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A better tomorrow: towards human-oriented, sustainable transportation systems

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In a rapidly changing world, transportation is a big determinant of quality of life, financial growth and progress. New challenges (such as the emergence of the COVID-19 pandemic) and opportunities (such as the three revolutions of shared, electric and automated mobility) are expected to drastically change the future mobility landscape. Researchers, policy makers and practitioners are working hard to prepare for and shape the future of mobility that will maximize benefits. Adopting a human perspective as a guiding principle in this endeavour is expected to help prioritize the "right" needs as requirements. In this special issue, eight research papers outline ways in which transportation research can contribute to a better tomorrow. In this editorial, we position the research within the state-of-the-art, identify the needs for future research, and then outline how the included contributions fit in this puzzle. Naturally, the problem of sustainable future transportation systems is way too complicated to be covered with a single special issue. We thus conclude this editorial with a discussion about open questions and future research topics.

Keywords: *Transportation Systems, Future Mobility, Sustainability, Shared Mobility, Autonomous Vehicles.*

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1. Introduction

Transportation systems are central in everybody's lives. As the conditions and requirements change rapidly, often in unprecedented ways, e.g. with the emergence of the COVID-19 pandemic, we need to be vigilant and design and implement better, more sustainable future transportation systems. Using the human as a guiding principle in this endeavour is expected to help prioritise the "right" needs as requirements. This special issue contributes to this cause, with a number of papers in different transportation research disciplines, which create a consistent and coherent collection of state-of-the-art research about modelling techniques and sustainability issues of new modes and future transportation systems.

This special issue originated from the mobil.TUM 2019 Conference, organized in Munich, Germany, on September 11th - 12th, 2019. Selected papers from the conference were invited to submit an extended version to this special issue. After the journal's thorough review process, eight papers were finally accepted. This was the 11th time that the conference was organised. The mobil.TUM International Scientific Conference on Mobility and Transport is a platform for practitioners and researchers to meet and exchange their knowledge and experiences. International keynote speakers provoke the debate, and posters, presentations, as well as discussions offer inspiration from the latest innovations concerning transportation systems of the future. The conference series is organized by the Focus Area Mobility and Transportation Systems of the Department of Civil, Geo and Environmental Engineering of the Technical University of Munich.

2. Background: emerging transportation systems and data collection techniques

As needs and opportunities (for end users, but also for researchers) increase exponentially, mobility and transportation systems are becoming more interoperable and complex. Demand and supply components not only become more intricate, but also more inextricably linked together. As a result, conventional modelling techniques (originally targeted for individual components or trip legs), as well as similarly limited data collection processes often fall short in all their complexity. In order to develop methods that will adequately support the emerging paradigms, a switch towards a systems perspective is expected to be beneficial.

There are three radical changes that are already shaping mobility, and are expected to dominate it for the following decades, often referred to as the "three revolutions" (Sperling, 2018), in particular: (i) electric, (ii) shared, and (iii) automated mobility. Preparing the infrastructure needed to accommodate electric vehicles is one key issue, tackled by Villenueve et al (2020). Furthermore, energy needs and opportunities offered by other modes, such as electric railways, are also a significant tool in achieving a sustainable mobility future (Mueller et al., 2020). "Shared" is probably the aspect of the three, which is further along, in terms of being realized, as it depends on a complex mix of social, technological and policy factors. Reck and Axhausen (2020) are exploring the possible benefits of ride-sourcing as a first/last mile complement to mass public transportation, and the reasons why the current programs to formally integrate ride-sourcing into a public transportation network have usually failed. Duran-Rodas et al. (2020) exploit social media information to obtain insights about the positive and negative aspects of bike-sharing programs around the world. Finally, automation is expected to have a big role, but is also the one aspect that is going to take longer to have an impact (for a comprehensive recent review see Narayanan et al., 2020).

The realization of these transportation revolutions is being enabled in one way or another by the development and integration of Information and Communication Systems (ICT), which has also transformed data provision and use. Big data has been introduced to transportation as a way to replace or supplement the pre-existing data collection processes. New sources of data have been investigated to reduce the cost, or improve processes already in place. Mobile phone, bank card transaction, smart card, smartphone sensors, social media, new mobility services data are just some prominent examples (Chaniotakis et al., 2020, Chaniotakis et al. 2016, Toole et al. 2015, Pelletier et al. 2011). At the same time, new ways of collecting conventional datasets are receiving attention. Smartphone based travel-diary surveys are being tested to replace the costly data collection processes scarcely deployed (Vaughan et al. 2020) and drones for traffic monitoring are being investigated (Barmpounakis & Geroliminis, 2020).

