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Travel behavior shifts under extreme system-level disruptions

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Abstract

This paper attempts to identify and critically discuss how travel behaviour may be affected by any extreme system-level conditions of the transportation system in the cities. These disruptions refer to non-recurrent events and indicatively include hazardous events, and perturbations of the road network. To this end, the international literature on the changes in travel behaviour in the case where system-level disruption occur is collected and analysed. The analysis is conducted on the basis of the three pillars of travel behaviour, namely travel mode, route and departure time choices. The results show that most people tend to postpone their trip when extreme weather conditions occur, whereas in case of a public transportation disruption travellers are keen on altering their route choice. Finally, a clear mode shift towards cars has been observed due to the outbreak of COVID-19 pandemic.

Keywords: travel behaviour shifts; hazards; extreme weather; system disruptions.

1. Introduction

Travel behaviour is multifaceted and usually studied under typical network conditions. However, travel behaviour shifts may occur in the current reality – during which and with the development of technology – new services are introduced to the market and Transportation Management Strategies (TSM) measures are applied in order for people to have access to more functional and ecological transportation networks. Accessibility to new services, such as electrical cars and bikes, autonomous vehicles (Avs) and Connected Autonomous Vehicles (CAVs) and Mobility-on-Demand (MoD) services, may alter people's travel behaviour. EVs are novel technology in the transportation sector, and thus multiple studies have examined the acceptability of EVs (De Gennaro et al., 2014; Nordlund et al., 2018). Policies focusing on making a more environmentally friendly mode of transport attractive to people, aim to stimulate the purchase and the use of EVs, which would reduce the negative effects of Conventional Vehicles (CVs) (Barbarossa et al., 2015; Bockarjova & Steg, 2014). It has been shown that in urban areas EVs can cover a large share of the mobility demand, replacing the usage of CVs.

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In the near future, autonomous vehicles are expected to be part of transportation networks. Within this new reality, the average speed of vehicles is expected to be lower and as a result the congestion levels will be increased (Davidson & Spinoulas, 2015). During the first stage of the implementation of AVs in the traffic, which will have as a priority to follow the speed limits and provide comfort to the travellers, there is going to be a negative effect in the congestion. As a result, the high penetration rate of AVs is expected to lead to a reduction of the usage of PT or active modes of transport. In a network with vehicles equipped with technology that provides dynamic route guidance using real-time traffic information, travellers can pick the optimal route to save time. For low market penetration rates of CAVs in the network, the use of CAVs is significantly increased, whereas the use of PT is decreased. However, with high market penetration rates of CAVs, the share of CAVs is replaced by all the other modes (Minelli et al. 2015).

Furthermore, TMS measures obligate a number of users to change their typical travel behaviour. When the policy requires drivers not to use their cars one weekday per week, depending on their plates, a specific day was observed during which there was a higher level of congestion (Baghestani et al. 2020; Cools et al. 2011; Gu et al. 2017). Moreover, the acceptability of a road-pricing policy as a single dimension is not sufficient to entice changes in activity-travel behaviour. Specifically, there is a minimum threshold of road pricing charges, that when it is surpassed, it is sufficient to alter the perspective of a person in order to change their travel behaviour. A 3 years natural experiment in Milan, Italy (Gibson & Carnovale, 2015) examined the effects of road pricing in a specific area and time slot. It was found that the effect of pricing on traffic depends on the availability of public transportation. Routes without public transit experienced larger traffic changes compared to the ones with public transit. Furthermore, many drivers entered the area during hours when there is a lower charge, but the majority would choose to alter their mode choice, namely switch to PT or carpooling, or even use routes outside of the pricing area. Regarding the high demand in PT during peak hours, it was found that providing discounts in PT ridership during off-peak hours, most car drivers shifted towards PT (Adnan et al., 2020). Furthermore, it was indicated that the increase of PT use during A.M. peak was mainly attributed to workers, who generally preferred to shift their evening trip departure time instead of shifting their morning departure times.

