying migration, urban growth and population change (Volpati and Barthelemy 2020). Land use–transport interaction models, well known in transport studies, are advanced models used to predict land-use change and urban growth in the long term (decades) (Badoe and Miller 2000). Similarly, cellular automata, simpler in terms of data input and based on naïve mechanisms, have been widely used for simulating long-term future scenarios of urbanisation and population change (Batty 2007).

Making informed travel demand projections requires a deep understanding of the decision-making at appropriate levels, which is influenced by the nature of travel (such as the trip's purpose, duration and locations), as well as the characteristics and preferences of individuals (such as the value of time, Schäfer 2012). For example, the most critical factors influencing mode-choice decisions (e.g. biking vs walking, or driving vs taking public transit) are the characteristics of the individual and the trip; the land use and infrastructure conditions at the origin, destination and along the route; travel costs; and finally, the respective travel time and trip distances of individual trips by mode (Salonen and Toivonen 2013, Moeckel *et al* 2015, Hagenauer and Helbich 2017, Ton *et al* 2019, Liao *et al* 2020). Other considerations, such as the reliability and timing of trips, especially multimodal trips, safety, comfort, and convenience, also impact modal choice decisions.

Looking into the future, short-distance trips today carried out by walking, two- and three-wheelers, and buses are the most relevant trips affected by new mobility services (Kamargianni *et al* 2016), such as e-scooters, bike-sharing, or first- and last-mile autonomous vehicle services (Chee *et al* 2020). Trips shorter than 10–15 km constitute a large share of the total trips but only a tiny share of the total annual travel distance due to the long-tail distribution of mobility (Barabasi 2005, González *et al* 2008, Song *et al* 2010, Alessandretti *et al* 2020, Alessandretti and Lehmann 2021, Schläpfer *et al* 2021). The larger the land area of a region, the more skewed this distribution.

New low-emission vehicles such as electric vehicles (EVs) can present different challenges due to costs, range, and infrastructure availability. Early adoptions were influenced by visited locations, distributions of trip lengths and residency location (rural vs urban) (Björnsson and Karlsson 2015, Jakobsson *et al* 2016, Ramea *et al* 2018, Karlsson 2020), consumer preference, and vehicle costs (Münzel *et al* 2019). Infrequent long-distance trips could significantly impact EV purchase decisions, creating a sustained challenge against EV adoption that highlights the importance of charging infrastructure outside of homes (Hardman *et al* 2018). A significant challenge is incorporating these human mobility factors as a fundamental driver for model mode choice changes for projecting long-term travel demand.

4.4. Interdisciplinary approaches provide more robust policy insights and support

The recent COVID-19 pandemic has resulted in an unprecedented global crisis across health, economic, social, and political dimensions (Lambert *et al* 2020). The pandemic drives researchers, policymakers, governments, private companies, and non-governmental organisations to collaborate to provide solutions at a speed and scale that we had never experienced before. At the centre of all these efforts is the need to understand mobility patterns: how and how fast the disease spreads through human movements and interactions; what are the viable policy options to slow down the transmissions; and the potential consequences of lockdowns resulting in reduced mobility to different societal groups especially the socially disadvantaged minorities (Bonaccorsi *et al* 2020, Chang *et al* 2021). Fantastic progress has been made in mobility research over the past two years due to the COVID-19 crisis. Companies such as Google (2022) and Apple released weekly global mobility reports with detailed information regarding the change in mobility at regional spatial resolution without sacrificing privacy. This information has led to a new wave of open science, generating tremendous value and leading researchers to develop better models that more accurately track the spread of the disease and the short-term policy options to slow down the spread locally, regionally, and globally in a timely fashion (Candido *et al* 2020, Wang *et al* 2020, Kogan *et al* 2021). Other data sources, such as mobile phone data and Twitter (which require more pre-processing due to privacy concerns), have also been applied to enhance existing or build new models to inform policies (Wang *et al* 2020, Ma and Lipsitch 2021). There has also been voluminous research exploring the impacts of lockdown: on reduced mobility, especially to the socially disadvantaged minorities; by mode of transportation, including the effects of ridership on public transport; regional concerns, such as in the global South, where restrictions may be largely ineffective in emerging economies with high population densities, poor transportation infrastructure and large informal economies (Saha *et al* 2020, Kim 2021, Pereira *et al* 2021); and last but not least the impacts on climate and energy systems (IEA 2020, Le Quéré *et al* 2020, Liu *et al* 2020).

The long-term impacts of the COVID-19 pandemic can include future urban planning, freight transportation, logistics or food supply chains (Lambert *et al* 2020). We are at the right time to build on this momentum of interdisciplinary collaboration and expand it by continuing these open science efforts and to continue tracking, monitoring, and developing mitigation strategies to minimise the long-term impacts of the COVID-19 pandemic. We can apply the knowledge from the past two years to a greater challenge: transitions to equitable and sustainable net-zero emissions mobility systems in the coming decades.

By leveraging open science and interdisciplinary research, we can significantly improve access to high-quality data and advance our understanding of the behavioural aspects of human mobility and policy options to improve the sustainability impacts of future transport sector developments. These advancements allow policymakers to consider location-specific characteristics such as urban development and density patterns and local policy targets (e.g. on air pollution) when adopting measures to improve the sustainability performance at the local, city, national and global levels. These advancements could significantly enhance the analyses done by national governments, stakeholders, and local governments to affect the speed and depth of mitigating GHG emissions from the transport sector globally and the potential configurations of a carbon-neutral society in the long term. These advancements can also improve the theoretical and applied scientific modelling in other disciplines, including urban planning, transport management, epidemiology, ecology, human geography, data science, and machine learning.

