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Models and Methods for Transport Demand and Decarbonisation: A Review

Hugh Thomas [a,b,*], Luis Gabriel Carmona Aparicio [b], Felix Creutzig [d,e], Takuya Hara [c,f], Ayami Hayashi [g], Camila Ludovique [h], Luis M. Martinez [a], Paul Natsuo Kishimoto [c], Leila Niamir [c], Yamina Saheb [i], Mallory Trouvé [a]

[a] *International Transport Forum-OECD, Paris, France;*

[b] *Department of Engineering, University of Cambridge, Cambridge, United Kingdom;*

[c] *Energy, Climate, and Environment (ECE) Program, International Institute for Applied Systems Analysis (IIASA), Laxenburg, Austria;*

[d] *Land Use, Infrastructure and Transport Working Group, Mercator Research Institute on Global Commons and Climate Change, Berlin, Germany;*

[e] *Sustainability Economics of Human Settlements, Technische Universität Berlin, Berlin, Germany;*

[f] *Toyota motor corporation, Aichi, Japan;*

[g] *Systems Analysis Group, Research Institute of Innovative Technology for the Earth (RITE), Kyoto, Japan*

[h]*COPPE-UFRJ, Rio de Janiero, Brazil;*

[i] *Buildings Research Program, Climate Neutrality Department, OpenExp, Paris, France;*

*hmt54@cam.ac.uk

Models and Methods for Transport Demand and Decarbonisation: A Review

Rising global greenhouse gas emissions from the transport sector pose a major challenge to meeting the targets of the Paris Agreement. This raises questions of how technology, infrastructure and societal trends and policies can influence transport demand and thus also emissions, energy demand and service levels. Here the literature on factors relevant to shifting total transport activity and mode shares, categorised into exogenous drivers, socio-behavioural, infrastructural and technological aspects, is reviewed. For each factor, current approaches to modelling and measuring the impact of each factor on transport systems are summarised, resulting in a proposed taxonomy to classify transport demand modelling approaches. We then comment on the suitability and sufficiency of existing modelling approaches for representing scenarios consistent with the Paris Agreement targets in models of the entire global energy system. Factors that affect transport demand are currently insufficiently represented in integrated assessment modelling approaches and thus emission reduction pathways. Improving the comprehension and representation of diverse factors that affect transport demand in global energy systems models, by incorporating features of complementary models with high resolution representations of transport, holds promise for generating well informed policy recommendations. Accordingly, policies could influence the development of the factors themselves and their potential role in mitigating climate change.

Keywords: Transport demand modelling, Climate change mitigation, Transport demand, Energy demand transformation, Megatrends, IPCC

1. Introduction

Transport demand for both passenger and freight services is projected to increase significantly by 2050, driven by population growth, rapid urbanisation, and increases in economic activity and standards of living. Electrification is set to reduce the emissions intensity of many major transport modes. However, this will not happen fast enough to fully decarbonise the sector by 2050 (ITF, 2023). Thus, there is growing recognition that policies aimed at systemic changes and energy demand reductions are necessary alongside technological changes and improvements (IPCC, 2022).

Different scientific communities emphasise distinct solution domains for reducing transport emissions: integrated assessment models focus on fuel switching; transport sector-focused models highlight efficiency measures; and spatial- or place-based models put greater focus on behavioural changes and infrastructural mitigation options (Creutzig, 2016). To perform comprehensive, global, long-term assessments of the impacts of transport demand, mitigation options and knowledge from distinct research areas must be integrated. However, this integration is laborious; it requires significant effort in translation between concepts, metrics, and methods used to study both particular aspects of the transport system and the entire global human and earth system. One such pathway that aims to incorporate aspects of the solutions favoured by different research communities is the global low energy demand (LED) pathway proposed by Grubler et al. (Grubler et al., 2018). In the LED pathway, diverse phenomena including trends, dynamics, changes in activity, individual and business behaviours, technology, and environmental impacts— hereinafter collectively **factors** (that affect transport demand)—combine to reduce energy demand whilst still meeting sustainable development targets. This has further been developed in, *inter alia*, the Providing Decent Living with Minimum Energy global scenario, by Millward-Hopkins et al., who consider the convergence of living standards globally and the associated minimum energy and material requirements (Millward-Hopkins et al., 2020).

This review aims to contribute to advancing the representation of such diverse factors that affect transport demand in climate change mitigation pathways compatible with meeting the Paris Agreement targets of limiting global temperature rise to 1.5^{o}C above pre-industrial levels. We begin by distinguishing factors that are included in low (transport) energy demand narratives. These factors were identified, collated, and selected through collaborative meetings of the transport working group of the Energy Demand changes Induced by Technological and Social innovations (EDITS) network, consisting of expert researchers on demand side climate change mitigation solutions. A literature search was then performed using the research databases Google Scholar, Web of Science and Scopus, using the various names and terms given for the factors as well as additional search terms on modelling, transportation, and climate change mitigation. The papers were then manually assessed and selected if they had a significant modelling element and focused on future transformations resulting in emissions reductions. Due to the deliberately broad choice of scope, including all categories of factors that might affect transport demand, this selection identified modelling methods most commonly applied to study each factor, rather than aim to exhaustively list all methods and synthesize them. We also identified and referenced existing reviews which cover subsets of the transport system or of the full list of targeted factors. From the selected studies, we identified methods, quantitative models, data (particularly concerning demand measures), scopes, resolutions, and categorisations used in each literature. We then propose a taxonomy to characterise the transport demand modelling approaches used. Finally, we comment on how high-level narratives for each factor affecting transport demand could be incorporated into comprehensive, global, long-term modelling. This yields an agenda for research to perform such integration, which would enable valid and comprehensive assessments of how demand-related transport factors can contribute to a LED future.

2. Factors that affect transport demand

Factors that affect transport demand are observable phenomena, events, trends, developments, or interventions that could alter transport systems in ways that lead to changes in quantified transport activity, mode shares and vehicle use efficiency. Transport activity is the amount of transportation that happens; it is quantifiable in many ways, including number of trips, time spent travelling, monetary expenditure, and most commonly distance, using metrics such as passenger-distance travelled (PDT, measured in kilometres, thus PKM or PKT, or miles, thus PMT), vehicle distance travelled (VDT, or likewise VKM, VKT, or VMT) and freight volume (measured in tonne-km) Mode share is the allocation of this activity to different transport modes (Edelenbosch, McCollum, et al., 2017). Factors that affect transport demand have been identified and selected from decarbonisation pathways synergistic with LED, such as those in (IEA, 2021), (IPCC, 2022), and (ITF, 2023). These factors include both mega-trends, such as population changes, digitalisation, and urbanisation, which happen at a large scale and have widespread consequences across space and transport modes, and changes which may only impact specific aspects of transport demand, and/or occur in specific places (figure 1).

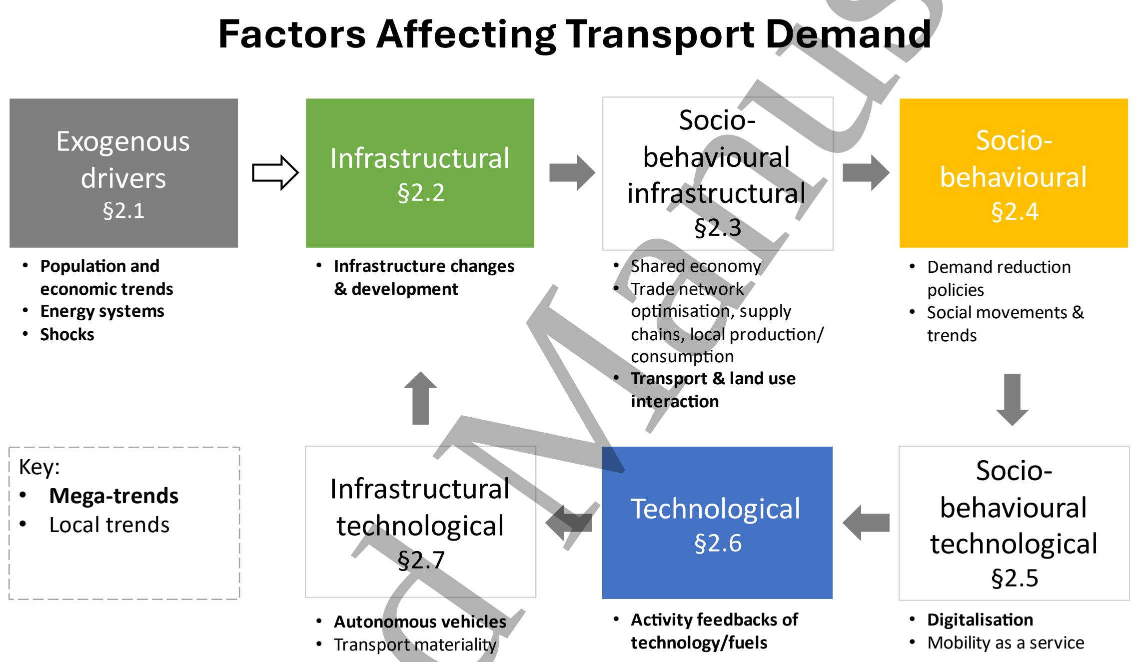

Figure 1: The primary domains of the reviewed factors affecting transport demand. Note that almost all factors will have secondary impacts and feedbacks which may indirectly impact all categories.

