Imagining a post-COVID world:

Exploring long term travel behavior changes due to the COVID-19 pandemic and its regional implications on urban mobility.

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Preface

At the beginning of October 2020, I started my research at the Sustainable Urban Mobility and Safety department of TNO. My first day at TNO at the New Babylon office in The Hague was quite special, as I was able to pick up my laptop and other essentials in an almost empty office. Since then I haven't visited the office often, as working-from-home was the new norm. Nevertheless, I have met some great colleagues online and even experienced a very successful digital SUMS 'Sinterklaas' evening. I was very inspired to see how everyone is working from home with this high degree of flexibility and perseverance. I'm proud that I was able to perform my master thesis at TNO, as this allowed me to work on such a novel topic as the COVID-19 pandemic. I enjoyed the exploration of activity and travel pattern changes, experimenting within an advanced travel model, and being able to attend interesting online knowledge sessions about the world of transportation and passenger travel. I want to express my gratitude to Maaike Snelder as my supervisor from TNO for allowing me to perform my thesis at TNO, and for guiding me through this research. I also want to express my gratitude to Marieke van der Tuin as without her expertise and extensive knowledge I would never have found my way through the VMA travel model, to Bachtijar Ashari for the great support during the start of my internship which allowed me to quickly find my way within the digital office, and to Vinicius Aronna Cruz for the great fun we had as interns and for the mental support during challenging thesis-times.

I want to express my gratitude to the TU Delft graduation committee consisting of Jan Anne Annema, Bert van Wee and Mark de Bruijne for their support, experience, and knowledge.

Finally, I want to thank my brother, for listening to my endless stories about travel behavior changes due to the COVID-19 pandemic and my lovely girlfriend and parents for their tireless support and wisdom.

Summary

With the global outbreak of the COVID-19 pandemic, governments worldwide have taken measures to mitigate the spread of the virus. These include policies regarding social distancing, protective masks, and the temporary closing of societal sectors such as schools and workplaces. These policy measures, in combination with subjective perceptions of the virus such as the fear of contamination, have influenced mobility in an unprecedented way. In the Netherlands for example car traffic was reduced by -50% during the COVID-19 pandemic and public transportation usage dropped by -87% in comparison to the year 2019. Due to this disruptive character of the COVID-19 pandemic on the way people travel it might be travel patterns might have been changed permanently and won't return to pre-COVID-19 activity and travel patterns when the pandemic reaches a final stage in which the social-economic impacts of the pandemic can be largely contained. This could pose a problem as a misalignment of supply and demand within the public transportation and road network might occur. Moreover, the effectiveness of transportation policies aimed at reducing congestion, air pollution, and traffic noise could be reduced.

The way people travel is grasped by the theory of travel behavior, which refers to the choices individual travelers make regarding mode, route, departure time and destination choices, and so on. As long term travel behavior effects from the COVID-19 pandemic might especially be visible within urban areas, this thesis focuses on transportation within urban areas. Moreover, as the COVID-19 pandemic shows to drastically influence the number of vehicles on the road and as a result, some cities are already temporarily transforming the allocation of public space by allocating more space to cyclists and pedestrians instead of cars, this thesis aims to explore the potential implications of long term travel behavior changes that may be expected post-COVID-19 on the accessibility and allocation of public space within an urban area. The city of Amsterdam is used as a case study for this research as this city already faces accessibility challenges due to high levels of congestion while at the same time already featuring a unique cycling infrastructure with high levels of cyclists. Because of this potential implications of travel behavior changes due to the COVID-19 pandemic might be explicitly visible here. The main research question this thesis answers is: "What could be the implications of potential long-term travel behavior changes caused by the COVID-19 pandemic on accessibility and the allocation of public space within the urban transportation system of Amsterdam?".

Given the disruptive effects of the COVID-19 pandemic on mobility, an important question is which long-term travel behavior changes may be expected due to the COVID-19 pandemic. The current impact of the COVID-19 pandemic on travel behavior is already partially established in literature, however, a literature study on the citing databases of Scopus and ScienceDirect revealed no scientific literature with substantiated scenarios of post-COVID-19 travel behavior. Non-scientific (i.e. gray literature) however, does provide projections about potential post-COVID-19 travel behavior. These include (1) digitalization which might reduce the demand for long-distance trips between cities, (2) flexible working hours might enable re-spacing and retiming of trip patterns and (3) the increased consciousness regarding health, safety, and reliability might result in an increased interest in active modes of transportation such as walking

and cycling. Given these projections are from non-scientific publications, the first step of this research establishes a theoretical basis on why which long-term travel behavior changes may be expected. Literature research on travel behavior change theories enabled the conceptualization of direct effects of the COVID-19 pandemic and policy measures on travel and activity patterns within a theoretical framework, resulting in the identification of three general direct effects: (1) a shift from onsite to online activities, (2) the respacing and retiming of travel patterns and (3) a modal shift towards active modes of transport such as walking and cycling. This thesis particularly addresses a shift from onsite to online work-related activities which, reasoning from the theoretical framework, are dependent on (1) the utility towards working-from-home, (2) attitudes towards working-from-home and (3) habitual behavior including working-from-home. Furthermore, the respacing and retiming of work-related travel patterns shows to be a direct result of the increased flexibility due to a shift from onsite to online work-related activities. A modal shift towards active modes within this thesis is addresses as a modal shift towards cycling, which shows to be dependent on (1) the utility towards cycling, (2) attitudes towards cycling and (3) development of new habitual behavior including cycling.

With the identification of the three general direct long term travel behavior changes that may be expected post-COVID-19 this thesis explores how the travel behavior changes that may be expected due to the COVID-19 pandemic could develop post-COVID-19. This exploration is done through the creation of exploratory post-COVID-19 travel behavior scenarios using the intuitive logic scenario planning approach. This process consists of two phases. The first phase entails four individual and identical workshops where each of four mobility experts creates a scenario matrix by (1) listing key factors and driving forces, (2) ranks critical driving forces within an Wilson matrix on both impact and uncertainty of the driving force on future travel behavior, and (3) selects two critical driving factors as dimensions for the scenario matrix. Each scenario matrix provides four distinct post-COVID-19 travel behavior scenarios. As this process resulted in a total of sixteen post-COVID-19 storylines, the individually created scenario matrices where combined within a novel scenario switchboard. Based on the critical driving forces as identified by the mobility experts potential future development paths of post-COVID-19 travel behavior show to depend on five critical uncertainties: (1) the valuation of active modes of transportation through personal drivers of travelers, (2) travelers' attitude towards online activities, (3) technological developments to enable the substitution of onsite for online activities, (4) policy of employers with regards to flexibility in both working location and office hours as well as supporting working-from-home and (5) governmental policies. Based on these uncertainties this thesis formulates four distinct post-COVID-19 travel behavior scenarios: (1) scenario 1; 'back to normal' shows no travel behavior changes. (2) Scenario 2; 'minor changes' indicates both a low shift from onsite to online work-related activities, a low respacing and retiming of work-related travel patterns and a slight modal shift towards active modes. (3) Scenario 3; 'working from home is here to stay' indicates a medium shift from onsite to online work-related activities, a medium respacing and retiming of work-related travel patterns and no modal shift towards active modes. (4) Scenario 4; 'the cyclist paradise' indicates both a high shift from onsite to online work-related activities, a high respacing and retiming of work-related travel patterns and a strong shift towards active modes.

The implications of the post-COVID-19 travel behavior scenarios on accessibility and the allocation of public space are analyzed within the VMA travel model; a conventional, tour-based four-step travel model of the city of Amsterdam. Four-step-models such as the VMA travel model do not allow to dynamically change travel behavior, but statically models the way people travel through the four main modelling steps (1) trip generation, (2) trip distribution and time-of-day, (3) trip mode choices (i.e. modal split) and (4) network assignment (i.e. rout choice). This is why this thesis aims to replicate the three general post-COVID-19 effects rather than changing travel behavior dynamically. Reasoning from the theoretical framework this thesis assumes: (1) a shift from onsite to online work-related activities will cause less work related trips to be generated within the VMA travel model,(2) any respacing and retiming of work-related travel patterns will directly relate to the reduced work-related trips, and (3) a modal shift towards active modes will be expressed by increased attractiveness of the bicycle as mode of transport. In order to quantify the magnitude of these three general direct effects within the VMA travel model of each post-COVID-19 travel behavior scenario two data analysis are performed. First, data analysis of COVID-19 cases and policy data for the Netherlands reveals that between week 28 and 33 from the year 2020 both confirmed COVID-19 cases where relatively low as policy measures where maximally eased, it is assumed that travel data from this moment in time provides an indication for future travel behavior changes. Secondly, data analysis of COVID-19 travel data from the Netherlands between week 28 and 33 reveals that on average -11.5% fewer trips were made for all travel motives and, on average, -42% fewer trips were made to the office. Moreover, between week 28 and 33 a modal shift is observed of -2% car, -61% public transportation, +15% cycling, and +4% walking. This thesis continues on these observations by aligning them to the post-COVID-19 travel behavior scenarios to set a bandwidth for the quantitative operationalization of the scenarios. With regards to the modal shift, only a +15% increase of cycling is taken into account as this aligns with the assumptions made earlier.

With the quantified post-COVID-19 travel behavior scenarios in place this thesis explores in which way potential long-term travel behavior changes due to the COVID-19 pandemic could impact the accessibility and the allocation of public space within the city of Amsterdam. Simulation results show that the total number of trips gradually reduces up to -9,3% less trips in total when comparing scenario 4; 'The cyclist paradise' to scenario 1; 'Back to normal'. This is the result of reduced work-related trip generation as modelled within each scenario. The time of day of trips also gradually shifts as a result of the reduced work-related trip generation. When comparing scenario 4; 'The cyclist paradise' to scenario 1; 'Back to normal' the morning and evening rush hours show a -6.1% and -3.7% reduction in trip share respectively, while a 2.1% larger share of trips can be assigned to the rest-of-day. This dynamic is the same in each scenario and gradually increases from scenario 1; 'back to normal', to scenario 4; 'the cyclist paradise'. Notably, all results show a modal shift away from public transportation, with a reduced public transport share ranging from -4.2% as a result from scenario 3; 'Working from home is here to stay', to -17.3% as generated within scenario 4; 'The cyclist paradise'.