The occurrence of non-recurrent events, that occur more frequently than ever and provoke system-level disruptions, renders the study of travel behaviour shifts to be imperative and the effects of such events to travel behaviour are gaining significant attention. Such events indicatively include hazards, namely extreme natural conditions and the COVID-19 pandemic (Anwari et al., 2021), and perturbations of the road network, such as PT service disruption. In general, travellers must adjust their travel behaviour during system-level disruptions and as a result they may (Zhu & Levinson, 2012): i. change their normal route because of road and ramp closure or congestion caused by traffic reallocation, ii. alter their departure time to avoid congestion, iii. satisfy their needs at other destinations, iv. consolidate trips, v. switch to alternative travel modes, and vi. share travel duties among family members. The understanding of the parameters that affect travel decision-making during the occurrence of non-recurrent events is of great importance both for the efficient planning and management of transport, as well as for improving transport services and system conditions. With the understanding of traveller behaviour, transportation authorities can most effectively plan for and manage the transportation system to be ready to respond and recover from emergency situations for many hazards. In order to assess the requirements for any response and recovery effort, it is crucial to understand how travellers, and especially transit users, respond and adapt to emergencies.

2. Literature review on travel behaviour shifts under system-level disruptions

During the occurrence of extreme disruptions related to the system-level, the usual travel behaviour of users might alter, based on different factors than those affecting one’s typical behaviour. To this end, the international literature on the changes in travel behaviour in the case where hazardous events and additional system-level disruptions occur is collected and analysed. The analysis is conducted on the basis of the three pillars of travel behaviour, namely departure time, route and travel mode choices.

2.1. Hazards

In today's reality, with the climate change resulting in extreme weather conditions and, also, the outburst of COVID-19 pandemic, it is of utmost importance to study the impacts of such events on the field of transportation and specifically on daily travel behaviour shifts.

Hazardous events, that happen to occur unexpectedly and under specific circumstances, cause shifts in travel choices of people. Such an event is the pandemic of COVID-19, during which travel behaviour was altered completely (Bhaduri et al., 2020; De Vos, 2020; Scorrano & Danielis, 2021; Shakibaei et al., 2021; Yang et al., 2021), not only because citizens were overwhelmed with fear and as a result they limited their trips, but also because the governments took strict traffic measures. Travel mode choice is the dimension of travel behaviour mostly affected by such events. PT usage is being reduced, since people recognize the increased risk of transmission, and the measures making protective surgical masks mandatory inside PT has made it less convenient. The share of PT usage is being replaced by private cars, taxis and ride-sharing services. However, people who do not have the flexibility to change travel mode would prefer travelling during off-peak hours. Furthermore, PT users do not present anymore a precise preferred route for a recurrent trip, and they often use different routes for the same OD (Marra et al. 2022). In general, travel demand is reduced, since telework and remote assistance was implemented for most occupations, while people change their everyday habits and spend more time walking and cycling.

Travel risk perception is significantly correlated with the possibility of altering travel plans during extreme events, such as pandemics. In particular, travel risk perception decreased with older people, females and lower frequency of trips (Neuburger & Egger, 2021). The destination of the trip also influences the probability of changing the plans, for example altering the travel preferences (e.g., travel mode and route) or even cancelling trips. If the destination is characterised by numerous reported COVID-19 cases, people would tend to change their plans. In such cases, travel behaviour gradually returns to the original levels, sometimes leaving residues.

People present a travel behaviour shift also in the framework of extreme weather events. During these occasions travel behaviour is altered not only because the built environment and the infrastructure might be damaged, but also because people are usually panicking in their effort to stay safe. Multiple studies have examined the travel behaviour adaptation to extreme weather circumstances and natural disasters (Zanni & Ryley, 2015; Zheng et al., 2015), such as flooding (Lu et al., 2014). Findings revealed that people travelling for business purposes are more likely to change their plans during a disruption due to extreme weather conditions, instead of those travelling for personal reasons. It is worth mentioning that during extreme natural events that cause significant disruptions to the network (e.g., greater delays, difficulty in accessing the destination point or the PT infrastructure) travellers change their plans as indicated by transport organisation staff. This could mean leaving at a different time in the same day or even postpone their trip till the next day. Changing the route of the trip is also the case of a shift during extreme weather events. People may adjust their route according to the safety in case of such a disruption. Finally, transport organisation staff and communication with family and friends in combination with accessibility to the internet seem to influence the decision-making process when travellers are about to alter their plans under such conditions.