Following the recent demand-side classification of the IPCC sixth assessment report (Creutzig, Roy, et al., 2022), we sort transport policies into those concerning infrastructure types, locations and capacities; technology development and deployment; and socio-behavioural factors.

In each of the following subsections, we summarise identified studies specific to the factor or phenomenon, including their methods, data, and findings. We contrast these with mentions of how the factor is incorporated (or not) in typical global, integrative, long-term transport models. Quantitative projections from the latter are also used to frame the subsections.

2.1 Exogenous drivers of transport demand

Transport is often understood as a “derived” demand, in that most freight and passenger activity are undertaken to satisfy other, more fundamental, human needs. The systems that meet this demand are intrinsically linked with and strongly affected by population, industrial and economic activity, energy systems, and are affected by major regionally or globally disruptive events. Causal relationships in the other direction are weaker: for instance, while population change affects (aggregate) transport demand, changing demand does not strongly influence population. For this reason, these factors are commonly represented as exogenous drivers.

2.1.1 Population and economic trends

The global population is projected to reach 9.7 billion people in 2050, characterised by aging societies, increased life expectancy and, if climate change impacts are not considered, a doubling of the population of sub-Saharan Africa. Countries such as Japan, China, Germany, and Italy, will experience ageing and declining populations (IEA, 2022). Population distribution and settlement patterns are a significant driver of transport demand. Economic activity, transport costs, geographic factors, and urban form determines around 90% of urban transport energy use (Creutzig, Baiocchi, Bierkandt, Pichler, & Seto, 2015). If long-term economic growth persists, as projected in most climate mitigation scenarios, it will stimulate transport activity (ITF, 2023).

Sectoral models estimating global transport demand typically utilise population and economic projections to forecast future demand (Yeh et al., 2017). Exogenous population projections are used in the International Transport Forum (ITF) and International Energy Agency (IEA) transport demand models (ITF, 2023; Fulton, Cazzola, & Cuenot, 2009). The ITF models disaggregate transport into urban passenger travel, non-urban passenger travel, urban freight and non-urban freight. These models project a 79% increase in passenger transport demand, from 2019 to 2050 under current mitigation policies (ITF, 2023). There are however particular opportunities to avoid lock into high transport demand pathways in rapidly developing areas where current urban planning policies will drive future transport demand (Creutzig, Baiocchi, et al., 2015).

Population change and economic conditions are exogenous transport demand drivers in Integrated Assessment Models (IAMs). These typically contain aggregate transport demand metrics and endogenous links to other sectors, including energy systems, agriculture, and land use (Yeh et al., 2017). One such IAM is the MESSAGE model, which uses population projections and settlement patterns to determine technology adoption (McCollum et al., 2017). Similarly, the Global Change Assessment Model (GCAM), a technology-rich partial equilibrium model, assumes total PDT to be proportional to population (Speizer et al. 2024), while in practice overall transport activity is also influenced by the design of human settlements and urban areas.

2.1.2 Energy system

The deployment of technological transport mitigation options depends on the transition of energy systems. There must be sufficient infrastructure for electrification and alternative fuel uptake, as well as enough material feedstock and renewable energy supply that can be allocated to transport (IEA, 2022). The observed rapidly accelerating development of intermittent renewable energies and their declining costs will play a key role (Creutzig, Hilaire, Nemet, Müller-Hansen, & Minx, 2023). Energy system and transport interactions are modelled within IAMs and energy, environment, economy models, which can assess different energy mixes and policies (Edelenbosch, McCollum, et al., 2017). Within optimisation-based models, fuel mix is typically derived from least cost vehicle configurations categorised by fuel type (McCollum et al., 2017). The integrated nature of these models allows representation of trade-offs and cost-related interactions with other energy end-use sectors.

Changes to commodities traded in a LED future will also impact trade routes and flows. Transportation of fossil fuels accounts for 45% of global shipped trade by weight. As the energy system transitions away from fossil fuel use to alternative energy sources, demand for shipping such commodities will fall (Sharmina et al., 2021). This has been modelled using the ITF non-urban freight model, which disaggregates trade flows by commodity and uses a multinomial logit model to estimate mode shares on specific routes (ITF, 2023).

2.1.3 Shocks

Global events, such as pandemics, conflicts, natural disasters, and financial crises can significantly shape transport activity and energy demand (IEA, 2022).

Between 2019 and 2020, global PDT decreased by 20% due to the COVID-19 pandemic (ITF, 2023). Mode shares were also affected, with a comparative analysis of 16 cities showing an 80% reduction in public transit use under lockdowns and a 64% reduction in individual motorised transport. Transport land use and infrastructure also changed, with cities globally providing 550 km of temporary cycling infrastructure and planning an additional 1500 km (Creutzig, Lohrey, & Franza, 2022). Reduced long-distance travel particularly impacted aviation, with 60% less revenue PDT globally in 2020 compared to pre-pandemic levels. Scenario analysis with the AIM2015 aviation system dynamics model, incorporating vehicle fleet information, economy and population-based demand projections, and passenger activity, suggested that cumulative aviation fuel use may be 6-9% lower than in scenarios not including the pandemic (Dray & Sch¨afer, 2021).

Shocks can also trigger long-term structural changes. For example, teleworking has increased since the COVID-19 pandemic, impacting commuting and other travel. Regression can identify patterns in propensity to telework within populations, based on characteristics such as age, job sector, income and education level (Hensher, Beck, & Wei, 2021). These relationships can be incorporated in transport demand models, including sectoral transport models, by separating the impact on trip generation, distribution, and mode shares. For example, remote working patterns and risk avoidance attitudes, modelled using a 4-stage transport demand model, were found to increase car ownership and cause reductions in public transport use (Christidis, Christodoulou, Navajas-Cawood, & Ciuffo, 2021).

As transport demand is driven by economic activity, land use, and urban planning, disruptions from shocks have been studied through economic modelling using computable general equilibrium models. Interactions between supply side and demand side shocks can be assessed simultaneously, whilst decomposition analysis can disaggregate impacts of different factors (Chen, Rose, Prager, & Chatterjee, 2017).

2.2 Infrastructural factors

Transport demand in a LED future will depend on infrastructure, as infrastructure dictates the places accessible by transport (Creutzig, Roy, et al., 2022). Infrastructure planning typically uses cost-benefit analysis to evaluate project outcomes in terms of meeting policy objectives. However, cost-benefit analyses are critiqued as being often too narrow in scope to incorporate social and environmental externalities (Laird & Venables, 2017).

2.2.1 Passenger transport infrastructure

Providing infrastructure in a LED future may involve strategically investing in public transport infrastructure, operating with high occupancy rates in compact urban areas, rather than providing infrastructure as a reaction to predicted business as usual demand (ITF, 2023). Research using an integrated transport demand and energy systems model, reveals synergies between policies to reduce transport emissions and energy system transitions, with comprehensive and wide-ranging policies deemed to be most effective at reducing emissions (Zhang & Hanaoka 2022).

Agent-based modelling can be used to estimate behavioural responses to proposed infrastructure development (W Axhausen, Horni, & Nagel, 2016). An agent-based model for electric vehicle charging infrastructure development in Switzerland, revealed that electricity grid infrastructure development is necessary to support peak charging loads (Pagani, Korosec, Chokani, & Abhari, 2019). In New York, active travel infrastructure development was predicted to be conducive to increasing walking and cycling rates, alongside complementary social promotions (Aziz et al., 2018).

Infrastructure decisions can be a direct result of policies or an indirect result of population behaviour changes and technology development (Malmaeus et al.,2023). Empirical observations can retrospectively analyse infrastructure impacts. Improved cycling infrastructure led to a 5% increase in cyclist numbers in Copenhagen (Skov-Petersen, Jacobsen, Vedel, Thomas Alexander, & Rask, 2017). Pop-up cycling lanes during COVID-19 resulted in a 10-40% increase in cycling for every 10km additional bicycle lane built (Kraus & Koch, 2021). Also, 30% increases in walking and cycling were observed after active travel infrastructure development in small cities in New Zealand (Keall, Shaw, Chapman, & Howden-Chapman, 2018).

Further studies combine empirical data with regression models to disaggregate the effects of infrastructure on transport demand. A synthesis of empirical studies found that high-speed rail can stimulate the redistribution of air travel and that the spatial distribution of economic activity can change as accessibility changes (Zhang, Wan, & Yang, 2019). Further substitution effects were identified using a difference-in-differences econometric model that shows how high-speed rail development in China induced a reduction in passenger vehicles on parallel roads (Lin, Qin, Wu, & Xu, 2021).