Based on the results of the four post-COVID-19 travel behavior as calculated within the VMA travel model, this thesis concludes that the reduced work-related activities and its consequential changes to work-related travel patterns: (1) strongly alleviates congestion rates during the morning and evening rush hours, (2) decreases travel time from the city center of Amsterdam to certain zones with 1 to 2 minutes per person per trip, and (3) provides arguments to allocate more public space towards cycling infrastructure.

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Abbreviation	Reference
COVID-19	Referencing to the novel coronavirus (SARS-CoV-2) in relation to the 2019-nCoV outbreak
e.g.	Exempli gratia (example given)
i.e.	Id est (in other words)
MaaS	Mobility as a Service
MPN	'Mobiliteitspanel Nederland', dataset containing travel data based on a yearly survey
NVP	'Nederlands Verplaatsingspanel', dataset containing aggregated activity and travel data
ODiN	'Onderweg in Nederland', dataset containing travel data based on a yearly survey
PMT	Probabilitsic Modified Trends
SRI	Stanford Research Institute
SRQ	Sub-Research Question
SUMS	Sustainable Urban Mobility and Safety
TPM	Transport Planning Model
VMA	'Verkeersmodel Amsterdam', a tour-based four-step model of the city of Amsterdam
WHO	World Health Organization

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People entering the tram during the COVID-19 pandemic in Amsterdam, the Netherlands | Photo by Fons Heijnsbroek onUnsplash, edited by author.

Chapter 1

Introduction

This chapter describes in section 1.1 how the outbreak of the novel coronavirus pandemic and associated policy responses changed the way people travel within cities, and elaborates on the scope of this thesis in section 1.2. The state of the art in science regarding potential long-term travel behavior changes due to the COVID-19 pandemic is addressed in section 1.3, followed by the theoretical and practical relevance of the study in section 1.4. In conclusion, this chapter provides the problem definition, objectives, and research questions in section 1.5, a brief outline of the research in section 1.6, and a reading guide in section 1.7.

1.1 Problem indication

By the end of 2019, a cluster of 27 case patients in Wuhan, China, was infected with the novel coronavirus (SARS-CoV-2), which can cause the disease known as COVID-19 (Wang et al., 2020). Due to the rapid spread of COVID-19 cases in the following months, the World Health Organization (WHO) declared the coronavirus outbreak (2019-nCoV) a global pandemic on March 11th, 2020 (Eurosurveillance, 2020). Governments worldwide have taken radical measures to mitigate the spread of the virus, including policies regarding social distancing, protective masks, and the temporary closing of societal sectors such as schools and workplaces (Rijksoverheid, 2020c; Roser et al., 2020). These policy measures, in combination with subjective perceptions of the virus such as the fear of contamination, have influenced mobility in an unprecedented way (de Haas et al., 2020).

In the Netherlands for example, the first COVID-19 case is reported on February 27th, throughout the following month a major reduction in car traffic (-50%), public transportation usage (-87%) and flight movements (-90%) was experienced in comparison to 2019 (KiM, 2020; Rijksoverheid, 2020a). Mobility responses to COVID-19 consisted of changes within city services, altered regulations, and a different allocation of public space. For example, speed limits were reduced in the city of Tilburg, shared mobility such as bicycles and e-scooters were provided within the city of Rotterdam and Amsterdam, and roads were temporarily transformed to allocate more space to bikes and pedestrians instead of cars within Utrecht (Covidmobilityworks.org, 2021).

With promising preliminary results of COVID-19 candidate vaccines and vaccination strategies in place, it seems that the pandemic reaches a final stage in which the social-economic impacts of the pandemic can be largely contained (Bakadia et al., 2021; European Commission, 2020). Although unknown, it is likely that the pandemic permanently changed the way people travel, and thus travel patterns will not return to a pre-COVID-19 situation after vaccination is implemented and social distancing measures are lifted (van Wee, 2020). If the way people travel changed permanently, misalignment of supply and demand within the public transportation and road network might occur. Moreover, the effectiveness of transportation policies aimed at reducing congestion, air pollution, and traffic noise could be reduced.

1.2 Scope

The way people travel is grasped by the theory of travel behavior, a dominant concept within transportation analysis. Travel behavior refers to the choices individual travelers make regarding mode, route, departure time, destination, and so on (Li et al., 2019). If long-term (defined in this thesis as >5 years) travel behavior changes may be expected due to the COVID-19 pandemic, its implications are probably most visible within urban areas given, "above all, urban areas are confronted with transport-related air pollution, noise, congestion, occupation of public space by traffic, and increased morbidity and mortality rates caused by traffic accidents and pollution" (Brůhová Foltýnová et al., 2020). This is why this thesis focuses on transportation within urban areas.

Transportation can be defined as collective, individual, or freight transportation (Rodrigue, 2020). These categories can be respectively interpreted as subsystems about the movement of people with public transport (e.g. train, bus, and metro) and individual transport modes (e.g. car, moped, bicycle and on foot) and the movement of freight and goods. As travel behavior explicitly conceptualizes the movement of people, freight transportation is kept out of scope. Transport movements can be further taxonomized into obligatory (i.e. scheduled activities) and voluntary (i.e. leisure activities) (Rodrigue, 2020). Leisure activities are still quite broad, for example, shopping, going to a gym, and holiday trips can be arguably considered leisure activities. As the focus of this research is mainly on transportation movements within an urban area, leisure activities that can be performed within the same urban area (e.g. shopping, recreational activities, visiting cafés and restaurants, and so on) are included within the scope of this thesis while activities performed outside the urban area are not (e.g. going on a holiday, visiting other cities, and so on). The same applies to scheduled activities, where visiting the office or a supermarket in the same urban area is included while activities performed outside, or in a different urban area are out of the scope of this thesis.

As delineated within section 1.1, the COVID-19 pandemic shows to drastically reduce the number of vehicles on the road. Moreover, during the COVID-19 pandemic, certain cities are already temporarily transforming the allocation of public space by allocating more space to bikes and pedestrians instead of cars (Covidmobilityworks.org, 2021). As accessibility and the allocation of public space (i.e. use of available resources) are contemporary challenges within cities and the effects of potential long-term travel behavior changes may be most visible on these two issues this thesis explicitly focusses on the potential implications of long-term travel behavior changes post-COVID-19 on accessibility and the allocation of public space within urban areas. Moreover, as described by Banister (2003) in the Netherlands "specific policies fall into four categories, each of which is of equal importance" among which "improving accessibility" and "managing mobility – measures to reduce the use of the car" are two of them. This thesis focuses on the city of Amsterdam particularly as this city already faces accessibility challenges due to high levels of congestion while at the same time already featuring a unique cycling infrastructure with high levels of cyclists (Gemeente Amsterdam, 2019). Potential implications of travel behavior changes due to the COVID-19 pandemic might be explicitly visible here.

1.3 State of the art literature about travel behavior change due to the COVID-19 pandemic

The current impact of the COVID-19 pandemic on travel behavior is already partially established in literature. This literature can be generally divided into case studies analyzing the spread of the virus in relation to mobility patterns (i.a., Gatto et al., 2020; Kraemer et al., 2020), the effect of changing mobility patterns on transportation side-effects such as air quality, traffic accidents and seismic noise (i.a., He et al., 2020; Lecocq et al., 2020; Otmani et al., 2020) and the impact of COVID-19 policy measures on mobility patterns (i.a., Aloi et al., 2020; Goscé et al., 2020; Hadjidemetriou et al., 2020).

In contrast to descriptions of the current implications of COVID-19 on urban mobility, scientific literature about post-COVID-19 travel behavior is less prominent. There are exploratory studies based on survey data that indicate potentially lasting changes in lifestyles and travel behavior after the COVID-19 pandemic (i.a., de Haas et al., 2020; Echegaray, 2021; Shamshiripour et al., 2020). Moreover, post-COVID-19 travel behavior regarding tourism is also explored by some studies (i.a., Febri Falahuddin et al., 2021; Miao et al., 2021).

Substantiated scenarios about, or at least projections of, post COVID-19 travel behavior with global or continental implications to urban transportation can be found within gray literature. A global scenario projected for a three-to-five-year time frame can be found in the report of Corwin et al. (2020), global projections for an undefined "medium- to long-term" are made within the report of Van Audenhove et al. (2020), continental (e.g. European, North America, and East Asia) projections for the year 2030 are described within the report of Hattrup-Silberberg et al. (2020) and European projections are given in the report of Lozzi et al. (2020). As the reports are published during different moments of the pandemic (i.e. within May, July, and September respectively), base their projections on different time-frames (i.e. undefined and 2023 until 2030) and from different perspectives (i.e. global or continental) prudence is needed when comparing these different publications. Nevertheless, insightful similarities are found within the projected implications of mobility trends accelerated by the COVID-19 pandemic on post-COVID-19 travel behavior:

1. Digitalization (e.g. teleworking, e-learning and e-shopping) might reduce the demand for long-distance trips between cities (Corwin et al., 2020; Hattrup-Silberberg et al., 2020; Lozzi et al., 2020; Van Audenhove et al., 2020);

2. Flexible working hours might enable re-spacing and retiming of trip patterns (e.g. travel outside peak hours and more locally) (Corwin et al., 2020; Hattrup-Silberberg et al., 2020; Lozzi et al., 2020; Van Audenhove et al., 2020);

3. Increased consciousness regarding health, safety, and reliability might result in an increased interest in active modes of transportation such as walking and cycling (Hattrup-Silberberg et al., 2020; Lozzi et al., 2020; Van Audenhove et al., 2020);

4. The pandemic provides opportunities for policymakers to shape mobility's future by, among others, reallocation of public space, reassessment of infrastructure investments, and managing new mobility demand (e.g. promoting e-bikes/scooters, shared mobility, and peak flattening) (Hattrup-Silberberg et al., 2020; Van Audenhove et al., 2020).

The evolution of urban mobility trends before the pandemic is different per region and country, as well as the course of the pandemic which may also vary by location (Hattrup-Silberberg et al., 2020; Lozzi et al., 2020). This creates high uncertainty in the actual long-term travel behavior changes that might take place. Moreover, even if the long-term effects can be foreseen to a certain degree, it is still very uncertain to what extent or magnitude this will influence the functioning of an urban transportation system. This thesis aims to fill this knowledge gap with an exploratory local analysis within an urban area to provide more insight into (1) which long-term travel behavior changes may be expected and (2) what the magnitude of impact of these changes could be on an urban transportation system.