Residents in coastal areas respond differently to flooding and extreme weather compared to those in inland locations, but most people change their travel behaviour under the pressure of flooding events. The key factors that mostly affect travel behaviour choices are road disruption, isolation by flood water and flood frequency, which are perceived differently in the two areas. Furthermore, coastal residents have experienced more flood conditions in over a long time. However, the limited alternative routes and transportation modes in the coastal locations result in decisions that involve the cancellation of trips. Generally, the majority of the people during these conditions have a negative transportation experience and it has been found that people during a flooding prefer to cancel their trips or change their destination. The study of Abad et al. (2020) (Abad et al. 2020) indicates that the most common type of adaptation during a flood event is changing the departure time and it occurs most frequently during the trip from home to work rather than the opposite.

Earthquakes are also natural hazardous events during and after which the travel behaviour is affected (Aghababaei et al. 2020). Trips generated from areas that were impacted due to the earthquake occur taking alternative routes and causing increase in flow on these roads. Furthermore, in the short-term post-disaster situation the trips of heavy vehicles are considerably limited.

During all the hazardous events, travellers experience conditions of emergency evacuations. Studying of route choice decision under emergency evacuation conditions is crucial (Wang et al., 2017). It was proven that, based on the value of damage concept, during emergency evacuations situations, people are willing to sacrifice travel time in order to gain perceived safety benefits. Furthermore, most evacuees are highly sensitive to the perceived road damage probability and the perceived service level. In general, the values of damage reflect the evacuees' regret aversion psychology. There is also the case that people during such occasions tend to make independent evacuation decisions and not follow the orders from public officials (Pel et al. 2012).

2.2. Network disruptions

Travel and transportation disruptions refer to disruptions on the infrastructure and operation of the transport system and can cause major shifts on the travel choices of users. Disruptions of the network may occur during the existence of major events or even due to PT disruption, vehicle breakdown and road accidents.

Disruptions in PT cause passenger dissatisfaction and also results to travel behavioural shifts (Rahimi et al., 2019). When unexpected transit disruptions occur, a significant percentage of passengers that are affected by this condition chooses to alter the travel and either use a taxi or an alternative PT route (Auld et al. 2020; Drabicki et al. 2021). Furthermore, transit riders are more likely to use shuttle service instead of waiting for service restoration, even when there is no difference in the total travel time (Teng & Liu, 2015). The study of (Pnevmatikou et al., 2015)Pnevmatikou et al.)2015) showed that travellers' available income is a key factor that affects their willingness to shift to buses or cars in such cases. In occasions when long-term PT disruptions are planned, everyday commuters are decreased after the reinstatement to usual operation (Eltved et al., 2021; Friman, 2004).

Several studies have examined the effects of PT disruption on travel behaviour in rural areas (Papangelis et al., 2013, 2016) as well as the respective effects in urban areas (Nguyen-Phuoc et al., 2018). It has been observed that travellers in rural areas adapt in such disturbances either by altering their travel choices temporarily or by changing their travel plans on a permanent level. According to the purpose of the trip and its importance, most travellers may change the mode or route option for their trip. For disturbances that occur on a frequent basis users may adopt new habits customised in these events (e.g., allocating their departure time or avoiding social arrangements on the day of the travel). However, disturbances that may occur frequently and have significant effect in the users' travel plan may lead to a more drastic course of actions, namely buying a car or relocating, in order to have a more convenient trip. Additionally, previous experience in a similar condition plays an important role in the decision-making process. Specifically, past successful actions usually result in considering them as future options in analogous situations. Overall, the population in rural areas is more prepared to adjust to the consequences of network disruptions than people in urban areas.