5. Conclusions

The long-term trends of travel demand are affected by the interaction of various factors, including, but not limited to, socio-economic growth (i.e. population and GDP), urbanisation, migration, infrastructure, technology, policies, attitudes, and behaviours. Many of these factors are changing rapidly, including demographics (particularly in developing countries), social attitudes, urban forms, emerging new technologies (such as electric cars and automated vehicles), and the costs of transport vehicles, fuels, and services. Projecting how much and how people will travel in the coming decades and to the end of the century is extremely challenging. The future of transport is likely to look very different from the past four decades, given the changes in human behaviour combined with rapid technological transformation in digitalisation, electrification, new mobility services, and automation (Fulton 2018). To generate realistic future projections of transport demand and provide robust insights to policymakers, it is crucial to have a deep understanding of individuals' decision-making in mobility choices and the aggregate impacts.

Broad, interdisciplinary collaboration can help improve the estimates of past, present and future travel demand and its potential for transformative change at a global scale towards achieving net-zero emissions targets in the post-COVID world. This broad collaboration can be done by (a) enhancing the collection, harmonisation and assessment of new data sources for describing human mobility with complete transparency and open access; (b) capturing behavioural heterogeneity, such as using data fusion and models to create 'synthesised' and coherent mobility data; and (c) developing practical and implementable modelling frameworks to improve the existing approaches of estimating future regional, national and global travel demand. These efforts should be publicly accessible, reproducible, and set up to be continuously expanded by any research teams or individuals.

Our call for collaboration is an ambitious plan to combine innovative mobility research using big data with large-scale global transport and energy system models. It is a promising new direction closely related to the advanced, cutting-edge research initiatives in the other disciplines. New data, skill sets, and knowledge are still needed to apply these applications reliably across temporal and spatial scales. Big data and artificial intelligence will become increasingly valuable for updating the baseline activity and infrastructures such as trip distance, travel time, and accessibility; and reducing the uncertainty range for historical values.

These recommendations will improve the representation of critical drivers of technical, behavioural, and socioeconomic change and the associated implications for meeting sustainable development goals, including decarbonising the transport sector, improving accessibility, and enhancing socio-economic development. This work should be shared in an open data platform that is replicable and can be continuously improved and expanded by any research team or individuals beyond the lifetime of a particular project. In turn, these advancements will significantly improve the analysis of the speed and depth of mitigating GHG emissions from the transport sector and the assessment of potential configurations of a carbon-neutral economic and transport system and society in the long term.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://zenodo.org/record/4287423.

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Appendix. International Transport Energy Modeling (iTEM) intercomparison

The shared goal of iTEM https://transportenergy.org/ is to understand better the methods and data that are employed to study this system—especially models with international or global scope—and through dialogue to improve knowledge of the system, its ongoing evolution, and the policy and technology options for guiding its changes.

Participants

Models that contribute to the iTEM intercomparison include groups that approach transport and energy from broadly different directions, with different immediate objectives. The participants include academic groups at universities and independent research organisations, departments within national governments, international government organisations, non-governmental organisations, energy firms, and consultancies. See the complete list of participants here https://transportenergy.org/participants/. The models and scenarios contributing to the figures in this article are listed below.

(a) *Global Change Assessment Model*
  1. Organization: Joint Global Change Research Institute—Pacific Northwest National Laboratory, U.S. Department of Energy & University of Maryland.
  2. Model website: www.globalchange.umd.edu/gcam/
  3. Scenarios: *HiBio Ctax, HiElec Ctax*
  4. Data collected: 1 July 2019

(b) *Global Transportation Roadmap*
  1. Organisation: International Council on Clean Transportation
  2. Model website: https://theicct.github.io/roadmap-doc/
  3. Scenarios: *ICE Policy Potential, With Currently Adopted Policies*
  4. Data collected: 15 January 2021

(c) *International Transport Forum, ITF*
  1. Organisation: ITF, Organization for Economic Co-operation and Development
  2. Model website: www.itf-oecd.org/itf-transport-outlook-project
  3. Scenarios: *R*1, *R*3
  4. Data collected: 8 February 2021

(d) *International Transportation Energy Demand Determinants*
  1. Organization: Energy Information Administration, U.S. Department of Energy. Part of the World Energy Projection System (WEPS+) framework
  2. Model documentation: www.eia.gov/reports/index.cfm/T1601
  3. Scenarios: *Reference*
  4. Data collected: 1 July 2019

(e) *Mobility Model (MoMo)*
  1. Organisation: International Energy Agency
  2. Model website: www.iea.org/topics/energy-technology-perspectives
  3. Scenarios: *EV30@30, NPS*
  4. Data collected: 1 July 2019

(f) *PROMETHEUS energy system model*
  1. Organisation: E3Modelling S.A.
  2. Model website: https://e3modelling.com/modelling-tools/prometheus/
  3. Scenarios: *Baseline, Baseline COVID*
  4. Data collected: 12 March 2021

Definitions of regions

As described in the iTEM documentation (Linero *et al* 2020), all the ITEM regions are listed in the file at https://github.com/transportenergy/metadata/blob/master/model/regions.yaml. The ISO code of each country is in the library *PyCountry*. However, in some datasets, certain countries do not have the exact names as those appearing in the library; therefore, a section called Country and ISO Code in each dataset indicates what name is used for the countries not found in PyCountry.

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