2.2.2 Freight transport infrastructure

Global freight demand is projected to triple between 2015 and 2050. Significant changes to trade routes and trade network traffic may also occur. Large transcontinental infrastructure projects could establish new routes between East Asia and Europe, whilst increasing market accessibility in Central Asia and Africa (ITF, 2019).

Although unlikely, new arctic shipping routes opened by melting sea ice could reduce shipping times between Asia, Europe and North America by 2050. It was estimated, using a general equilibrium model and trade elasticities, that the Northern Sea Route could account for 4.7% of global trade value (Bekkers, Francois, & Rojas-Romagosa, 2016). Arctic shipping has considerable environmental impacts, with short-lived pollutants causing significant damage and offsetting emissions savings from shorter routes. Further, complications include reduced fuel efficiency, uncertain transit times and safety considerations, reducing economic benefits and increasing uptake uncertainty (Theocharis et al., 2018).

China's Belt and Road initiative is a complex set of interlocking trade and transport infrastructure policies. Its impact on bilateral trade flows was estimated using a gravity model and comparative advantage model. New trade routes could increase bilateral trade by 4.1%, with countries experiencing the greatest increases if they become heavily involved in global supply chains (Baniya, Rocha, & Ruta, 2020). Further consideration of infrastructure developments was modelled in the ITF freight model. The model disaggregates trade flows and allocates trade value-to-weight using a discrete mode choice model and an equilibrium-based route choice model (ITF, 2019).

The environmental impacts of infrastructure are modelled using life cycle assessments. For example, the lower environmental impact of electric road systems compared to the current diesel system for heavy goods vehicles across several impact categories has been demonstrated through life cycle assessments (Schulte & Ny, 2018).

2.3 Infrastructural-socio-behavioural factors

Infrastructure provision and land use can determine transport activity and mode shares. Reciprocally, transport service availability can influence infrastructure development choices and land use (Acheampong & Silva, 2015). Car use is strongly related to land use diversity; walking and public transport use is related to presence of pedestrian routes; and cycling is associated with active travel infrastructure (Eldeeb, Mohamed & Paez. 2021).

2.3.1 Compact urbanisation

70% of the total population is projected to live in urban areas by 2050 (ITF, 2023). Compact urbanisation is typified by dense and proximate development patterns, enabling good accessibility to services and jobs (Ye et al., 2018). Urban sprawl prevention, rural and agricultural land protection, and urban community development can improve quality of life (ITF, 2023). Compact urbanisation reduces average travel distances and promotes public transport use, thus avoiding the need for private vehicle ownership (Matsuhashi, Ariga, & Ishikawa, 2023). Urban compaction can however be detrimental for urban resilience and climate adaptation, which can be analysed by combining land use and transport with environmental models (Dehghani, Alidadi, Sharifi, 2022), and also in an urban economic modelling setting (Pierer & Creutzig, 2019).

Retrospective studies have quantified the impact of population density on passenger transport use. Empirical travel survey data is typically analysed alongside categorised land use and population density information (Berrill et al. 2024; Matsuhashi et al., 2023; Xu, Haase, Su, & Yang, 2019). For example, annual car mileage per capita and per vehicle was found to be low in Japanese municipalities with high population densities (Matsuhashi et al., 2023). Within the EU, urban compactness and population density are not necessarily correlated, with high population density and low physical compactness beneficial for reducing energy use (Xu et al., 2019). A recent high-resolution study of 19 European cities suggested that distance to the city centre rather than population density is the most important predictive factor of trip distance, car ownership and mode choice, thus driving transport GHG emissions (Berrill et al., 2024).

Future scenarios typically indicate that compact urbanisation has a complementary effect on transport emissions reductions. Passenger vehicle emissions in Japanese municipalities were estimated to fall by 64% by 2050, due to vehicle efficiency improvements and electrification, with a further 6% emissions reduction possible from urban compaction (Kii, 2020). Furthermore, wider factors impacting urban emissions and energy consumption, such as freight patterns, buildings, private vehicle ownership, disaster resilience and well-being, should be considered as well (Xu et al., 2019; Ye et al., 2018).

2.3.2 Transit oriented development

Transit-oriented development (TOD) is an urban planning strategy concerning organising compact and diverse mixed land use urban areas around public transport (Ford, Dawson, Blythe, & Barr, 2018). This can ensure good accessibility by active transport and reduce travel times, travel distances, urban sprawl and private car use (Ali et al., 2021). As buildings and infrastructure can have long service lifetimes adjustments to urban structure and stimulating changes to associated travel patterns can be complex and expensive (Ford et al., 2018).

Integrated land use transport models have evolved from assessing relationships between transport and land use using aggregate data with gravity and entropy maximisation models; to better represent behavioural theories and spatial choices using discrete choice models; to using agent-based models to analyse responses to land use changes (Engelberg et al., 2021). Urban planning uses integrated land use transport models to prescribe suitable land uses based on land-use-by-activity ratios and maximum density limits (Moeckel, Garcia, Chou, & Okrah, 2018). Further, transport demand influenced by land use patterns can be disaggregated by mode and time, allowing calculation of transport flows and accessibility metrics (Hawkins & Habib, 2019). Future integrated land-use transport models are expected to adopt disaggregate, activity-based accessibility metrics, enabling individual changes in use of communication and mobility technologies, activity patterns and time use to be aggregated into behaviour of the whole system (Engelberg et al. 2021).

Machine learning models based on “big data” can assess transport and land use interactions (Milojevic-Dupont & Creutzig, 2021). Pattern recognition algorithms can identify spatially explicit urban forms predictive of travel patterns, energy use and emissions (Wagner et al., 2022). These algorithms have been used in Porto to identify drivers of greenhouse gas (GHG) emissions and estimate future emissions under different urban planning scenarios (Silva, Horta, Leal, & Oliveira, 2017; Silva, Leal, Oliveira, & Horta, 2018). Another study used a double machine learning approach to identify induced transport demand by newly planned settlements in Berlin (Nachtigall, Wagner, Berrill, & Creutzig, 2023).

Integrated land use transport models that integrate environmental factors are still uncommon (Ford et al., 2018). The OECD Multi-Objective Local Environment Simulator (MOLES) attempted this integration by modelling interactions between urban land use, mobility patterns, economic activity, policy interventions and their impacts, notably air pollution and emissions (OECD, 2020). Further models containing this integration include the IRPUD model and Urban Integrated Assessment Facility (UIAF) which model relationships between population, economic conditions, land use, transportation and the environment (Moeckel et al., 2018)

2.3.2 Trade network optimisation, supply chains, local production and consumption of goods

Optimising trade networks can decrease product’s embodied energy and emissions, by reducing supply chain travel distances and promoting local production and consumption (Sharmina et al., 2021). Further, global trade flow changes could stem from consumer behaviour changes, relocation of industrial production facilities, and technology adoption altering the commodity types traded (Moran et al., 2018).

Re-configuring global supply chains by sourcing commodities from nearby locations can reduce cargo ship use. Linear optimisation has been used to calculate which flows need to be re-routed to reduce global shipping emissions by a maximum of

38% (Wang et al., 2021). Logistics facility location is largely driven by market proximity and is commonly observed using Geographic Information Systems (GIS). GIS are typically used to make observations rather than to predict impacts on transport demand (He, Shen, Wu, & Luo, 2018).

Local supply chains can also be reconfigured by using different vehicle types. Traffic simulation models suggested that cargo bikes can replace up to 10% of conventional vans for trips in a 2 km radius without changing the overall network efficiency in Porto (Melo & Baptista, 2017). Further, cost analyses found cargo bicycles to be effective in displacing vans for deliveries close to distribution centres, in densely populated areas, and with low delivery volumes at each stop (Sheth, Butrina, Goodchild, & McCormack, 2019).

Additive manufacturing is the construction of three-dimensional objects from digital models, through deposition, joining or solidification of material (Savolainen & Collan, 2020). Additive manufacturing could reduce freight transport demand through consolidating manufacturing activities and simplifying supply chain logistics (IPCC, 2022). Despite recent growth, there is uncertainty around short to medium-term growth of these impacts, due to limited economies of scale, and regulatory, cost, material, and product size limitations for the underlying technologies (Boon & van Wee, 2018).

Life-cycle assessments can model the impact of factors related to transport demand, including vehicle fleets and supply chains. For instance, light-weight aeroplane components produced by additive manufacturing are found using a life cycle inventory model to reduce cumulative emissions from the global fleet by 215MtCO_2 by 2050 (R. Huang et al., 2016). Additive manufacturing is also found using a linear programming model to reduce costs and tonne-kms per component through the reconfiguration of supply chain networks (Barz, Buer, & Haasis, 2016).

2.3.4 Shared economy

The term “shared economy” refers to peer-to-peer based activity of obtaining, giving, or sharing access to goods and services, often coordinated through online platforms (Craig Standing & Biermann, 2019).