1.4 Problem statement, goal, and research questions

Urban mobility and the associated transportation systems play a crucial role in the function and physical appearance of urban areas and have major influences on the economic and social aspects of modern society (Cascetta et al., 2007; Washington et al., 2011). Given more than half of the world's population lives, works, and travels within urban areas, effective urban mobility is of key importance (OECD/European Commission, 2020). However, governance of transportation systems is challenging due to its socio-technical functioning and complex system behavior (Cascetta et al., 2007). Policy interventions within the transportation system are often faced with uncertainty as human behavior forms one of the fundamental elements of the system, giving rise to stochastic system behavior (Chakroborty, 2013).

Given the uncertain and complex behavior of transportation systems, policymakers use travel models as "a tool to support transport policy appraisals in metropolitan areas", mainly in forecasting travel demand which "is a crucial element in the overall transport planning process" (Hatzopoulou & Miller, 2009). Moreover, travel models aim to replicate a part of the real-world transportation system behavior as mathematical equations to explore mobility patterns, trends, and implications of policy interventions by utilizing what-if scenarios (Anda et al., 2017; Castiglione et al., 2014; Van Wee, 2015). While big data sources (e.g., mobile phone and GPS data) prove to be a valuable improvement to the input of demand models in theory, the dominant use of time and resource taxing traditional data sources such as travel diaries, roadside observations, and surveys are still the status quo for demand models in practice (Anda et al., 2017; Nabizade Gangeraj et al., 2017). As a result, transportation models are not recalibrated with updated data frequently and risk becoming obsolete when a significant disturbance of travel behavior occurs (Bera & Krishna Rao, 2011).

Long-term travel behavior changes due to the COVID-19 pandemic pose a problem for the governance and functioning of transportation systems. Conventional transportation models may become obsolete and inadequate to accurately forecast the effectiveness of future transportation policies if travel behavior changes permanently. Moreover, existing urban transportation systems might encounter reduced efficiency and effectiveness. For example, reduced demand for long-distance trips could change the cost-benefit ratio for new infrastructure investments. The re-spacing and retiming of trip patterns could allow for a different allocation of public space. And a modal shift towards active modes could introduce new bottlenecks in existing infrastructure. It is highly uncertain which long-term travel behavior changes may be expected post-COVID-19, and potential implications of travel behavior changes are yet unknown. This is why this thesis aims to explore potential implications of likely long-term travel behavior changes caused by the COVID-19 pandemic.

Given the disruptive character of the COVID-19 pandemic on travel patterns and the high uncertainty of both potential long-term travel behavior changes and its implications on urban transportation this raises the main research question:

> What could be the implications of potential long-term travel behavior changes caused by the COVID-19 pandemic on accessibility and the allocation of public space within the urban transportation system of Amsterdam?

To answer this main research question, the following sub-research questions (SRQ) are formulated:

1. Which long-term travel behavior changes may be expected due to the COVID-19 pandemic?

2. What are potential future development paths of travel behavior post-COVID-19?

3. What could be the magnitude of post-COVID-19 travel behavior change effects on the urban transportation system of Amsterdam?

4. In which way could potential long-term travel behavior changes due to the COVID-19 pandemic impact the accessibility and the allocation of public space within the city of Amsterdam?

1.5 Research design outline

The first step of this research is the conceptualization of the direct effects of the COVID-19 pandemic and policy measures on travel and activity patterns. Based on a literature review on travel behavior change theories a theoretical framework is constructed. Reasoning from this framework it becomes clear why and which kind of travel behavior changes may be expected due to the disruptive COVID-19 pandemic, answering SRQ 1.

With the identification of general direct travel behavior changes that may be expected due to the COVID-19 pandemic, the second step of this research is to explore potential future development paths of these long-term travel behavior changes post-COVID-19. Based on scenario planning methodology exploratory post-COVID-19 travel behavior scenarios are constructed using the intuitive logic scenario planning approach. This is done in two phases, where the first phase uses a participatory approach including workshops with four mobility experts, and the second phase applies a novel approach including a scenario switchboard, as introduced in this thesis, which is used for the construction of four distinct post-COVID-19 travel behavior scenarios. The four post-COVID-19 travel behavior scenarios enable to answer SRQ 2.

With the post-COVID-19 travel behavior scenarios in place, its potential implications on accessibility and the allocation of public space are explored using a transport planning model (TPM) as this allows "to examine the city and region at the aggregate level" (Banister, 2003). Besides exploring potential implications of post-COVID-19 travel behavior the aim of this thesis is to assess to what extend the implications of travel behavior changes can be analyzed with a conventional TPM. This is why the post-COVID-19 travel behavior scenarios are analyzed within a four-step model (FSM), as these types of models can be considered conventional TPMs (Castiglione et al., 2014). As this thesis is conducted in cooperation with the Sustainable Urban Mobility and Safety (SUMS) department of TNO it enabled access to a detailed tour-based FSM of Amsterdam; 'Verkeersmodel Amsterdam' (VMA). As the VMA contains a projected transportation scenario for the year 2030 this will be used as a reference scenario which sharpens the scope of this thesis to explore the potential implications of post-COVID-19 travel behavior for the year 2030.

FSMs such as the VMA do not allow to dynamically change travel behavior, but statically models the way people travel through "four linked submodels: Trip Generation, Trip Distribution, Modal Split, and Trip Assignment" (Banister, 2003). This is why first the potential magnitude of post-COVID-19 travel behavior effects to either one of the four modeling steps are examined by reasoning that observed travel patterns during the COVID-19 pandemic provide a glimpse of (to be expected) post-COVID-19 travel behavior effects with regards to trip generation, trip distribution, and modal split. This can be aligned with the causal logic scenario planning principle, assuming that "the future will be shaped just as the present was shaped by actions in the past" where future development paths of urban travel behavior post-COVID-19 are formed based on the "notion of causality" (Pillkahn, 2008). The potential magnitude of post-COVID-19 travel behavior change effects on the urban transportation system of Amsterdam is established by analyzing trip patterns during the COVID-19 pandemic, allowing to answer SRQ 3. This is done through data analysis using a dataset from the 'Nederlands Verplaatsingspanel' (NVP), which is especially suited to observe travel pattern changes during the COVID-19 pandemic as "due to the continuous data feed the datafile is comprehensive and up-to-date" (Beemster et al., 2019).

Results from SRQ 3 enable to set of bandwidth needed to quantify the scenarios (i.e. future development paths) resulting from SRQ 2. Together, these quantified scenarios allow simulating potential post-COVID-19 travel behavior within the VMA, allowing to explore potential implications to accessibility and the allocation of public space within the city of Amsterdam, answering SRQ 4. The combined SRQ results enabled to answer the main research question.

1.6 Theoretical and practical relevance of this study

As to what extend long-term travel behavior changes will affect the accessibility within cities is unknown, this poses high uncertainty for policymakers and city planners aiming to resolve accessibility bottlenecks and balance the allocation of public space to either cars or other modes of transportation. Moreover, transportation models calibrated on pre-pandemic travel behavior might be unsuitable to project implications of future developments or policies aimed at these urban planning challenges if travel behavior is permanently changed.

Investigating the potential long-term travel behavior changes and assessing the potential magnitude of its impacts on urban mobility can provide insight for policymakers and city planners as advantages and disadvantages of policy options focused on the transportation system might be valuated differently given different travel behavior (van Wee, 2020). From a scientific standpoint, it is not only useful to investigate the implication of a disruptive event, like the COVID-19 pandemic, on travel behavior change but also to explore to what extend strong changes of travel behavior can be captured within conventional transportation models. Insights from this study might be useful for future research about innovations that could provide a disruptive change of travel behavior such as fully autonomous vehicles, the hyperloop, the Mobility as a Service (MaaS) concept, or any other currently unknown potentially disruptive innovation. Given the common use of TPMs, it will be valuable to see to what extent these conventional travel models can be useful for the assessment of potential implications when a disruption of travel behavior occurs or when travel behavior changes are expected.

1.7 Reading guide

Chapter 2 covers how this research is performed and why certain choices were made. Section 2.1 introduces scenario planning methodology and presents the methodological approaches for constructing exploratory scenarios. Section 2.2 provides an overview of the five main research steps in which this thesis is performed within a research flow diagram and provides a general description of each research step. Section 2.3 delineates how the direct effects of the COVID-19 pandemic and policy measures on work-related travel and activity patterns are conceptualized within a theoretical framework based on travel behavior change theories. Section 2.4 describes how potential future development paths of long-term travel behavior changes post-COVID-19 are explored through the creation of explorative scenarios. Section 2.5 describes how post-COVID-19 travel behavior scenarios are translated to parameters of the VMA travel model. Section 2.6 presents how a bandwidth of VMA travel model parameters is estimated based on corrected COVID-19 travel data. Finally, section 2.7 describes how the travel model results are evaluated with indicators of accessibility and indicators for the allocation of public space.

Chapter 3 describes the theoretical framework which explains why certain long-term travel behavior changes may be expected post-COVID-19 and combine these general effects to the four modeling steps from the FSM paradigm. The first three sections describe why post-COVID-19 three general effects may be expected, namely, a shift from onsite to online activities (section 3.1), the re-spacing and retiming of trip patterns (section 3.2), and a modal shift towards active modes (section 3.3). Finally, section 3.4 presents the theoretical framework which conceptualizes the direct effects of the COVID-19 pandemic and policy measures on travel and activity patterns.

Chapter 4 shows how potential future development paths of travel behavior post-COVID-19 are constructed, resembling the result of the scenario planning approach. Section 4.1 describes different post-COVID-19 travel behavior perspectives of four mobility experts and presents, among others, the scenario matrices as created by the individual experts. Section 4.2 introduces the scenario switchboard which combines the four scenario matrices as created by the experts. Section 4.3 explains how the scenario switchboard is used to create four distinct post-COVID-19 travel behavior scenarios. The storylines of the different scenarios are presented from sections 4.4 to 4.7. Finally, section 4.8 describes how the post-COVID-19 travel behavior scenarios are used to project the future state of the three direct effects of the COVID-19 pandemic and policy measures on travel behavior.

Chapter 5 describes how the scenarios are quantified to explore potential effects within the VMA travel model. Section 5.1 continues on the scenario switchboard by translating the individual sliders to VMA model parameters. Section 5.2 describes how trip data from the COVID-19 pandemic is used to estimate a bandwidth for the individual parameters per post-COVID-19 travel behavior scenario.