The sustainability of new modes currently being used or under development is a matter of increasing research, as a complex set of elements push towards having more sustainable or unsustainable mobility patterns with current innovations, such as ride-sourcing (Tirachini, 2020), and with the new technologies of the future, such as the deployment of automated vehicles for day-to-day use (Sperling, 2018). Within this context, the issue of equity has emerged as a key element of mobility innovations and new modes. Equity impacts have been discussed in the context of ride-sourcing (e.g., Shaheen et al. 2017; Atkinson-Palombo et al. 2019; Reck and Axhausen, 2020) and bike-sharing (e.g., Duran-Rodas et al., 2020). If these innovations increase or reduce equity gaps is a multifaceted problem. By means of a ride-sourcing platform, a person that does not personally own a car can have quick (sometimes immediate) access to a car and driver and pays on a per-trip basis. Therefore, the inability to pay the full costs of owning a car is no longer a barrier for car access. Cars are then accessible by a wider audience than before. Moreover, cities can partner with ride-sourcing companies to provide subsidised mobility to specific groups such as seniors and low-income citizens, and for trips in combination with public transportation, in the pursuit of equity and sustainability outcomes. In the case of partnerships between public transportation and ride-sourcing, success has been elusive in reality, an issue that is further analysed by Reck and Axhausen (2020). Other issues related to the relationship between ride-sourcing and equity remain, such as the facts that long ride-sourcing trips are unaffordable for low-income riders, ride-sourcing drivers can freely choose the areas of a city to work (and to avoid) and that ride-sourcing companies can freely increase fares through surge pricing, which harm low-income travellers harder.

The radical advancement of existing transportation systems, as well as the emergence of new mobility concepts (e.g. urban air mobility or hyperloops), call for the development of advanced methodological concepts which can cope with the volume and diversity of the corresponding data. In recent years, the introduction of statistical learning approaches (e.g. machine learning) has offered new capabilities in modelling human mobility patterns and estimate the effect of novel transportation solutions. Deep Learning, for example, a powerful enhancement of classic Multi-Layer Perceptron (MLP) Neural Networks (NN) can be exploited for dealing with transportation big data (Katrakazas et al., 2019) such as social media (Chaniotakis et al., 2017) and cellular network data (Wang et al., 2019). For example, in Vaughan & Miller, (2020), deep NNs were utilized to predict travel behaviour and different travel modes from cellular network data, while topic clustering and sentiment analysis was utilized in Duran-Rodas et al. (2020) for analysing tweets concerning bike-sharing.

Moving forward from the typical exploitation of Origin-Destination (OD) matrices, new approaches aim to predict trips, infer activities and identify spatiotemporal patterns of individual travels or collective (shared) systems. To that end, graph-theoretical concepts (Ballis & Dimitriou, 2020) and spatiotemporal choice modelling (Zhao et al., 2019) can be coupled with optimization approaches for trip or activity identification and the corresponding maximization of trip utility to solve relevant research questions. Nevertheless, these novel modelling approaches need to be compared or combined with traditional predictive models (e.g. logistic regression in Blumthaler et al., 2020). This is because statistical learning approaches usually act as “black boxes”, which limits their explanatory potential and may prevent them from dealing with the endogeneity of variables included (Rudin, 2019). To overcome these issues, models such as Structural Equation Models (SEMs) that can provide more explainable outcomes, can be used to study the inter-relationship between travel behaviour or travel choice indicators, as this type of model has been proven to cope well with endogenous measurements in the context of driving behaviour analysis (as in Lu, 2020). Moreover, in order for new mobility concepts or data collection methods to be assessed, novel survey designs (e.g. Tirachini et al., 2020), rule-based assessments (Blumthaler et al., 2020; Haddad et al., 2020) and cost-effective before-after constructs (Mueller et al., 2020; Reck & Axhausen, 2020) need to be further explored. Finally, as different and more complex data volumes are to be expected in the near future (Antoniou et al., 2019), interdisciplinary and holistic approaches that combine the state-of-the-art from spatiotemporal travel demand and behaviour modelling, statistical learning and computer-scientific approaches, as well as social science perspectives, may offer more thorough insights into a new shared 3-dimensional transportation ecosystem, combining new opportunities, such as Urban Air Mobility (Al Haddad et al., 2020) or underground freight transport, such as Cargo Sous Terrain (Kunze, 2016).