Freight sharing through business-to-business collaboration can reduce costs, vehicle ownership rates and induce time savings (Craig Standing & Biermann, 2019). Similarly, crowd-shipping can create informal urban delivery networks where people act as couriers on trips they are making already, with optimisation algorithms used to allocate deliveries to suitable travellers (Allahviranloo & Baghestani, 2019). The propensity to participate in crowd shipping is studied through stated preference surveys to identify socio-demographic characteristics that typically indicate a greater willingness to work (Miller, Nie, & Stathopoulos, 2017).

Shared mobility allows users to access transport services without owning the vehicle they use. Ubiquitous digitalisation has enabled on-demand shared services and allows efficient matching of supply and demand over short time periods, especially in densely populated areas with potentially large user bases (Machado, De Salles Hue, Berssaneti, & Quintanilha, 2018). Shared mobility could impact mode shares and vehicle ownership rates, with current implementations indicating mode shifts away from public transport and active travel, and lower vehicle ownership rates amongst car sharing program participants (Javaid, Creutzig, & Bamberg, 2020; Craig Standing & Biermann, 2019).

Shared mobility can also improve accessibility and first and last mile connectivity with public transport (IPCC, 2022). However, a stated/revealed preference study found that additional policies and incentives would need to be provided to prevent shifts away from public transport, as public transport users are the most likely to adopt trip sharing (Li & Kamargianni 2020). Agent-based models can simulate shared vehicle uptake, including the use of shared autonomous vehicles. An agent-based model applied to Singapore found that shared autonomous vehicle introduction could double the size of the current national taxi fleet, cause a shift away from public transport use, and increase vehicle-km by up to 17% (Oh et al. 2020). An agent-based model applied to Lisbon suggested that full implementation of shared autonomous vehicles, replacing private car, bus and taxi use, would significantly reduce distances travelled and emissions (Martinez & Viegas, 2017).

Bike sharing schemes are growing in popularity in urban areas. Data collection from dock stations and location information from free-floating bicycles enables collection of large quantities of trip data. This information can be used alongside regression and optimisation techniques to determine bike relocation strategies to areas of high demand (Faghih-Imani, Hampshire, Marla, & Eluru, 2017). Further, agent-based models can estimate bike sharing uptake potential in terms of impacts on mode shares, accessibility, emissions and energy use (Lu, Hsu, Chen, & Lee, 2018).

2.4 Socio-behavioural factors

Transport energy use is dependent on several factors, including the need to travel, the transport mode and vehicle used, and destination and route choice. Furthermore, transitioning away from the self-reinforcing incumbent car-centric transport system in many countries will depend on interactions between economies of scale, industry, consumers, public policy, infrastructure and cultures (Mattioli, Roberts, Steinberger, & Brown, 2020). Additionally, transport systems transitions will depend on considerations related to the social and cultural aspects of transport, such as the non-use value users place on private cars (Moody, Farr, Papagelis, & Keith, 2021).

2.4.1 Social movements and trends

Individual, social and infrastructural factors influence transport mode choice. Individuals are more likely to shift towards low energy and emission modes if these transport modes are accessible, affordable and safe in the areas where they live and work. Mode choice is also influenced by perceived social norms resulting from observations of social norms which are in turn determined by public policy (Javaid et al., 2020).

Society-centric transport planning involving community engagement could improve transport justice by addressing inequalities in access to goods and services (Karner et al. 2020). Transport planning often employs state-maintained sectoral transport demand models, with generally relatively little consideration of social equity (Vecchio, Tiznado-Aitken & Hurtubia, 2020). Further inclusion of social equity metrics could generate outcomes that stimulate new social norms and changes in mode shares and transport activity (Karner et al., 2020).

Flygskam (flight shame) is a social movement that emerged in Sweden in 2017, concerning an individual's unease with flying due to the climate implications and social stigma of air travel (G¨ossling, Humpe, & Bausch, 2020). Social movements and opinions, such as flygskam, can be tracked using surveys. Survey results indicated that flygskam had increased awareness of aviation impacts and there is some public support for policies that increase the cost of flying (Go¨ssling et al., 2020).

In 2013, tourism was estimated to contribute 8% of global emissions (Lenzen et al., 2018). As a major emitting sector, tourism is typically endogenously included within larger-scale decarbonisation scenarios. Measures relating to touristic transport, in the IEA's net zero roadmap, included keeping long haul leisure air travel at 2019 levels, choosing closer destinations, shifting short haul flights to rail and introducing carbon prices to influence travel costs (Scott & Go¨ssling, 2022).

General theory of planned behaviour models are psychological behavioural models used to predict and explain destination decisions (Cao, Zhang, Wang, Hu, & Yu, 2020). Prospective transport demand is studied through the push-pull framework and perceived fit theory, which aims to understand destination choice decisions (Tojib, Tsarenko, Hin Ho, Tuteja, & Rahayu, 2022). Further, potential changes in destination choice, due to climate adaptation in alpine regions for example, have been studied through agent-based modelling (Scott, Steiger, Rutty, Pons, Johnson, 2020).

2.4.2 Demand reduction policies

Policy can stimulate transport demand changes, by encouraging mode shifts and restricting vehicle use. Ghent and Pontevedra have banned cars from inner cities, with Paris planning to do so in 2024 (Creutzig, 2022). Congestion charges in cities, including London, Milan, and Singapore, have reduced urban traffic and associated externalities (Green, Heywood, & Navarro Paniagua, 2020).

Price-based measures can be analysed using elasticities that measure the sensitivity of demand to changes in price (B¨orjesson & Kristoffersson, 2018). Price elasticities can be integrated into transport and energy optimisation models to represent modal shifts (Salvucci, Tattini, Gargiulo, Lehtila¨, & Karlsson, 2018). Stated preference surveys can monitor the impact of demand reduction measures on passenger behaviour. Responses to congestion management strategies, including changing parking charges, introducing shared bicycles and subsidising public transport, can be recorded in cross sectional stated preference surveys to evaluate the effectiveness of different strategies (Guzman, Arellana & Alvarez 2020).

Demand reduction measures can also be included within travel demand simulation models. Travel demand management policies have been found to contribute to emissions reductions and can be included in urban location decision models by incorporating travel costs and comparing them with household incomes (Wegener, 2021). Discrete choice modelling can also be used to model demand reduction measures. For example, a multinomial logit model was used to evaluate the utility of different mode choices when congestion pricing policies are applied in New York (He et al. 2021).

2.5 Socio-behavioural-technological factors

Adoption of technologies can stimulate behaviour changes that impact transport demand. For example, remote working where possible can reduce the need for commuting trips; e-commerce can alter shopping trips and increase consumer deliveries; and online tools can help change accessibility and perceptions of passenger transport services (ITF, 2023).

2.5.1 Mobility as a Service

Mobility as a Service (MaaS) generally refers to integrated platforms that allow users to access services provided by various different transport modes (ITF, 2023). Inter-modal connectivity could facilitate increased public transport and shared mobility use. In a trial in Japan, GPS data and questionnaires were used to empirically observe behaviour changes caused by the introduction of MaaS and free public transport access. Introduction of MaaS accelerated modal shifts towards public transport and changed trip frequency and locations visited (Miyawaki, Tomioka, Takayama, & Morimoto, 2020).

There is uncertainty surrounding the potential impacts of MaaS on transport demand, with several barriers currently limiting widespread adoption (Zhao, Andruetto, Vaddadi, & Pernest˚al, 2021; Laine et al., 2018). Scenario analyses, containing assumptions on adoption rates, car ownership and vehicle-km travelled, have been used to estimate impacts on transport activity (Zhao et al., 2021). For example, the role of MaaS in changing travel behaviour was studied using a vehicle fleet model. Reducing car ownership by 10%, viable through increased use of MaaS, could lead to greater emissions reductions than a 10% increase in vehicle efficiency (Laine et al., 2018).

An activity-based transport demand model was used to simulate the impacts of MaaS on travel activity and mode shares in Amsterdam, with propensity for adopting MaaS determined using a multinomial logit model. It was estimated that emissions could be reduced by 3-4% if 20% of the population adopt MaaS or 43-54% if 85% of the population adopt MaaS (Labee, Rasouli, & Liao, 2022).

2.5.2 E-commerce

E-commerce is the sale of goods or services over computer networks using methods specifically designed for receiving or placing orders (ITF, 2023). The share of e-commerce in all sales tripled between 2014 and 2019. Growth is set to continue, with last mile transport demand set to grow by 78% between 2020 and 2030 and e-commerce projected to increase unabated freight emissions by 4% by 2050 (Deloison et al., 2020; ITF, 2019). This growth is driven by urbanisation, widening customer bases globally, online product availability, and new digital business models (Deloison et al., 2020).

Urban density, mode shares, the energy mix, as well as physical, psychological and socio-demographic factors will determine the direction and magnitude of e-commerce's impact on transport demand. Empirical evidence as to the effect of e-commerce on transport demand is currently inconclusive, with diverse purchasing models, complex behaviour changes and rebound effects making it difficult to define system boundaries to assess the overall impact (Buldeo Rai 2021). Furthermore, on-demand deliveries in narrow time windows reduce vehicle payload factors and customer returns increase overall delivery vehicle-km (ITF, 2019).