Chapter 6 covers the VMA travel model simulation results of the different post-COVID-19 travel behavior scenarios. Section 6.1 provides an overview of the general implications of the shift from onsite to online work-related activities and a modal shift towards cycling. Section 6.2 covers the implications of post-COVID-19 travel behavior scenarios on congestion within the network of Amsterdam. Section 6.3 continues on this by elaborating on the travel time savings resulting from the reduced congestion rates. Finally, section 6.4 presents the potential implications of the post-COVID-19 travel behavior scenarios on the allocation of public space based on the modal shift from cars to cycling per district.

Chapter 7 presents the conclusions drawn from this research.

Chapter 8 provides a discussion by reflecting on the choice of Amsterdam as case study in section 8.1, the unique execution of the scenario planning process which includes the novel scenario switchboard in section 8.2. A reflection on the usefulness of exploratory scenarios when investigating future travel behavior is provided in section 8.3. Choices that directly influence the results of this thesis are addressed in section 8.4, and suggestions for future research are provided in section 8.5.

Aerial view on the city center of Amsterdam | Screenshot from 3d.amsterdam.nl, edited by author.

Chapter 2

Research design

This chapter describes how this research is conducted and provides the reasoning behind the used methodologies, approaches, and undertaken research steps. Section 2.1 introduces scenario planning methodology and presents the methodological approaches for constructing exploratory scenarios. Section 2.2 provides an overview of the five main research steps in which this thesis is performed within a research flow diagram and provides a general description of each research step. Section 2.3 delineates how the direct effects of the COVID-19 pandemic and policy measures on work-related travel and activity patterns are conceptualized within a theoretical framework based on travel behavior change theories. Section 2.4 describes how potential future development paths of long-term travel behavior changes post-COVID-19 are explored through the creation of explorative scenarios. Section 2.5 describes how post-COVID-19 travel behavior scenarios are translated to parameters of the VMA travel model. Section 2.6 presents how a bandwidth of VMA travel model parameters is estimated based on corrected COVID-19 travel data. Finally, section 2.7 describes how the travel model results are evaluated with indicators of accessibility and indicators for the allocation of public space.

2.1 Methodological approach

With the aim of this thesis to explore post-COVID-19 travel behavior, there is a desire to envision the future. Attempts to study the future, which is captured in the discipline of future studies, were already practiced in antiquity where ancient civilizations aimed to predict the future with well-known instruments such as "the crystal ball, the stars and other heavenly bodies" (Pillkahn, 2008). Initial systematic approaches to study the future can be traced back to the development of forecasts by the Stanford Research Institute (SRI) in the year 1947 and the development of scenario methodology, known as scenario planning, by the RAND Corporation and Hermann Kahn in 1948 (Pillkahn, 2008; Ringland, 1998). The scenario method at the time was aimed at military-strategic planning, the Royal Dutch Shell Corporation under the guidance of Pierre Wack formalized scenario planning to support corporate strategies (Pillkahn, 2008; Ringland, 1998). During the following decades, the use of scenario planning increased and "is now more or less a standard tool in many companies and consulting firms" (Stojanović et al., 2014). Moreover, scenario planning is increasingly used in the field of transport planning as it "encourages strategic thinking and helps to overcome thinking limitations by creating multiple futures" which makes scenario planning useful "in times of uncertainty and complexity" (Banister, 2003; Stojanović et al., 2014).

Scenario planning is defined in several ways (Thomas J Chermack & Payne, 2005; Dean, 2019; Stojanović et al., 2014):

1. Scenario planning is "a disciplined methodology for imagining possible futures in which organizational decisions may be played out" (Schoemaker, 1995);

2. "Scenario planning is that part of strategic planning which relates to the tools and technologies for managing the uncertainties of the future" (Ringland, 1998);

3. Scenario planning is "a process of positing several informed, plausible and imagined alternative future environments in which decisions about the future may be played out, for the purpose of changing current thinking, improving decision making, enhancing human and organization learning and improving performance" (T. J. Chermack & Lynham, 2002);

4. Scenario planning is "a strategic planning method which can be employed to explore possible future situations and development paths, typically over a medium-term horizon" (Dean, 2019).

The advantage of scenario planning given the aim of this thesis is that, as a methodological tool, scenario planning enables to systematically imagine alternative future storylines of post-COVID-19 travel behavior which can be used to explore the uncertain post-COVID-19 future in the area of transportation. Moreover, "scenarios have the advantage over forecasts in that they are more flexible, creative and not necessarily probabilistic outlines of plausible futures" (Milakis et al., 2017).

Although "various typologies of scenarios have been suggested," the scenario planning process can result in three types of scenarios: (1) exploratory scenarios "which start from past and present trends and lead to likely futures (what can happen)", (2) anticipatory or normative scenarios "which describe the desired future or the feared future" and (3) "predictive scenarios, which describe the most probable future (what will happen)" (Stojanović et al., 2014). Given the novelty of the COVID-19 pandemic, the fact that potential long-term travel behavior changes due to the COVID-19 pandemic are highly uncertain and potential implications to the transport system are unknown, anticipatory or normative, and predictive scenarios are arguably inconceivable. Moreover, in line with the exploratory aim of this thesis, exploratory scenarios are created to envision potential alternative future storylines of post-COVID-19 travel behavior.

For the design of the scenario planning process there are "three major schools of scenario techniques: (1) intuitive logic, (2) probabilistic modified trends (PMT) methodology and (3) the French approach of La prospective" (Stojanović et al., 2014). The intuitive logic approach is followed in this research as this school "does not use any mathematical algorithms" (Stojanović et al., 2014). Moreover, the intuitive logic school is arguably suitable for the creation of exploratory scenarios as this approach is "focused on the development of multiple scenarios that explore the limits of possibility for the future, rather than on the development of singular, normative scenarios of some ideal future" and explores "how the future might evolve" from the present to a future horizon (Wright et al., 2013).

When building scenarios there are three approaches: (1) minimal, (2) standard, and (3) maximum approach (Pillkahn, 2008). The chosen approach is based on the number of uncertainties of the inquiry, as well as costs in terms of the time spend on various scenario building techniques (Pillkahn, 2008). When "the overview of all elements reveals two criteria that will allow one to determine the further development" the minimal approach is usually suitable (Pillkahn, 2008). The minimal approach is interesting when building post-COVID-19 travel behavior scenarios as it allows to explore the most extreme system states based on the two main uncertain elements in a four-quadrant matrix. However, as the uncertainties of post-COVID-19 travel behavior are arguably not easily reduced to just two uncertain elements, Pillkahn (2008) recommends the standard approach which "allows for a more differentiated assessment of continued development". For this research, it is chosen to use the Wilson matrix from the standard approach to identify two critical elements which in turn are used as input for the four-quadrants matrix from the minimal approach. The maximum approach is unsuitable given time and resource limitations which do not allow to, for example, carry out a cross-impact analysis.

The methodological steps used to construct exploratory post-COVID-19 travel behavior scenarios for this thesis are described in detail in section 2.4. Besides scenario planning, other methods are used throughout this thesis such as desk research (i.e. literature study and data analysis) and travel modeling. Section 2.2 provides an overview of the research steps.

2.2 Research flow diagram

There are five main research steps for this thesis. Figure 1 provides an overview of these five main steps and illustrates how the different parts of this research are related. A general description of each research step is given throughout this section, whereas sections 2.3 to 2.7 provide a detailed description of the methodological steps within each research step.

	Research step	Method	Output	Results enable to answer	
1	Conceptualizing how the COVID-19 pandemic might change long term travel behavior.	Literature study	1. Theoretical framework 2. General post-COVID-19 travel behavior effects	SRQ 1 |	Which long-term travel behavior changes may be expected due to the COVID-19 pandemic?
2	Exploring potential future development paths of long term travel behavior change post-COVID-19.	Scenario planning	Four post-COVID-19 travel behavior scenarios	SRQ 2 |	What are potential future development paths of travel behavior post-COVID-19?
3	Translating post-COVID-19 travel behavior scenarios to parameters of the VMA travel model.	1. Literature study 2. Travel modelling	Operationalized qualitative post-COVID-19 travel behaviour scenarios		
4	Estimating bandwidth of VMA travel model parameters using corrected COVID-19 travel data.	1. Data analysis 2. Travel modelling	Operationalized quantitative post-COVID-19 travel behaviour scenarios	SRQ 3 |	What could be the magnitude of post-COVID-19 travel behavior effects on the urban transport system of Amsterdam?
5	Evaluating travel model results with indicators of accessibility and allocation of public space.	1. Literature study 2. Travel modelling	Potential implications of post-COVID-19 travel behavior scenarios.	SRQ 4 |	In which way could potential long-term travel behavior changes due to the COVID-19 pandemic impact the accessibility and the allocation of public space within the city of Amsterdam?

Fig. 1: Research flow diagram.

Research step 1: To explore which long-term travel behavior changes may be expected due to the COVID-19 pandemic literature study is conducted on (1) post-COVID-19 travel behavior projections and (2) travel behavior change theories. By researching post-COVID-19 travel behavior projections general post-COVID-19 travel behavior effects could be identified, where the travel behavior change theories allowed to conceptualize the potential influence of the COVID-19 pandemic on travel behavior change within a theoretical framework. Section 2.3 provides a detailed description of how the literature study is conducted.

Research step 2: With general post-COVID-19 travel behavior effects identified from research step 1, the next research step was to explore potential future development paths of travel behavior post-COVID-19. This is done by creating four exploratory post-COVID-19 travel behavior scenarios using scenario planning. The scenario planning process as applied in this thesis can be divided into two phases; (1) a scenario construction phase and (2) a scenario reduction phase. The first phase includes the creation of four scenario matrices by four mobility experts, resulting in a total of sixteen storylines. In the second phase, these sixteen storylines are reduced to four using a novel approach including a scenario switch board. Section 2.4 provides a detailed description of how the post-COVID-19 travel behavior scenarios are created.

Research step 3: To operationalize the four post-COVID-19 travel behavior scenarios as created in research step 2, relevant parameters within the VMA travel model were identified based on the technical documentation of Van den Elshout et al. (2020). The identified parameters were verified individually by changing the associated input values and analyzing changes to the model results. Section 2.5 provides a detailed description of how the post-COVID-19 travel behavior scenarios were operationalized within the VMA travel model.