The majority of people in urban areas, when PT is unavailable, are likely to shift to cars. The most related factors that seem to influence this decision of users are context-related and refer to the travel distance, time and cost. More specifically, for individuals, whose trip distance is longer than a typical walking or bicycling distance, the option of taking a private car is the preferred way for accessing their destination. Travel time affects the decision of travellers in the same way. However, in some cases the fastest travel mode might be the bicycle, if the travel distance allows it. Travel cost has also a crucial role in opting for an alternative transport mode. For individuals who do not have access to a private car, taxi is the least preferred travel mode due to the high cost. Instead, they tend to ask friends or relatives for car-pooling as they can share the expenses. Finally, the purpose of the trip plays an important role in these situations, since many users might cancel their trip if it is not of high importance when the PT ceases.

Travel behaviour can also be altered due to incidents in the transit networks, such as transit accidents. Murray-Tuite et al. (2014) examined the travel behavioural shifts after a fatal rapid transit accident in Washington. It was found that most people prefer to use the middle train cars, since the majority is not willing to alter their mode choice. However, there was a number of people, who changed their travel mode choice or limited the frequency of use of the Metrorail.

3. Conclusions and discussion

A travel behaviour shift has been observed during the last decades as a result of the introduction of new services and the implementation of TMS measures. The introduction of new services, such as electrical, autonomous and connected vehicles and AMoD services, motivates people to adopt a more environmentally friendly travel behaviour. Additionally, TMS measures are affecting the travel behaviour of users. More specifically, pricing road strategies that are implemented in specific areas and time zones aiming at reducing congestion and emissions in the network, are prompting users to switch to other modes of transport that are not so expensive to use in the preferred area. Respectively, others may opt to use a different route or depart a different time in order to avoid entering the area and paying a fee.

However, non-recurrent events, that have occurred during the previous years, also obligate users to alter their usual travel behaviour and adapt to the conditions. The scope of the present paper is to identify the circumstances under which travel behaviour alters due to non-recurrent events and assess how it is affected in terms of mode, route and departure time choices. Findings indicate that because of hazardous events (i.e., extreme natural conditions and the COVID-19 pandemic), people change their travel patterns – temporarily or for a longer period – in order to stay safe and follow the regulations. Moreover, network disruptions that occur unexpectedly, such as the disruption of a PT service, affect users' travel choices; depending on the purpose of the trip and its importance, most travellers may change the mode or route option for their trip.

From a modelling perspective, the importance of developing an accurate and understandable model is crucial for the analysis of travel behaviour. The ability to explain the underlying dynamics in a model has been proven critical for the justification of the decisions made based on the results, the improvement of the model and the exploration of new insights from it (Adadi and Berrada 2018). Machine Learning (ML) techniques have been widely used during the last decade for analyses in the travel behaviour and transportation sector (Karlaftis & Vlahogianni, 2010). In general, ML techniques may have better predicting accuracy when feeding the model with new and unseen data compared to simple MultiNomial Logit (MNL) models. However, classic MNL models maintain their importance against ML methods due to the concept of interpretability. This term refers to the concept of providing understandable information of the developed models and the interrelations between the variables (Rudin, 2019). Interpretability can be also linked to model's transparency which implies some level of accessibility to the data or algorithm (Miller, 2019). Furthermore, in order to achieve transferable outcomes that can be applied universally, it is necessary to collect data from a generalized sample, in terms of sociodemographic characteristics, that is representative of the people.

Finally, the need to move from aggregated behaviour analysis to a more personalized understanding of individual travel behaviour, agent-based modelling has gained a lot more attention over the last decades. The advantages of using agent-based travel demand models for the analysis of travel behaviour has enabled the shift towards an evidence-based traffic management paradigm (Bernhardt, 2007). These tools are valuable for planning and analysing in the field of transportation and can encapsulate the processes, hierarchical relations among individuals, and micro-level decision-making, which generate emergent behaviour in the complex transportation environments of the cities.

The conclusions drawn by this research can be useful in the policy-making scheme. Identifying users' travel behaviour patterns and their adaptation to system-level interventions in correlation with understanding the tools and methods in order to collect and analyse such data is crucial for the efficient traffic management. The key in this new era of traffic management is to have the ability to develop models that could be generalized in a macro level aggregated travel behavior.

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