Collection points, off-peak deliveries, zero-emission zoning and distance-based charging can encourage distribution companies to use vehicle capacity better, thus limiting emissions and congestion from last mile deliveries. Traffic micro-simulation can predict congestion and emissions impacts of additional delivery vehicles in urban areas (Laghaei et al., 2015). Agent-based modelling can also compare the dynamics of door-to-door deliveries and consolidated delivery patterns, by simulating customer movements and freight deliveries (Calabr`o et al., 2022). Econometric models can analyse longer-term impacts of e-commerce, such as changes in urban form and employment types, linking e-commerce activity with specific transport mode use (Bonilla, 2016).

2.5.3 Teleworking

Teleworking is where work is completed away from an employer's site while staying connected via network technologies (Hook, Court, Sovacool, & Sorrell, 2020). Globally, between 2-40% of employees telework, with rates influenced by country, labour laws, cultures, and occupation sector (Gschwind et al., 2017). Certain socio-demographic and geographical factors determine propensity to telework, with women and employees with high incomes, children, high education levels, and long commutes more likely to telework than other groups (Singh, Paleti, Jenkins, & Bhat, 2013).

The trip and transport mode displaced, climate, induced energy use patterns, office and remote working environment energy characteristics, and electricity mix determine the net effects of teleworking. Further, there is large uncertainty concerning rebound effects including increases in non-work travel, home energy use and the distances people live from their workplace (Hook et al., 2020). For example, regression models found that teleworking has a complementary rather than substitutive effect on the total number of trips made, especially in larger metropolitan areas in the USA (Zhu, Wang, Jiang, & Zhou, 2018). Despite this, empirical evidence suggested that teleworking can reduce traffic volumes by up to 2.9% (Giovanis, 2018). Illustrating the interaction with exogenous shocks (§2.1.3 above), teleworking during the Covid-19 lockdowns contributed to a 40% reduction in land transport emissions (Le Qu´er´e et al., 2020).

Teleworking’s impact on transport can be modelled using empirical data from household travel surveys (Zhu et al., 2018; Giovanis, 2018). Further, binary probit regression can be used in generalised ordered response models to represent the choice to telework (Singh et al., 2013). Scenario analyses can also estimate potential impacts. In a scenario, where teleworking affects between 3-30% of urban trips by 2050, global urban PDT and related CO_2 emissions were found to be 2% lower than in a current policy ambition scenario (ITF, 2019).

2.6 Technological factors

Transport decarbonisation strategies involve significant transformation to the technologies used in the transport sector (ITF, 2023). In hard-to-decarbonise sectors such as marine transport and aviation, decarbonisation strategies rely heavily on alternative low-carbon fuels, whose development and deployment are highly uncertain (IPCC, 2022).

2.6.1 Activity feedbacks of technology/fuel changes

Heavy goods vehicles account for 23% of transport emissions globally, with road freight demand expected to increase in the future (ITF, 2023; Mulholland, Teter, Cazzola, McDonald, & O Gallachoir, 2018). Short-term decarbonisation strategies comprise vehicle efficiency improvements and measures to improve freight systems efficiency (Mulholland et al., 2018). Under such strategies, liquid fuels remain prevalent due to their high energy density, portability, storage stability, and ease of delivery owing to the extensive distribution infrastructure (Mulholland et al., 2018). However, decarbonisation will ultimately depend on using alternative energy sources, such as electricity, hydrogen or low-carbon liquid fuels (Sharmina et al., 2021). Biofuels could reduce net emissions, have high energy density, and have been produced at scale from crops in Brazil and the United States (IEA, 2022). However, significant increases in crop-based production would entail large-scale land conversion, potentially impacting food supply and land use change, offsetting emissions savings (Maia & Bozelli, 2022). Difficulties in scaling up fuel production, fuel costs, high life-cycle emissions, limited infrastructures, vehicle costs and performance limitations all currently limit alternative technology deployment (Moultak, Lutsey, & Hall, 2017).

Electric road system capital costs are projected to be lower than hydrogen fuel cell and liquefied natural gas vehicles by 2030 in China, the USA and Europe (Moultak et al., 2017). The potential environmental impact of alternative power trains can be studied through life cycle assessments. Generally, catenary electric heavy goods vehicles have lower life-cycle emissions than conventional diesel vehicles and hydrogen fuel cell vehicles due to inefficient hydrogen production pathways (Moultak et al., 2017).

Aviation decarbonisation pathways typically include: low-carbon fuels, aircraft efficiency improvements, operational efficiency measures, novel propulsion technologies and residual emission offsets (Dray et al., 2022). Hydrogen and electric aircraft are under development and could complement conventional aircraft using sustainable aviation fuel, however they will likely only operate on short to medium-haul routes due to technological limitations (Scha¨fer et al., 2018). Sustainable aviation fuel typically refers to cellulosic biofuels or synthetic fuels produced using hydrogen and carbon dioxide. Widespread biofuel use may be constrained by land use and feedstock yields and synthetic fuel uptake is currently limited by high production costs and limited production infrastructure (Dray et al., 2022).

System dynamics methods have been used to construct global integrated aviation models representing interactions between demand generation, aircraft technology and cost, fleet dynamics, and environmental and economic outputs. Future passenger activity is estimated using a gravity-based demand sub-model and is updated by achieving partial equilibrium with supply through factors such as airfares and operational costs (Dray et al., 2022). The ITF non-urban passenger model is also used to simulate global air transport activity, mode shares, and emissions for intercity and regional travel to 2050. For each air route, the optimal fuel type and propulsion technology is assessed every 5 years, with sustainable aviation fuel mandates used to update fuel costs. In a high ambition scenario, this model projected that high fuel costs will likely limit passenger demand, reducing PDT by 30% compared to a current ambition scenario (ITF, 2023).

The shipping sector has set a goal to halve its sectoral emissions by 2050 compared to 2008 (Tillig, Ringsberg, Psaraftis, & Zis, 2020). For this transport mode, short-term emissions savings rely on fleet planning, improved harbour logistics, route planning, slow steaming, and ship design improvements (Tillig et al., 2020). Using a profit maximisation model combining economic inputs and technical ship data, studies have found that fuel use impacts the viability of ship use for different purposes and on different routes (Joseph et al. 2021).

Wind-assisted ship propulsion could reduce fossil fuel use between 1- and 50% depending on the specific technology used. This energy saving can be maximised through using shipping routes with stronger winds, changing travel distances and times (Chou, Kosmas, Acciaro, & Renken, 2021). Route optimisation tools, using techniques including the branch and bound approach, can incorporate wind speed and weather data to assess the most fuel-efficient routes (Bentin et al., 2016). Further models couple economics and ship energy systems models to assess decarbonisation strategies that will alter trip distances and travel times. Emissions savings from wind-assisted propulsion and slow steaming are greatest when fuel prices are high, as lower speed operation becomes economically optimal (Tillig et al., 2020).

2.7 Infrastructural-technological factors

Infrastructure and technology use are highly interdependent. Infrastructure allows transport technologies to be used and technology determines infrastructure choices and development.

2.7.1 Autonomous passenger vehicles

The future energy use of autonomous passenger vehicles is uncertain, and will depend strongly on use patterns, ownership models, induced demand, and regulations (Millard-Ball, 2019; Bo¨sch, Becker, Becker, & Axhausen, 2018). Automation may improve vehicle efficiency, reduce congestion and increase public transport use by providing first and last-mile accessibility. Conversely, it may decrease travel costs, stimulating increases in travel activity and shifts away from conventional public transport (Fagnant & Kockelman, 2014). The Swiss national transport model, which uses origin-destination matrices containing capacity and demand data, has been used to model autonomous vehicle adoption. Autonomous vehicle use improved accessibility, with the magnitude of the improvement dependent on network capacity (Meyer, Becker, & Axhausen, 2017). The potential impact of autonomous vehicles on transport demand has also been assessed using micro-simulation models (Fagnant & Kockelman, 2016; Millard-Ball, 2019). Autonomous vehicle parking was also investigated by combining traffic micro-simulation with an activity-based transportation model. Autonomous vehicle parking may induce additional car use from decreased parking costs and increase congestion from vehicles relocating to access inexpensive parking (Millard-Ball, 2019).

Shared autonomous vehicle adoption could decrease vehicle ownership rates and reduce the number of vehicles required to meet car transport demand (Bo¨sch et al., 2018; Meyer et al., 2017). An agent-based model has been used to estimate the impact of shared autonomous vehicles compared to conventional private car use, in a theoretical grid network. Each shared autonomous vehicle is estimated to replace eleven conventional vehicles but travel 10% further than equivalent private vehicles from picking up passengers (Fagnant & Kockelman, 2016). However, cost analysis suggested that uptake may be limited due to competition with private autonomous vehicles with less variable costs (Bo¨sch et al., 2018). Furthermore, compared to conventional privately owned and operated vehicles, the additional costs of driving without passengers and high operator profit expectations may hinder uptake (Nunes & Hernandez, 2022)

Autonomous vehicle uptake may induce urban land use changes (Hawkins & Habib, 2019). Reductions in travel time sensitivity from increased productivity while travelling may induce urban sprawl (Meyer et al., 2017). Conversely, streets could be redesigned for walking and cycling, with land previously devoted to parking repurposed for pedestrian oriented urban centres (Millard-Ball, 2019).