Research step 4: To quantify the operationalized post-COVID-19 travel behavior scenarios within the VMA travel model, travel patterns during the COVID-19 pandemic were analyzed and input values of model parameters were altered accordingly. As the post-COVID-19 scenarios are not entirely aligned with the situation as during the COVID-19 pandemic, corrections are applied to the observed travel patterns. First, through data analysis of datasets from Roser et al. (2020) a moment in time during the COVID-19 pandemic was determined where COVID-19 policy measures in the Netherlands were maximally eased. Secondly, through data analysis of a dataset from Dat.mobility (2021), combined with the adaptive exploration of input values associated with the identified VMA travel model parameters from research step 3, a bandwidth was set which matched the selected observed travel data during the COVID-19 pandemic. This bandwidth allowed to assign parameter values for each scenario. Section 2.6 provides a detailed description on the methodological steps associated with this research step.

Research step 5: With quantitatively operationalized post-COVID-19 travel behavior scenarios as created through previous research steps, the potential impact of these scenarios could be calculated with the VMA travel model. To define accessibility and the allocation of public space needed to interpret the model results, corresponding scientific literature was analyzed. Section 2.7 provides a detailed description of the methodological steps associated with this research step.

2.3 Conceptualizing how the COVID-19 pandemic might change long term travel behavior

To identify which trends –accelerated by the COVID-19 pandemic– might lead to long-term travel behavior changes, desk research is conducted on citing databases Scopus and ScienceDirect to explore the state of art literature about travel behavior changes during the COVID-19 pandemic, travel behavior change in general, and potential post-COVID-19 scenarios. With the absence of long-term post-COVID-19 travel behavior scenarios within the citing databases of Scopus and ScienceDirect, post-COVID-19 projections within gray literature were analyzed (i.e. Corwin et al. (2020), Hattrup-Silberberg et al. (2020), Lozzi et al. (2020), and Van Audenhove et al. (2020)). However, given these are non-scientific publications, the first step of this research was to establish a theoretical basis on why long-term travel behavior changes may be expected. Van Wee (2020) provides a discussion on why long-term travel behavior changes may be expected and to what extent certain travel behavior-related changes may or may not be expected based on economical, psychological, and geographical travel behavior change theories. Based on travel behavior change theories as identified within the paper of Van Wee (2020) a theoretical framework could be constructed which conceptualizes the direct effects of the COVID-19 pandemic and policy measures on work-related travel and activity patterns.

2.4 Exploring potential future development paths of long term travel behavior changes post-COVID

With a clear overview of the general travel behavior changes that may be expected post-COVID-19 the explorative scenario process could commence exploring the potential future development paths of post-COVID-19 travel behavior. Dean (2019) distinguishes conventional explorative scenario planning methods on (1) thematic coverage (i.e. using a narrow or wide research scope),

(2) design of the process (i.e. using formalized techniques or intuitive methods), (3) input into the scenario process (i.e. using qualitative or quantitative inputs) and (4) actors involved in the process (i.e. using an analyst-led or participatory approach).

The scope of this thesis involves one particular theme (i.e. travel behavior) and one sector (i.e. urban transportation), hence the thematic coverage can be topologized as simple scenarios. Moreover, as the VMA provides a reference scenario within the year 2030, the timeframe of the constructed scenarios is set to be the year 2030.

The input of the explorative scenario planning process can be either quantitative or qualitative (Dean, 2019). This research uses qualitative data to construct exploratory scenarios as this typology of data can be "conveniently employed for the analysis of complex and long-term planning problems, characterized by high levels of uncertainty" which is aligned with the aim of this thesis (Dean, 2019). Whereas quantitative inputs are "more appropriate for more analytical scenario planning procedures, focusing on rather short planning horizon" (Dean, 2019).

The actors involved in the explorative scenario planning process can be defined as an analyst-led or participatory approach, although "some methods also combine stakeholder-led and model-based scenarios" (Dean, 2019). With "analyst-led (or model-based) scenario planning methods, scenarios are developed autonomously by a team of specialists" where participatory approaches "involve workshops and focus group discussions in the attempt to explore different stakeholders' perspectives" (Dean, 2019). Due to resource limitations, this thesis uses the input of mobility experts for constructing the explorative scenarios, thus can be topologized as a participatory approach.

The scenario development process for this thesis involved two phases. In the first phase mobility experts created individual scenario matrices during individual expert workshops, using the following steps:

1. Generation of key factors, which are variables that might explain or influence the observed travel behavior changes during the COVID-19 pandemic. The key factors are listed by the participating experts by answering the following question: "What factors might be guiding travel behavior changes during the COVID-19 pandemic?";

2. Generation of driving forces, which are comparable to theoretical principles, (sub-) systems or phenomena that may underlie the key factor. The driving forces are listed by the participating experts by answering the following question: "What forces could drive these changes (i.e. key factors) during the COVID-19 pandemic?";

3. Identification of two critical driving forces by evaluating each key driver within a Wilson matrix, as shown in figure 1, with the x-axis consisting of the 'degree of uncertainty for future travel behavior' ranging from (low to high) and the y-axis consisting of the 'degree of influence on future travel behavior';

4. Creation of a scenario matrix, as depicted within figure 2, where both critical driving forces are used for either the x-axis or y-axis. The scenario matrix is constructed by the

participating experts by answering the following question: "What would be the extreme cases of each critical driving force?";

5. Creating post-COVID-19 storylines based on the resulting scenario matrix quadrants. The storylines are created by the participating experts by answering the following question: "What would be the resulting travel behavior in the year 2030, given the extreme values of the critical driving forces associated with this quadrant?".

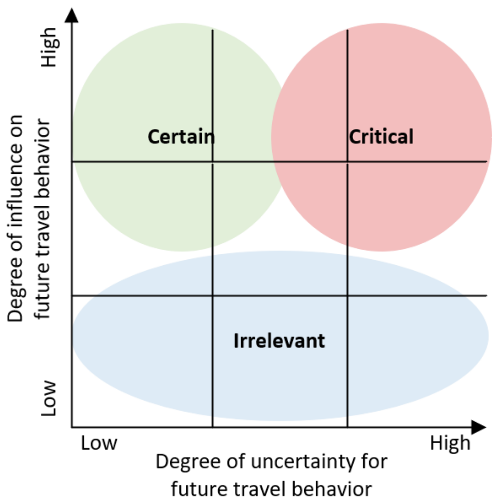


Fig. 2: Wilson matrix used to identify critical driving forces, adopted from (Pillkahn, 2008).

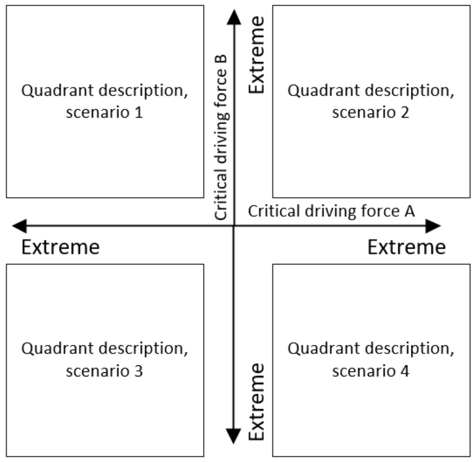


Fig. 3: Scenario matrix used to create post-COVID-19 scenarios based on two critical driving forces adopted from (Dean, 2019).

As the first phase was repeated with four different mobility experts, this process resulted in four scenario matrices, each with 4 quadrant descriptions resulting in a total of 16 post-COVID-19 scenarios. Although the optimal number of scenarios may depend on the use case and context, Stojanović et al., (2014) conclude from a literature analysis "that 3-5 scenarios are optimal". This is why, in the second phase, the different scenario matrices are superimposed based on similarities within the quadrant descriptions, as sketched within figure 3, to reduce the number of scenarios to four. This is done using the following steps:

1. An overview is created of all critical driving forces and their extreme ranges used as either the x-axis or y-axis within the resulting scenario matrices;

2. The number of critical driving forces is minimalized by combining critical driving forces with a similar definition or arguably similar ranges.

3. The resulting critical driving forces are resembled as horizontal sliders, as sketched within figure 4, with a neutral and alternate position delineated from the ranges as given within the scenario matrices. The neutral position resembles 'no change' of the critical driving force post-COVID-19 and the alternate position resembles 'positive change' of the critical driving force post-COVID-19. For example, if the critical driving force would be 'technology', its neutral position could be 'status quo' whereas the alternate position could be 'highly technological advanced'.

4. The position of the different sliders is assigned based on the extreme values used within the different scenario matrices.

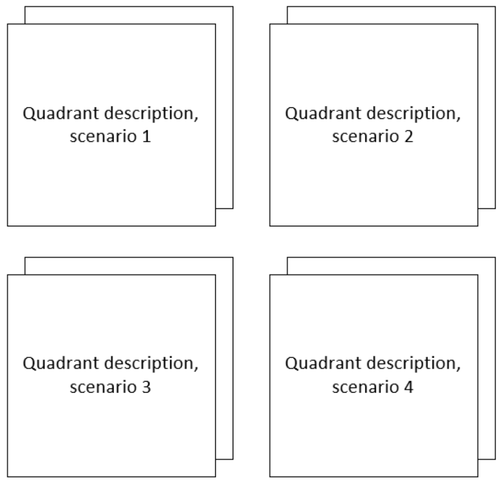


Fig. 4: Illustrative representation of superimposing scenario matrices based on similar quadrant descriptions.

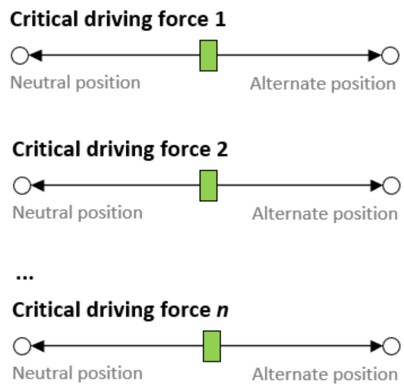


Fig. 5: Illustrative representation of the scenario switch board with *n* sliders.

2.5 Translating post-COVID-19 travel behavior scenarios to parameters of the VMA travel model

The exploratory scenario process resulted in four post-COVID-19 travel behavior scenarios. To assess the potential implication of these scenarios, the sliders from the scenario switchboard are translated to parameters within the FSM travel model of the city of Amsterdam (i.e. the VMA travel model). Relevant parameters within the VMA travel model were identified by a literature study of the technical model documentation by Van den Elshout et al. (2020) and validated by trial and error. For example, when parameters were identified within the VMA travel model that could change the trip generation in theory, this was tested by an adaptive exploration of input values altering the parameter value and examining the resulting number of trips as generated by the VMA.