3. Topics of the special issue

This special issue comprises eight papers that cover a wide spectrum of topics. Reck and Axhausen (2020), Duran-Rodas et al. (2020), Villenueve et al. (2020) examine emerging mobility systems and environments focusing on aspects of adoption, satisfaction, deployment and feasibility. Mueller et al. (2020) focus on the enrichment of transport data using novel approaches. Lu (2020) and Blumthaler et al. (2020) focus on the examination of traffic flow related advances. Finally, Vaughan et al. (2020) and Ballis and Dimitriou (2020) focus on aspects of travel demand modelling.

The design of shared mobility systems is gaining more attention as public agencies are exploring new ways to include app-based mobility solutions into their portfolio of transportation alternatives. Increasing the occupancy rate of vehicles has long been recognized as a move towards a more sustainable future, as it requires fewer vehicles to satisfy demand needs. In this context, some public transportation agencies are experimenting alliances with ride-sourcing platforms, in order to provide subsidized car-based mobility to and from main public transportation stations, as a way to encourage multimodality as an alternative to the use of private cars. However, where implemented, so far the idea has failed to deliver satisfactory results in terms of patronage. Reck and Axhausen (2020) provide two possible explanations for such an outcome. First, the disutility of the transfer car/train and car/bus may play a larger role than expected. The authors show that depending on the disutility of the transfer and the relative valuation of access, waiting and in-vehicle times, for short access distances (e.g., below 700 meters) walking is more convenient than ride-sourcing as an access mode to public transportation. A detailed analysis of three US locations shows that adding transfer penalties and waiting times for ride-sourcing significantly reduces the amount of trips in which ride-sourcing is more convenient than walking as an access mode. Second, in contexts where public transportation users are mainly from low- and middle-income households, the fare of the ride-sourcing trip might be relatively high. A full inclusion of the ride-sourcing trip into the public transportation fare (full ride-sourcing subsidy) only when connecting with public transportation is suggested by the authors as an equitable alternative. The findings of this paper point to the inclusion and full account of out-of-vehicle quality attributes (waiting, transfers) into the cost-benefit assessment of partnerships between traditional public transportation and shared-mobility providers. Such attributes are usually overlooked by shared mobility providers in their business models and are also relevant for the success of other mobility solutions that are increasingly proposed, such as Mobility-as-a-Service (MaaS) platforms.

Duran-Rodas et al. (2020) present a mixed-method approach to analyse people´s sentiments towards bike-sharing systems based on English language opinions posted on Twitter. The authors find that the largest acceptance of bike sharing systems by the public is reached when the systems are public, inclusive and affordable. People seem to favour hybrid systems with both dockless and docked bicycles. Integration between ride-sharing and public transportation is also a highly desirable attribute for users that want to use a bicycle to access a public transportation mode for long trips. In contrast, strategies by companies that have flooded public streets with dockless bicycles are heavily criticized by the public. The latter is an important finding, given that because of economies of scale (reduction of access times), providers have an incentive to place a large amount of bicycles in the public domain in order for their system to capture more clients. This points to the usual conflict between private and public interests in the provision of technology-based mobility innovations, where public regulation of private enterprises must play a key role to align private and public objectives (Tirachini, 2020)

Villenueve et al. (2020) examine electro-mobility and particularly the deployment of public charging infrastructure for Electric Vehicles (EV). They conduct a micro-Delphi survey with transportation, energy and urban planning experts to identify realistic scenarios for EV charging by 2035. The five most likely options were on-street public charging points, charging at work, fast-charging stations, using building domestic plugs and semi-fast charging in public areas. Results also show that EV drivers will most likely rely on a mix of solutions, when they have no home chargers. Therefore, no breakthrough or major shift is anticipated in charging infrastructures, rather a scale-up of existing solutions.