2.7.2 Autonomous freight vehicles

Automated trucks could reduce operating costs, as labour accounts for 35-45% of road freight operating costs in Europe (ITF, 2017). Driverless trucks could operate at all times, enabling better asset use and flexible fleet management. Furthermore, inter-vehicle communication could enhance safety and enable efficient driving practices (ITF, 2017). Currently, there are significant uncertainties around deployment timelines, operational capabilities, infrastructure requirements and regulatory acceptance of automated freight vehicles (Engholm, Kristoffersson, & Pernestal, 2021).

Operational costs of automated freight have been estimated to be 12-58% lower than for conventional vehicles (Engholm et al., 2021). Lower operational costs could stimulate decentralisation, increased specialisation in supply chains, and the development of freight consolidation centres (ITF, 2017). Transport economics can be combined with vehicle characteristics and routing optimisation to assess the impact of autonomous vehicles on routes and optimal vehicle types for logistics. Optimising for cost leads to adoption of smaller vehicles for trips with few stops and urban deliveries. For larger trucks transporting bulk commodities, using smaller vehicles had negligible impact on cost compared to driver removal savings (Bray & Cebon, 2022).

Agent-based traffic simulation models can assess impacts of automation on road freight logistics. Automated coordination of freight services and planning could improve dispatching process flexibility and speed, reduce empty vehicle mileage and increase vehicle capacity utilisation (Arendt, Klein, & Barwig, 2016). Furthermore, connected autonomous vehicles could reduce travel times in congested areas by using optimised vehicle routing strategies (Djavadian, Tu, Farooq, & Hatzopoulou, 2020).

2.7.3 Transport materiality

Decoupling the services provided by in-use material stocks from material stocks has large mitigation potential, with long-term management of in-use stocks crucial for meeting climate targets (Haberl et al., 2021). Circular economy principles such as recovery and re-use of energy-intensive and critical materials, re-use of components, material substitution and material efficiency improvements can reduce material use impacts (Walker, Coleman, Hodgson, Collins, & Brimacombe, 2018).

Future transport sector material requirements are highly dependent on several factors, including average vehicle size, use intensity, lifetimes, overall fleet numbers and fleet composition (Zeng et al., 2022).

Material requirements are modelled using dynamic stock models, that for instance have shown how rapid lithium demand increases could cause a mismatch with supply by 2050, limiting electric vehicle deployment rates (Watari et al., 2019). At the global scope, forecasts using dynamic material flow analysis suggested a 15- to 31- fold increase in global demand for critical battery materials, requiring a substantial expansion of manufacturing capacity (Xu et al., 2020). Recycling electric vehicle batteries could provide 60% of cobalt, 53% of lithium and 53% of nickel required globally by 2040 (Richter, 2022). Reducing primary material demand for vehicle batteries could be achieved through increasing battery energy density, commercialising cobalt-free battery technologies and increasing recycling rates (Abdelbaky, Peeters, & Dewulf, 2021).

Material substitution can reduce vehicle weight and increase vehicle efficiency. Reducing conventional steel and iron consumption in cars is possible by increasing use of high-strength steel, magnesium, aluminium, plastics and composites (Serrenho, Norman & Allwood, 2017). However, material substitution can be environmentally detrimental if it requires new mines, limits end-of-life product recovery, and/or increases transport demand in supply chains (Rodrigues, Carmona, Whiting, & Sousa, 2022).

Vehicle choice and consumer preferences can also greatly impact the material and energy requirements of transportation. Reversing trends towards larger and more powerful vehicles (downsizing) could be highly effective at reducing vehicle life-cycle emissions and material requirements. It was estimated, using life cycle assessment methods, that shifting all vehicles to the next smallest vehicle class could reduce vehicle mass by 16-44% and fuel consumption by 9-37% (Wolfram, Tu, Heeren, Pauliuk, & Hertwich, 2021).

2.8 Summary of factors' impact on transport demand

The classifications used in Table 1 indicate each factor's general effect on aspects of transport demand. For compactness, Table 1 uses abbreviations given in Table 2. These effects are representative of the dominant aspects and impacts mentioned in the reviewed literature. The supplementary information contains additional information on the specific model types used in each reviewed study.

Table 1: Summary of categorisation of factors affecting transport demand and the modelling approaches used.

Factor type	**Factor affecting transport demand**	**Impacts**					**Transport demand area**
		Location	**Modes**	**Direction**	**Areaa**	**Trip type**	
Exogenous drivers	Population and economic growth	All	All	I	All	All	Ac, MS, LU

§2.1	Energy systems	All	All	U	All	All	All
	Shocks	All	All	U	All	All	All
Infrastructural §2.2	Passenger infrastructure	All	P	U	All	All	All
	Freight infrastructure	All	F	U	All	All	All
Infrastructural - socio-behavioural §2.3	Compact urbanisation	All	All	D	Ur	L	Ac, MS, LU, R
	Transit-oriented development	All	All	D	Ur	L	All
	Trade network optimisation, supply chains, local production/consumption	All	F	D	All	All	Ac, EI, V, R
	Shared economy	All	All	D	All	All	Ac, MS, EI, V
Socio-behavioural §2.4	Social movements and trends	All	All	U	All	All	Ac, MS
	Demand reduction policies	All	All	D	All	All	Ac, MS, V, R
Socio-behavioural – technological §2.5	Mobility as a service	HIC	P	D	Ur	L	Ac, MS, EI
	E-commerce	HIC	All	U	All	L	Ac, MS
	Teleworking/conferencing	HIC	P	D	All	All	Ac, MS, R
Technological §2.6	Activity feedbacks of technology/fuels	All	All	U	All	All	Ac, MS, EI, V
Infrastructural – technological §2.7	Autonomous passenger vehicles	HIC	P	U	All	L, R	Ac, MS, EI, V, R
	Autonomous freight vehicles	HIC	F	U	All	All	Ac, MS, EI, V, R
	Transport materiality	All	All	D	All	All	EI, V

Table 2: Categorisations used to characterise factors that affect transport demand.

Impact variable	**Category**
Location	**HIC –** High Income Countries, **LMIC** – Low- and Middle-Income Countries, **All**- All countries

Trip type	**L** - Local, **R** - Regional, **I** - International, **All** - All distances
Modes	**P** - Passenger, **F** - Freight, **All** - All modes
Direction	**I** - Increase, **D** - Decrease, **U** - Uncertain
Area classification	**Ur** - Urban, **Ru** - Rural, **All** - All areas
Transport demand area impacted	**Ac** - Activity (Trip generation), **MS** - Mode share, **EI** - Energy intensity (Fuel type, Use efficiency i.e. Vehicle capacity utilisation), **R** - Routes, **LU** - Land use, **V** - Vehicles

3 Modelling and representation of factors that affect transport demand

In the previous sections, factors relating to transport demand that could conceivably contribute to a LED future were introduced and current approaches to modelling their effects on transport demand were reviewed. Naturally, the factors all have different impacts, transport modes they affect, uncertainties, and interactions with other factors and sectors. Therefore, the modelling techniques used are specific to their ability to represent the factors and the relevant aspects of transport demand. Here, we propose a taxonomy to characterise transport demand modelling approaches. This will help identify gaps in current modelling practices and shortcomings in the integration of the factors affecting demand in integrated models of the total global transport system.

3.1 Taxonomy of transport demand modelling approaches

There are a number of distinct modelling approaches, which differ in their scope, structure, assumptions, and inputs and outputs, that have emerged in transport demand modelling.

Microsimulation refers to approaches where the unit of analysis –individual people artifacts—used cannot be subdivided. It is used to model factors affecting transport demand where aggregate representations of demand, such as traffic flow within a set time or overall PDT, are not appropriate (Linton et al., 2015).

Agent-based models are used to capture behavioural and social changes by simulating individual agents' actions and interactions within a transportation system (Bastarianto, Hancock, Farheen Choudhury, & Manley, 2023). Agent-based modelling considers the heterogeneity and autonomy of agents, such as travellers, vehicles, or infrastructure components, allowing for a realistic representation of system dynamics. It incorporates various aspects of human behaviour and social dynamics that influence travel patterns, including mode choice, route selection, and interactions with social networks (Castiglione, 2020). Agent-based modelling enables the exploration of emergent phenomena and the effects of interactions between agents on system-level outcomes, offering insights into how individual decisions shape collective behaviour and system performance (J. Huang et al., 2022).

Sectoral transport demand models represent transport subsystems, with exogenous relationships with other sectors and drivers of demand. Modelling approaches are often modular with distinct steps used to model different aspects of demand. The classical "four-step model", or trip-based model, for example, uses trip generation, trip distribution, mode choice and route choice stages to simulate transport demand (McNally, 2007). Activity based models generally better represent trip chaining, with activity generation used instead of trip generation, derived from activity sequences, locations and durations (Joubert & de Waal, 2020).