2.6 Estimating bandwidth of VMA travel model parameters using COVID-19 travel data

With the identification of relevant parameters within the VMA travel model, the scenarios could be quantified. Meaning that the potential magnitude of post-COVID-19 travel behavior as described within the scenarios had to be estimated. For this, the causal logic scenario planning principle is applied, assuming that "the future will be shaped just as the present was shaped by actions in the past" where future development paths of urban travel behavior post-COVID-19 are formed based on the "notion of causality" (Pillkahn, 2008). In other words, it is assumed that travel behavior during the COVID-19 pandemic –especially during the time where policy measures were maximally eased– could provide a glimpse of its post-COVID-19 equivalent.

Similar to other Dutch transportation models, future projections within the VMA are based on a high and low economic forecast for the years 2030 and 2050 provided by the Dutch national institute for strategic policy analysis in the field of environment, nature, and spatial planning (CPB/PBL, 2015). This means that the reference scenario (i.e. projection year 2030 within the VMA travel model) could provide a proverbial edge for the parameter bandwidth, where the observed travel patterns during COVID-19 provide the other edge for the parameter bandwidth. For this purpose, two insights had to be established: (1) a clear overview was needed of the COVID-19 policy responses within the Netherlands to pinpoint the moment in time where policy measures were maximally eased, and (2) a dataset had to be obtained which would include travel movements during COVID-19, most preferably segmented to the level of urbanization, activity location and mode of transport.

To get an overview of COVID-19 policy measures in the Netherlands, first, desk research was performed on COVID-19 related policy resolutions as published by the national government, resulting in an overview of the COVID-19 lockdowns within the Netherlands. To further pinpoint a moment in time where policy measures where maximally eased the publicly available data as collected by Roser et al. (2020) provided a detailed insight. The results of Roser et al. (2020) provide an overview of the course of the COVID-19 pandemic throughout different countries as well as policy responses which are determined in a stringency index; a composed measure of nine response metrics (Hale et al., 2021). Policy responses related to economic (e.g. income support and debt/contract relief for households) and health systems (e.g. public information campaign and testing policy) were considered irrelevant and thus removed when calculating the stringency index, after all, considering the aim of this research it was needed to get an idea about policy measures related to the limitation of travel movements and activities. Details about how the stringency index has been calculated are described in appendix 1. The resulting stringency indices made it possible to determine the weeks where policy measures were maximally eased.

With the identification of the policy relaxations during COVID-19, the next step was to analyze travel movements during the pandemic, for which a dataset from the 'Nederlands Verplaatsingspanel' (NVP) was used. The dataset consists of an Excel file containing processed aggregates (anonymized, not traceable) about observed travel behavior ranging from week 23 from the year 2019 until week 8 from the year 2021 and provide insight into several indicators such as the number of trips, travel time (in minutes), distance (in kilometers), destination categories and peak hours (Dat.mobility, 2021).

Alternatives datasets to the NVP (n=13.000) are 'Onderweg in Nederland' (ODiN) (n=35.000) and 'Mobiliteitspanel Nederland' (MPN) (n=2.500) (Beemster et al., 2019). The main difference between these datasets is the way the data is collected. The NVP uses "an automated process with a mobile application enabling the continuous collection of travel movements", whereas ODiN and the MPN uses a yearly single survey study where ODiN respondents fill in one randomly selected travel day and MPN respondents fill in three consecutive travel days in a travel diary (Beemster et al., 2019). "The automated analysis allows the NVP to result in a better model split for short trips under the 3 kilometers" and "due to the continuous data feed the datafile is comprehensive and up-to-date" (Beemster et al., 2019). This fitted explicitly well with the aim of this research to scope on specifically travel movements within cities and given the novelty of the COVID-19 pandemic. A disadvantage of the NVP dataset is that all participants are panelists and "thus less randomly selected than in the ODiN, the users are not constant as in the MPN and no survey takes place for background information on, for example, travel expenses or choices made" (Beemster et al., 2019).

Other, publicly available, alternative sources are the COVID-19 community mobility reports by Google (2020) which represent the relative change of activity location, and the COVID-19 mobility trend reports by Apple (2020) which represent the relative change in routing requests. Both data sources enable the analysis of data specifically on a national or municipal level relative to a baseline set around January 2020. These datasets are used to verify the magnitude of change observed within NVP with regards to activity location and mode choice.

By adaptive exploration of input values, the selected VMA travel model parameters were altered until the results would resemble similar travel pattern changes as during the COVID-19 pandemic. The resulting parameter values were assigned to scenario 4 and divided among the other scenarios in line with their storylines.

2.7 Evaluating travel model results with indicators of accessibility and allocation of public space

With the quantified scenarios in place, the VMA travel model could run and its results could be analyzed. The VMA travel model distinguishes Amsterdam –and the rest of the Netherlands– within a total of 5.473 zones (Van den Elshout et al., 2020). The level of detail (i.e. relative size) of each zone intensifies towards the center of Amsterdam, in other words, the number of zones within Amsterdam is very high compared to locations outside the city of Amsterdam. The zones of the VMA travel model are displayed in figure 5. Given the scope of this thesis results from the VMA travel model are drawn from the zones that can be considered part of the Amsterdam municipality. The study area is displayed within a detailed overview in figure 6.

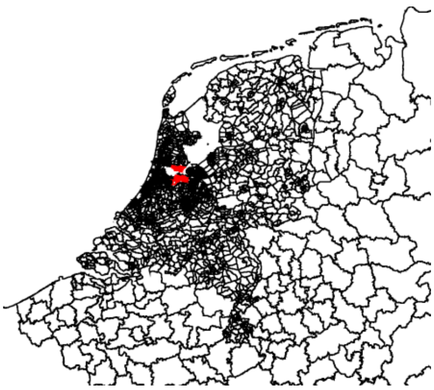


Fig. 6: Selection of zones within the VMA travel model of the Netherlands, the city of Amsterdam is marked in red.

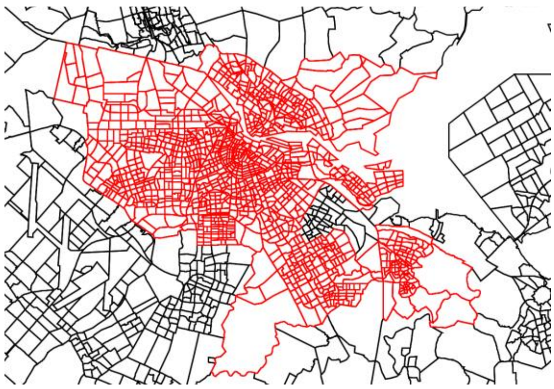


Fig. 7: Detailed overview of the study area, highlighted in red, consisting of the zones considered part of the Amsterdam municipality.

The network of the VMA transport model consists of nodes and links, where links resemble the roads and nodes resemble connections between links (e.g. an intersection, roundabout, etc.). The origins and destinations of trips within the VMA travel model are from and to nodes positioned within the center of each zone, these nodes are referred to as centroids. Compared to nodes, centroids consist of demographic information such as the number of residents, workplaces, and so on. Figure 7 shows an overview of the network and centroids within the study area. Within the study area, eight districts can be distinguished, as depicted in figure 8: (1) Center, (2) Westpoort, (3) West, (4) South, (5) East, (6) North, (7) Southeast and (8) New West.

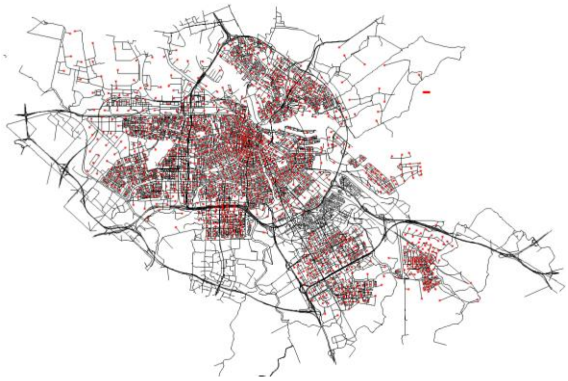


Fig. 8: Network of the VMA travel model, consisting of links within the study area. Centroids are marked in red.

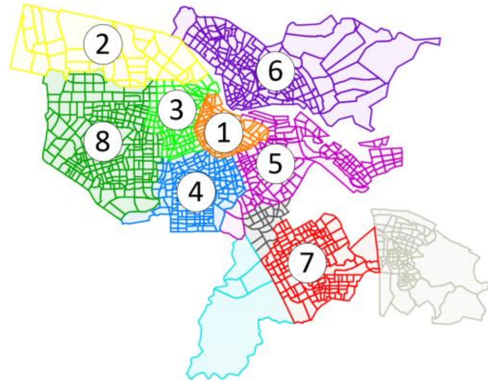


Fig. 9: Different districts within the study area: (1) Center, (2) Westpoort, (3) West, (4) South, (5) East, (6) North, (7) Southeast and (8) New West.

The main research question of this thesis aims to explore potential implications of long-term travel behavior changes due to the COVID-19 pandemic on accessibility and the allocation of public space. The meaning of accessibility seems obvious but heavily depends on its contextual application (Ahuja & Tiwari, 2021). Accessibility in transportation can be described as “the ease of reaching a destination from an origin by utilizing the available travel mode options with inherent impeding properties of the route-generally time, speed, distance, and mode of transport” (Ahuja & Tiwari, 2021).

Throughout the world, the “main aim of Ministries of Transport (…) is to improve accessibility” (van Wee, 2016). Although there are many indicators of accessibility, “all accessibility indicators have three main aspects: spatial (i.e. space), temporal (i.e. time) and economic (i.e. costs)” (Ahuja & Tiwari, 2021). For this thesis, it is assumed that, based on the potentially reduced demand for long-distance trips, potential re-spacing and retiming of trip patterns and the potential increase of active modes as delineated within chapter 1, section 1.3, the effects of long-term travel changes post-COVID-19 are most likely visible in terms of reduced travel times. This is why the indicator of accessibility used in this thesis consists of travel time. The potential impact of the post-COVID-19 travel behavior scenarios on accessibility is analyzed by plotting the travel times from a zone within the center of Amsterdam to any other zone within the study area and comparing the differences between each scenario to the reference scenario. The reference scenario is a projection of the year 2030 without any travel behavior changes, this is considered to be the base case. The VMA travel model includes four types of travel modes: (1) cars, (2) public transport, (3) bicycles, and (4) walking and three travel moments: (1) Morning rush hour (i.e. 7:00 to 9:00 AM), evening rush hour (i.e. 4:00 to 6:00 PM) and rest-of-day (Van den Elshout et al., 2020). This is why travel times are analyzed per mode and per travel moment by plotting the travel time from a zone to all other zones within the study area and comparing the results of the different scenarios.