Mueller et al. (2020) explore the feasibility of electric railway vehicles (in particular Battery Electric Vehicles, BEVs, and Fuel Cell Electric Vehicles, FCEVs) in reducing, or even eliminating, the emissions associated with regional railways. The authors collected the required data and evaluated the degree to which regional rail lines in Bavaria can be replaced with electric vehicles. It is concluded that the overwhelming majority of the lines can be operated using the novel vehicles, although not all technologies can cover a wide range of needs.

Lu (2020) uses loop detector data from California to explore the endogeneity of traffic and estimate lane-mean speed. Structural equation models are developed and compared in terms of performance with other state-of-the-art approaches, with favourable results. Conventional data sources are thus used to explore traveller behaviour in detail. The contribution of this research is interesting as it adds on the literature of obtaining disaggregate insights from aggregate data. The author also considers lateral aspects, and not only longitudinal parameters, in the analysis. In relation to previous literature, the underlying methodology solves the endogeneity problem by utilizing a three-stage least squares model. One of the main contributions of the proposed approach is the consideration of the effect of downstream speed on upstream speed.

Blumthaler et al. (2020), investigate the exploitation of floating car data (FCD) for congestion analyses in motorways. Using an FCD dataset from the Austrian A12 motorway, and a rule-based classification of trajectories according to jam duration and number of speed drops, the authors developed binary logistic regression models to investigate the correlation between congestion detection and the quality of FCD data. Their results demonstrate that short-term congestion detection is unlikely if FCD data are of low quality, but can provide a promising alternative for the identification of large-scale congestion incidents.

One of the challenges today is that large amounts of data are available, e.g. from cell-phone data, but these data sets often miss important attributes. Vaughan et al. (2020) propose a framework for the imputation of travel mode for trips identified from cellphone traces. The authors use datasets from other sources, travel surveys and smart card data, for which mode is available, to train a deep learning algorithm. Compared to previous models, the authors use a richer set of cellphone data, including all cellular network base transceiver stations (BTS) connection events and not only the call detail record (CDR) events. The trained model is then applied to infer travel modes for the original dataset. The results can be used to describe detailed representations of OD trip-making processes, further disaggregated by time of day and travel mode.

Ballis and Dimitriou (2020) use aggregate information (origin-destination matrices and travel surveys) to generate detailed, synthetic trip-chains, which can support agent- and activity-based models. The methodology is formulated as an optimisation problem, where the objective function seeks to identify the utilisation of each tour, so that the number of "unused trips" as expressed in the input OD flows is minimized. It is found that the performance of the proposed methodology is encouraging, as the authors report high estimation accuracy (greater than 85%) even for the most challenging case study. The presented results suggest that information regarding travel behaviour on an individual level can be produced based on aggregated data sources such as OD matrices. This is an encouraging finding that can make the analysis of mobility at the person-level, especially within the framework of agent-based modelling, much more accessible, even when detailed, disaggregate data are not directly available.

4. Discussion

This special issue will of course not conclusively provide a definitive response to all challenges related to the vast field of future mobility. Instead, it strives to provide contributions to the discussion of i) how the future of mobility will look, and -perhaps more importantly- ii) how can we prepare for it, and (iii) how we can shape it in a more sustainable way. Technology is expected to be a major driver of change, but it is also important to understand and analyse the traffic and mobility phenomena, even with conventional data. A big part of the game will be played in how human factors are put in the centre of the development of new technologies for mobility. Take for example the case of automated vehicles: their technology in segregated environments (mapping, localizing, planning and controlling operation) already exists and is even available in some cases as open software; however, interactions between automated vehicles and pedestrians in complex environments require a level of social intelligence in programming that is not yet available (Camara et al., 2020). Another issue is the willingness of public transportation users to ride buses without drivers, in places where personal security or other concerns may play a role (Salonen, 2018). Significant benefits in terms of increases in public transportation service supply could be realized if a large portion of the fleet is driverless (Tirachini and Antoniou, 2020). First analyses of data collected from actual users of regular automated public transportation services already provide valuable insights into how to further refine future solutions (Guo et al., 2020). This issue again points to the proper inclusion of human factors on technology or economic analyses of future transportation innovations.

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