Systems dynamics approaches model interactions such as positive and negative reinforcement and non-linear behaviour in complex systems. Quantitative system dynamics analysis uses stocks and flows which are represented using non-linear differential equations (Shepherd, 2014). System dynamics can be applied to model vehicle stocks, alternative fuel uptake, urban passenger demand and strategic policy at various geographical levels (ITF, 2023; Shepherd, 2014).

Integrated transport land use models directly consider interactions between transport and land use and are used in urban planning. Two main approaches exist, with equilibrium-based models assuming cities are markets that gradually approach economic equilibrium, and dynamic models focusing on adjustment processes of different speeds. Within integrated transport land use models, transport demand can be modelled using microsimulation, agent-based models and activity-based models (Wegener, 2021).

Aggregate transport demand metrics are also included within integrated models, including IAMs and energy, environment, economy (E3) models. Integrated models span multiple domains and link the main aspects of society, the economy and the environment within single modelling frameworks. One IAM classification differentiates between cost-benefit oriented models and technology-rich process-based models. Cost-benefit oriented IAMs use econometric relationships to examine the trade-offs between damage from climate change and mitigation costs. Technology-rich or process-based models, represent industrial production and consumption sectors and are used to identify and quantify mitigation pathways, assuming economic equilibrium (Pauliuk et al., 2017). Both general and partial equilibrium approaches are used, and many different techniques are used, including recursive simulation, inter-temporal optimisation, recursive dynamics and linear optimisation (Edelenbosch, McCollum, et al., 2017).

Table 3: Summary of modelling approaches used to assess factors that affect transport demand.

Modelling approach	Scope	Units/measures of analysis	Main model use	Granularity	Reference(s)
Microsimulation	Typically local	Individual or vehicle	Detailed description of transport movements.	High	(Linton, Grant-Muller & Gale 2015)
Agent-based models	Local to global	Autonomous agents	Interactions between independent entities.	Medium high	(J Huang et al., 2022; Linton et al., 2015)
Sectoral transport models	Local to global	Trip/ tour/ activity	Transport demand with exogenous interactions with other sectors.	Medium	(McNally, 2007; Joubert & de Waal, 2020; Linton et al., 2015)
Integrated transport land use	Urban areas	(Varies)	Relationship between land use and transport demand.	Medium low	(Wegener, 2021; Linton et al., 2015; Nachtigall et al., 2023)
System dynamics	Local to global	Stocks and flows	Interactions and causal relationships between different aspects of transport demand.	Low	(Shepherd, 2014; Linton et al., 2015)
Multi sector models	National to Global	Aggregated transport demand	Model transport as a derived demand and interaction with other sectors.	Low	(Edelenbosch, McCollum, et al. 2017; Pauliuk, Arvesen, Stadler & Hertwich, 2017; Linton et al. 2015)

There is no universal categorisation of transport demand modelling approaches. Modelling taxonomies have been proposed to characterise modelling approaches for land use transportation models (Torrens, 2000), travel behaviour models (Sharma et al., 2021) and for inter-modal freight simulations (Crainic, Perboli, & Rosano, 2018). Yet, no taxonomies exist for transport demand modelling approaches as a whole. Because, many approaches contain shared methods, scopes and techniques, constructing a hierarchical classification based on model characteristics, structure and methods is difficult. For example, optimisation methods can be used to determine agent behaviour within an agent-based model, while also being used to determine least cost pathways in IAMs; these and other applications will use different independent and dependent variables, and have different consequences for model validity. Thus, we propose a transport demand model taxonomy (figure 2) that characterises different transport demand models and multi-sectoral models containing explicit representations of transport demand.

For any existing or new model or model-based study, providing the seven attributes in this taxonomy can enable straightforward assessment of which subsystems of the complex global transport system are within the model boundaries, thus which demand factors are captured endogenously, partially, or treated as exogenous.

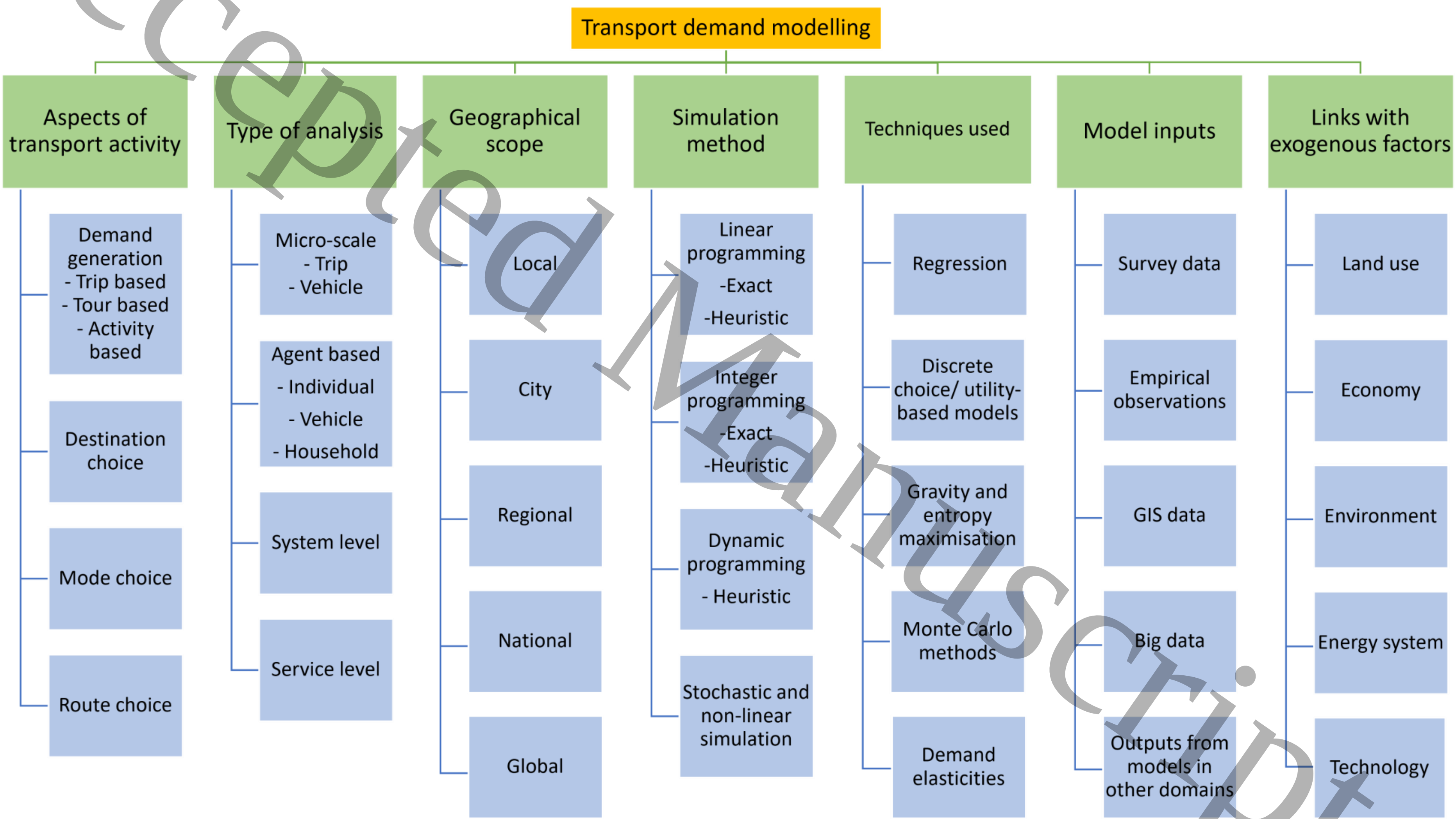

Figure2: Taxonomy of transport demand models. Each transport model can contain any number of elements from each column.

3.1.1 Complementary modelling approaches

Besides transport demand models, further modelling approaches and associated data are used to represent factors that interact with transport demand, such as land use and vehicle characteristics. Data outputs from these models can be useful inputs to transport demand models and can help ensure transport demand model outputs are physically and socio-economically realistic.

Industrial ecology techniques, including life cycle assessments and material flow analysis, can assess environmental and material impacts of vehicles and infrastructure (Pauliuk et al., 2017). Surveys can be used to derive activity patterns for activity-based models and monitor qualitative social and behavioural factors, helping to create realistic scenarios (Guzman, Arellana & Alvarez 2020). Similarly, empirical data can be used for model validation and to study statistical relationships in the absence of transport demand models (Skov-Petersen et al., 2017). GIS data can be input to transport land use models (He et al., 2018). Machine learning can be used to identify and categorise land uses and thus identify how urban form can be modified to encourage transport demand changes (Wagner et al., 2022).