Figure 10 provides an example of the accessibility plot, resembling the travel time by car within the morning rush hour from a random zone within the city center to all other zones within the study area of the reference scenario.

Regarding the allocation of public space, it is assumed that if for a certain part within the network congestion on the roads resolves, there might be space for other modes of transportation, hence, a different allocation on that road might be possible. The same logic applies to other modes such as cycling and walking. Although the VMA travel model does assign capacity to the bike and pedestrian paths, it is unknown if the intensity of bikes exceeds its capacity. Nevertheless a section of road where the intensity of cyclists or pedestrians increases might indicate that more space could be allocated to bicycle or pedestrian paths instead of cars. Figure 10 provides an example of the bandwidth plots used to indicate changed intensity or congestion between two different scenarios.

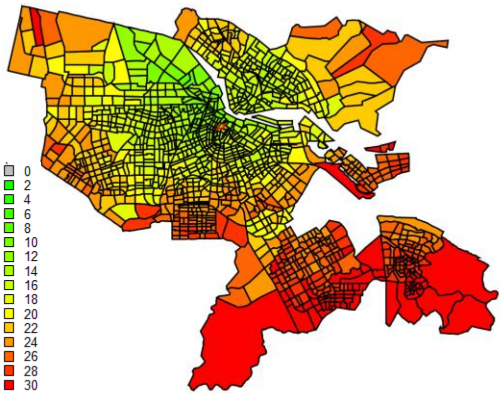


Fig. 10: Accessibility from a random zone within the city center to all other zones by car in the morning rush hour of the reference scenario. Legend shows travel time in minutes.

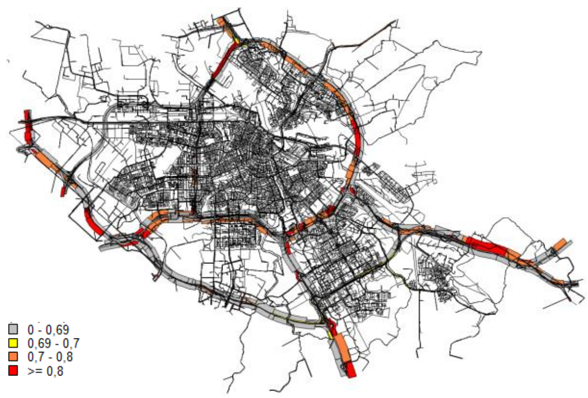
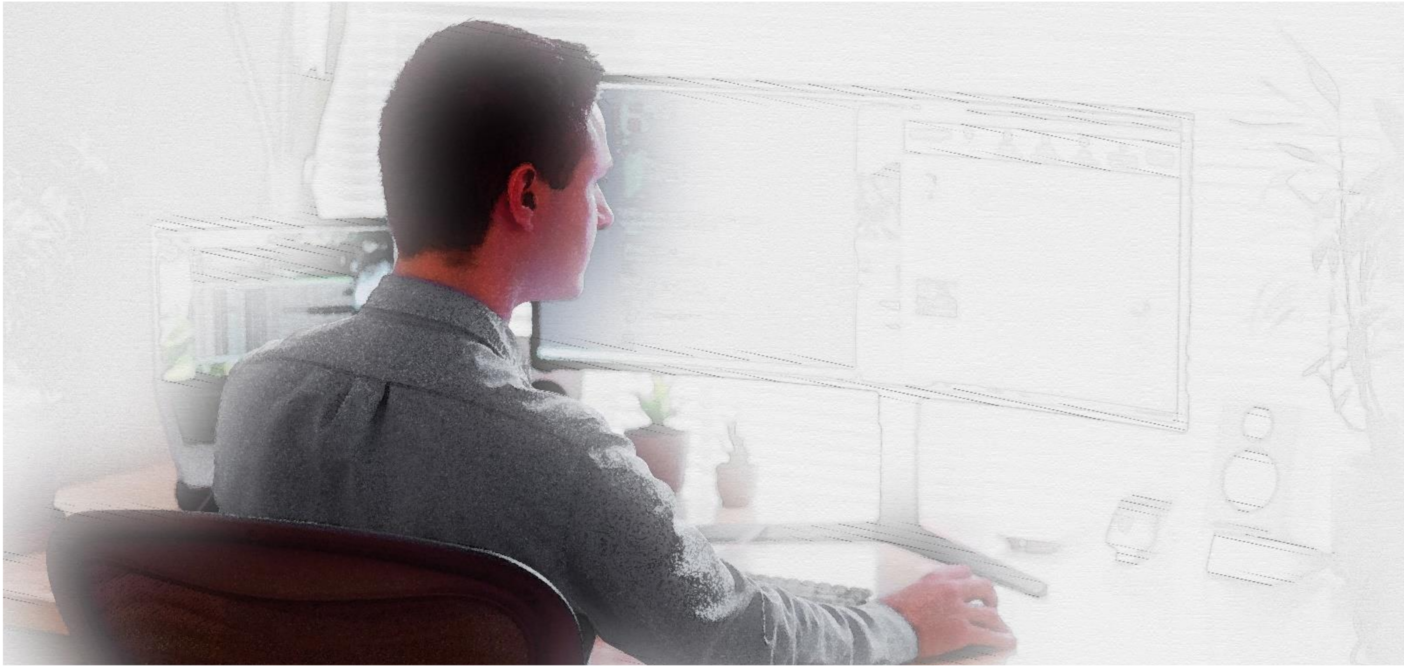


Fig. 11: Bandwidth plot of congestion of cars within the morning rush hour of the reference scenario. The legend shows congestion rate (i.e. intensity divided by capacity)



Person working-from-home | Photo by Luke Peters on Unsplash, edited by author.

Chapter 3

Potential long term travel behavior changes due to the COVID-19 pandemic

Given the disruptive effects of the COVID-19 pandemic on mobility, an important question is which long-term travel behavior changes may be expected due to the COVID-19 pandemic. This chapter aims to answer this question. As delineated in chapter 1, section 1.3, different non-scientific reports project similar long term travel behavior effects when the COVID-19 pandemic is over. However, given these are non-scientific publications, the first step of this research is to establish a theoretical basis on why which long-term travel behavior changes may be expected. Van Wee (2020) provides a discussion on why long-term travel behavior changes may be expected and to what extent certain travel behavior-related changes may or may not be expected based on economical, psychological, and geographical travel behavior change theories. This chapter briefly describes these travel behavior change theories and argues why a shift from onsite to online activities (section 3.1), the respacing and retiming of travel patterns (section 3.2) and a modal shift to active modes of transport (section 3.3) may be expected post-COVID-19. Section 3.4 combines these travel behavior change theories and conceptualizes the direct effects of the COVID-19 pandemic and policy measures on work-related travel and activity patterns within a theoretical framework.

3.1 Why a shift from onsite to online activities may be expected post-COVID-19

Van Wee (2020) anticipates that the shift from onsite to online activities is the most prominent long-term travel behavior effect from the COVID-19 pandemic based on both the random utility theory (Variant, 1992), the theory of habitual behavior (Verplanken et al., 1997), theory of planned behavior (Ajzen, 1991) and conceptual model for attitude change as proposed by (Van Wee et al., 2019). The first argument for this originates from the random utility theory which "assumes that people are fully informed about behavioral choice options and their characteristics and weigh up advantages and disadvantages of behavioral options" (van Wee, 2020). As COVID-19 forced people to stay-, work-, study- and shop-at-home the knowledge and experiences due to online activities increased during COVID-19 which might results in a more positive association with online activities to replace onsite activities (van Wee, 2020). In other words, the utility of online activities increases. This expectation is reinforced by the research of De Haas et al. (2020) which identifies that the majority (71%) of people have positive experiences working from home during the COVID-19 pandemic.

A second argument why online activities such as working-from-home may become the status quo comes from the theory of habitual behavior, which states "that people do not explore and weigh all options each time before making a decision" and because of bounded rationality "do not know all the options, and do not have all the knowledge about options, for various reasons" (van Wee, 2020). Moreover, "many behaviors are repetitive and in such case develop habitual behavior" especially "commuting to work is to a large extent habitual behavior" (van Wee, 2020). "Even though the scientific literature is not entirely clear, indications are that one to a few months are sufficient to break habitual behavior and form new habitual behavior" considering that, at the time of writing, the COVID-19 pandemic in the Netherlands started over a year ago it is very plausible to state that pre-pandemic habitual travel behavior has been broken and new habitual behavior might have formed around online activities (van Wee, 2020).

A third argument to expect a shift from onsite to online activities even when the pandemic has ended is given from the theory of planned behavior which states that travel behavior results from "intentions and perceived opportunities to exercise behavior" from which the "intentions depend on perceived opportunities to exercise behavior, attitudes, and social norms" (van Wee, 2020). Especially these social norms are influenced during the COVID-19 pandemic as employers might for example stimulate to work-from-home as much as possible, moreover, due to the increased experiences with online activities the "perceived behavioral opportunities might have changed with respect to the use of online tools" (van Wee, 2020). The stimulus from employers is observed during the COVID-19 pandemic as the majority (54%) of employers stimulate to work as much from home as possible (Taale et al., 2020). This stimulus (i.e. change of norms) might be supported by the plans of the 25 biggest employers in the Netherlands who expect to reduce their office space by 10 to 50% after the COVID-19 pandemic (NOS Nieuwsuur, 2021).

Finally, a fourth argument to expect a lasting shift to online activities post-COVID-19 is given from the conceptual model for attitude change as proposed by (Van Wee et al., 2019). "The model explains that attitudes can change through increased knowledge (cognitive dimension), through experiences (behavioral dimension) and by emotions (affective dimension)" for which "all three dimensions are influenced by COVID-19" (van Wee, 2020). As mentioned earlier the majority of people have positive experience working-from-home from which it can be determined that the attitude towards online activities changed during the COVID-19 pandemic. This positive attitude towards online activities will likely remain after the pandemic as "the adjusted attitudes based on knowledge, experience or emotions do not revert to the old attitudes, because those knowledge, experience, and emotions are not erased" (van Wee, 2020).