4 Discussion and conclusions

Transport demand is typically empirically measured and quantified within models using metrics such as PDT, VDT and freight volume (measured in tonne-km). Data for these measures can have different dimensionality, scope, and resolution or granularity. For example, at the most aggregate level multi-sector models may have representations of transport demand where *total* activity in terms of PDT, VDT or freight volume is represented as a single variable, often as a function of other model inputs. At the other end of the scale, microsimulation models can represent the activity of individual persons or vehicles, potentially with additional details such as routes taken, within the wider system, and compute *total* PDT, VDT or freight volume across many such individuals or vehicles. Other approaches fall in between these two extremes, with many approaches reporting PDT, VDT and tonne-km apportioned to different transport modes for example. Despite the ability of high-resolution models to represent different aspects of transport demand and influencing factors in detail, such detail introduces model complexity, data requirements for calibration, and increases the difficulty of testing model accuracy. We conclude this review by discussing potential methods of improving the representation of transport demand in aggregate or multi-sectoral models in particular by incorporating features of models with more detailed representations of transport demand.

Integrated models take a whole systems approach to modelling future energy, economic and environmental systems and their interactions (Edelenbosch, McCollum, et al., 2017). Yeh et al. (2017) introduce the term "global transport energy model" (GTEM) to refer to models that (a) have global spatial scope, (b) capture the entire transport system, as opposed to one or a few aspects of it, and (c) include energy use or demand as a dependent variable. Per this definition, global integrated assessment models

(IAMs) are included with GTEMs, as these satisfy condition (a); include (b) but also other sectors; and include (c) but also other outcomes including emissions, pollution, changes in natural systems, etc. The aggregated nature of GTEMs necessitates simplified representations of some factors, which are better represented using disaggregate or sector-specific models. Thus, translation between scales, model resolutions, and scopes is required to represent relevant factors in GTEMs (Hanmer, Wilson, Edelenbosch, & van Vuuren, 2022). Reducing transport activity growth and modal shifts towards less carbon intensive transport modes, caused by demand-side changes (e.g., more compact cities), typically have limited contributions in GTEM emission reduction pathways (Edelenbosch, McCollum, et al., 2017; Creutzig, Jochem, et al., 2015)—this can be viewed as a consequence of changes that are well represented in high-resolution models, but below the resolution of GTEMs. Many proposed improvements involve “soft linking” sector-specific and more disaggregate models to GTEMs (Pauliuk et al., 2017). For example, behavioural choices of individual travellers such as time budgets and luxury levels represented in modular transport sector models can be combined with GTEMs to estimate the impact of behavioural constraints (Andreou et al., 2022). Further, the outputs of transport sector models with behaviour representations can be used as inputs or constraints for GTEMs, to ensure consistency of model solutions between approaches (Anable, Brand, Tran, & Eyre, 2012). Such linking strategies allow continued representation of costs and aggregate multi-sectoral mitigation potentials, whilst ensuring quantifications of socio-behavioural and demand side factors and their effects are consistent with models where they are directly represented and not subsumed in spatial, temporal or sectoral aggregates.

Considering local infrastructure and land use change, current GTEMs lack the resolution to explicitly consider the effects of these factors (Creutzig, Jochem, et al., 2015). Furthermore, explicit physical representations of infrastructure and urban form could better depict links between energy and material throughput and service provision in GTEMs (Pauliuk et al., 2017). This could be achieved by better operationalising infrastructure costs and secondary effects, particularly infrastructure re-purposing costs. This could help prevent infrastructural lock-in which can be endogenised in integrated models, if projections stem from historical trends and developments. For example, re-purposing roads for active travel infrastructure is relatively inexpensive, but implementation requires policies that explicitly take non-standard preferences, beliefs, and decision-making processes into account (Mattauch, Ridgway, & Creutzig, 2016).

The geographic relevance of integrated transport land use models varies (Taki, Maatouk, Qurnfulah, Aljoufie, et al., 2017). However, no models are currently linked to global GTEMs, representing a major frontier in the cost-benefit analysis of LED scenarios. The regionally detailed patterns revealed by integrated transport land use models must be captured to translate factors affecting land use into GTEMs. A method to circumvent the problem could be to adopt urban types or categories from typological research to collectively model areas with similar land use and transport patterns. This aggregation reduces the number of regions modelled while allowing representative analyses for each urban agglomeration (Tang, Jayakar, Feng, Zhang, & Peng, 2019).

However, there is an inherent trade-off between the resolution of categorisations developed to capture idiosyncratic effects and model complexity (Creutzig, 2016).

Societal movements and trends surveys are often not repeated making it difficult to track trends in social acceptability of different measures and policies (G¨ossling et al., 2020). Continued monitoring of policy acceptability would allow politically and socially feasible scenarios to be regularly updated and input into GTEMs. As mitigation pathways involving behaviour changes are typically poorly represented in GTEMs, the mitigation potential of social trends is not fully accounted (Venturini, Tattini, Mulholland, & Gallach´oir, 2019). Thus, the impact of behavioural changes must be represented in the exogenous pathway narratives input into integrated models, as in (Grubler et al., 2018).

Further GTEM improvements could involve better representation of heterogeneous behavioural decisions of populations (Mercure, Pollitt, Bassi, Vin˜uales, & Edwards, 2016). Empirical evidence suggests that energy end users often do not make decisions in a completely rational way that can be captured by the economic relationships used in GTEMs. Furthermore, it is argued that consumer decisions are often over emphasised as a solution to ecological sustainability compared to systematic structural economic changes. Thus, their role in GTEM modelling pathways should be reflected as such (Akenji, 2014). Bounded rationality of decision makers, non-optimising heuristics in decision making and social influences and norms are typically not included in GTEMs (McCollum et al., 2017). Further representation of these behavioural aspects using heterogeneous decision-making agents could enable better representation of factors concerning technology uptake and deployment, as they can influence factors that cannot be operationalised as costs. Multi-Level Perspective approaches can generate quantitative narratives on the role of socio-technical solutions, to be input to GTEMs, capturing the actions of different actors, however this has not been completed on a global scale (van Sluisveld et al., 2020). At a practical level, simulation based GTEMs could endogenise heterogeneous decision-making, for instance, using (multinomial) logit functions (the core method in some of the other transport models reviewed), whereas decision making may need to be soft linked to optimisation based GTEMs (McCollum et al., 2017).

The future adoption of some technologies, such as autonomous vehicles, is highly uncertain. Modelling approaches must be able to account for incremental technology adoption, tipping points, and saturation. Static or equilibrium-based approaches often simplify technology adoption and assume discrete addition of new infrastructure and technologies. Conversely, dynamic modelling approaches often lack the structure needed to maintain reasonable outputs under large perturbations from base conditions (Hawkins & Habib, 2019). Stated preference surveys can be used to develop realistic model inputs and principles from complex and evolutionary systems theory could be incorporated into integrated models to capture uncertain dynamics (Wilson, 2016).

Short-term technology and fuel demand elasticities projected by GTEMs typically match up well with empirical evidence. However, demand elasticities of fuel prices in long-term forecasts (30-40 years) show significant divergence between different models (Edelenbosch, van Vuuren, et al., 2017). The uptake of different fuels can be represented in integrated models by soft linking the outputs from disaggregate models that capture effects of price changes on transport activity and mode shares to integrated computable general equilibrium models (Mittal, Dai, Fujimori, Hanaoka, & Zhang, 2017). Furthermore, new technology uptake could be limited by material supply constraints (Watari et al., 2019). Integrating material cycles into integrated modelling is required to ensure that scenario outputs are physically realistic. To achieve this, material stocks and flows should be linked to service indicators across different sectors, including transport (Wiedenhofer et al., 2019).

Models containing high resolution representations of transport demand, such as micro-scale or agent-based analyses, can capture specific effects of many factors that impact transport demand. Outputs from these models should be used to either generate detailed narratives that can be input to high level, multi sector, broad scope models used to assess decarbonisation pathways. Furthermore, high resolutions allow for changes in the co-benefits and externalities of the transport sector, such as access, safety and welfare, to be evaluated. Further, techniques from high resolution transport models could be used to generate detailed responses to factors influencing transport demand, which can be applied using different area or sector categorisations to capture local and regional impacts in aggregate models.

These modelling strategies, and the many kinds of soft-linking suggested in the cited literature, also point to the need for fluent and clear exchange of data representing many distinct but important aspects of transport systems and factors affecting transport demand. In addition to describing their models' characteristics according to the taxonomy of Figure 2—which draws the boundaries of the transport sub-systems represented in a model—researchers should seek to provide open data with clear and complete metadata in standard, interoperable formats, for both model inputs and outputs. Such interoperable data would improve the feasibility of constructing, using, and maintaining the model–model connections necessary to fully capture changing transport demand.

Given many factors that affect transport demand are uncertain, improving their representation in GTEMs could lead to better-informed policy recommendations stemming from models. Thus, policies informed by integrated modelling can more deliberately shape and use the factors and other phenomena, to more fully unlock their contribution to energy demand reduction, climate change mitigation and a LED future with high well-being for all.

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6 Disclosure statement

The authors report there are no competing interests to declare.

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