The projection as made by Corwin et al. (2020), Hattrup-Silberberg et al. (2020), Lozzi et al. (2020), and Van Audenhove et al. (2020) is that digitalization might reduce the demand for long-distance trips between cities. The shift from onsite to online activities post-COVID-19 can be underpinned by both the random utility theory, theory of habitual behavior, theory of planned behavior, and conceptual model for attitude change as proposed by Van Wee et al. (2019). Moreover, this will likely influence travel demand as digital activities don't need physical travel movements. If these travel demand reductions will only or specifically account for long-distance trips is less clear. It is for example plausible that the gains in terms of utility are greater when replacing long-distance trips for non-travel in contrast to replacing a short distance trip for non-travel, however, literature about the extent of this effect is not found. To conclude, a shift from onsite to online activities may be expected to last even after the COVID-19 pandemic as:

1. Knowledge and experiences most likely increased for online activities and online tools;
2. Potentially new habitual behavior is formed given the duration of the pandemic;
3. The social norms towards online activities may have changed positively;
4. Attitudes towards online activities and online tools may have positively changed.

3.2 Why re-spacing and retiming of trip patterns may be expected post-COVID-19

Besides a shift from onsite to online activities, another projection as made by Corwin et al. (2020), Hattrup-Silberberg et al. (2020), Lozzi et al., 2020, and Van Audenhove et al. (2020) is that flexible working hours might enable re-spacing and retiming of trip patterns. This can be underpinned by the travel behavior change theory of time-space geography (Hägerstrand, 1970) which "conceptualizes how people make choices regarding what they do where" (van Wee, 2020). "With the shift from online to on-site activities, people have become more flexible" mainly because "limitations within space" disappear when someone is for example working-from-home or ordering groceries online (van Wee, 2020). These reduced space limitations allow for "increased flexibility in activity patterns" (van Wee, 2020).

A side effect of this flexibility within the activity schedule of travelers may result in an increase of "the commuting distance due to the relocation of residences or job changes". This effect can be underpinned with the theory of constant travel time budgets (Peters et al., 2001) which "states that at an aggregated level direct effects that lead to less travel time are succeeded by indirect effects which in turn lead to longer travel times" (van Wee, 2020). As a result of the shift from onsite to online will increased flexibility re-spacing and retiming of trip patterns may be expected.

3.3 Why a modal shift may be expected post-COVID-19

Attitudes not only play a role when deciding upon where and when to undertake activities, but personality traits (i.e. beliefs and values) and attitudes towards certain modes of transportation also influences mode choice (Verplanken et al., 1994). Due to negative externalities regarding car use (e.g. congestion, emissions, and safety), travel behavior change strategies targeting car-use are common around the world (Tommy & Fujii, 2009). Some strategies aim to change the relative attractiveness (e.g. pricing strategies to make alternative modes more attractive or to charge car use) while other strategies aim to change "car users (e.g., informational and educational measures) without any changes in travel options" (Tommy & Fujii, 2009). Similar to travel behavior change policies, the COVID-19 pandemic is a forced change of travel behavior as opposed to an intrinsically motivated travel behavior change. As mentioned in the research of Tommy & Fujii (2009) some researchers argue that "a forced change of travel behavior only causes a change in beliefs, attitudes and/or values" if the outcome of this travel behavior change is positive.

As projected by Hattrup-Silberberg et al. (2020), Lozzi et al. (2020), and Van Audenhove et al. (2020) the increased consciousness regarding health, safety, and reliability might result in an increased interest in active modes of transportation such as walking and cycling. In addition to explaining how attitudes towards online activities may have shifted during the COVID-19 pandemic the aforementioned conceptual model for attitude change as proposed by Van Wee et al. (2019) could also explain why attitudes towards certain modes may have shifted. For example, if someone learns about the alternative to cycle to their destination instead of using public transport or the car (cognitive dimension), actually uses the bicycle as an alternative mode of transport (behavioral dimension) and has a good experience (affective dimension) the attitude towards this mode might change positively (van Wee, 2020). As such, a model shift may be expected as these altered "knowledge, experience and emotions are not erased" when the COVID-19 has disappeared (van Wee, 2020). Any signs of positive experiences may be cautiously noted from the increased sales of e-bikes (+38%) and speed pedelecs (+>100%) within the Netherland as compared to 2019 (Taale et al., 2020). Besides the potential attitude change towards active or individual modes, it is very plausible that owning a certain mode of transportation lowers the boundary to use it.

3.4 Theoretical framework: direct effects of the COVID-19 pandemic and policy measures on travel and activity patterns

The theoretical framework as presented in figure 12, conceptualizes the direct effects of the COVID-19 pandemic and policy measures on travel and activity patterns. First, this section covers the general structure of the theoretical framework, before elaborating on its contents. As this research aims to explore the potential implications of likely post-COVID-19 travel behavior scenarios within the VMA travel model, the theoretical framework also conceptualizes how long term travel behavior changes due to the COVID-19 pandemic relate to the modelling steps of a conventional travel model such as the VMA. Conventional transportation models can be defined as trip-based, 4-step models (i.e. FSM) (Castiglione et al., 2014). In alignment with the approach of trip-based FSM, the way people travel can be described and modeled by the following set of questions (Castiglione et al., 2014):

1. Trip generations: “What activities do people want to participate in?”,
2. Trip distribution: “When and where are these activities?”,
3. Trip mode choice: “What travel mode is used?”,
4. Network assignment: “What route is used?”.

The theoretical framework distinguishes dynamic and direct factors, respectively visualized as ovals and rectangles within the figure. Dynamic factors are related to the environment where direct factors relate to individual travelers. For example, the duration of the COVID-19 pandemic is a dynamic factor which, reasoning from the theory of habitual behavior, affects breaking through habitual behavior; a direct factor on travel behavior change. Factors related to a particular travel behavior change theory are contained within a gray rectangle. Different models belonging to the VMA travel model are depicted within a striped, white border. The three general post-COVID-19 effects, as delineated throughout section 3.1 to 3.3, are visualized with yellow rectangles. With the definition of the general structure of the theoretical framework, the following paragraphs within this section will describe the contents and relations of the theoretical framework, hence, will all apply to figure 12.

As conceptualized within the theoretical framework, a long term travel behavior effect that may be expected post-COVID-19 is the shift from onsite to online activities due to (1) changed utility of online activities, (2) change of attitudes towards online activities and (3) the development of new habitual behavior including online activities. It is important to note that, in regards to the shift from onsite to online activities, only the direct effects on work related activity patterns are addressed within this thesis due to time limitations. Moreover, travel patterns during the COVID-19 pandemic, as presented in appendix 3, show that travel to work-related activity destinations are consistently reduced even when policy measures where eased. Whereas travel to other activity destinations show to rebound to the related pre-COVID-19 baseline when policy measures where eased. Due to this observation it is assumed the shift from onsite to online activities will be especially work-related. In line with the FSM this would imply that a shift from onsite to online activities results in less trips generated for work related travel motives. Regarding the shift from onsite to online activities this thesis explicitly focusses on direct work-related effects. However, this does not mean there are no indirect (i.e. second and third order) effects to be expected post-COVID-19, as it is reasonable that there could be plenty. For example, travel time savings due to the substitution of working in the office (i.e. onsite) with working from home (i.e. online) might enable to engage in other activities, hence, might cause an increased generation of trips with other travel motives that are not work related.

Another long term travel behavior effect that may be expected post-COVID-19 is the respacing and retiming of travel patterns as a result from the shift from onsite to online activities. Reasoning from the theory of time-space geography the reduced time limitations increases flexibility, which allows to travel on different moments and to different locations. Important to note is that, in line with the FSM, the respacing of travel patterns only applies to the trip distribution (i.e. activity location) whereas the retiming of travel patterns only applies to the time-of-day (travel moment). As this general effect on post-COVID-19 travel behavior is directly related to a shift from onsite to online activities, the respacing and retiming of travel patterns will also include only the effects of the substitution of onsite work-related activities to its online counterpart. Moreover, indirect effects are also possible as, for example, the possibility to work online might enable people to find a job further from home, or visit a more preferred supermarket further from home. As the system configuration of the VMA travel model includes, among others, the demographic (i.e. household) characteristics within the model it would be necessary to know how the land use would change due to a shift from onsite to online activities in order to include these kind of indirect effects. Given the novelty of the COVID-19 pandemic, changes within land use are not included within this thesis, hence, only the direct effects of the respacing and retiming of work-related travel patterns are included.

A third long term travel behavior effect that may be expected post-COVID-19 is a modal shift towards active modes due to (1) changed utility towards active modes, (2) change of attitudes towards active modes and (3) development of new habitual behavior including active modes of transport. In line with the FSM this would relate to the trip mode choice, which would result in a greater share of active modes in the modal split. Similarly to the other two general post-COVID-19 travel behavior effects, also the shift towards active modes could have indirect effects. For example, an indirect effect of a modal shift towards active modes could be reduced car ownership within the population, as the potentially increased importance of a bicycle for most of the trips might reduce the necessity to own a private car. As the system configuration of the VMA travel model includes, among others, car ownership per household it would be necessary to know in which way car ownership would be affected by an increase share of active modes for all trips in order to include these kind of indirect effects. Given the novelty of the COVID-19 pandemic these kind of indirect effects are yet unknown, hence, only the direct effects of a modal shift towards active modes is included within this thesis. In contrary to the other two general effects, which only include work-related activities, this thesis assumes the modal shift towards active modes applies to all travel motives.

In order to explore these three general effects on post-COVID-19 travel behavior within the VMA travel modal it is necessary to identify the submodels that, in line with the FSM, account for (1) trip generation, (2) trip distribution and time-of-day and (3) the trip mode choice. As presented within the theoretical framework the trip generation is modelled through the tour frequency model (i.e. TOURFREQ) within the VMA travel model. Choices regarding destination, time-of-day and mode are calculated simultaneously within the MODEST model within the VMA travel model. As the loads assigned to the network might affect the distribution, time-of-day and mode choice of trips (e.g. congestion might change route choice) FSMs usually have an iterative character (Castiglione et al., 2014). This iterative component is modelled within the VMA travel model with the level-of-service, which refers to the accessibility quality in terms of travel distance, travel times and travel costs (Van den Elshout et al., 2020). Important to note is that within the VMA travel model, only infrastructure for cars is dependent on its capacity (Van den Elshout et al., 2020). In other words, high congestion within the car infrastructure might cause car travelers to decide for example not to travel, to travel on a different moment in time, or to travel by a different mode. A more detailed analysis of the submodels within the VMA travel model can be found within chapter 5, section 5.1 which includes the identification of parameters in order to model the general post-COVID-19 travel behavior effects.

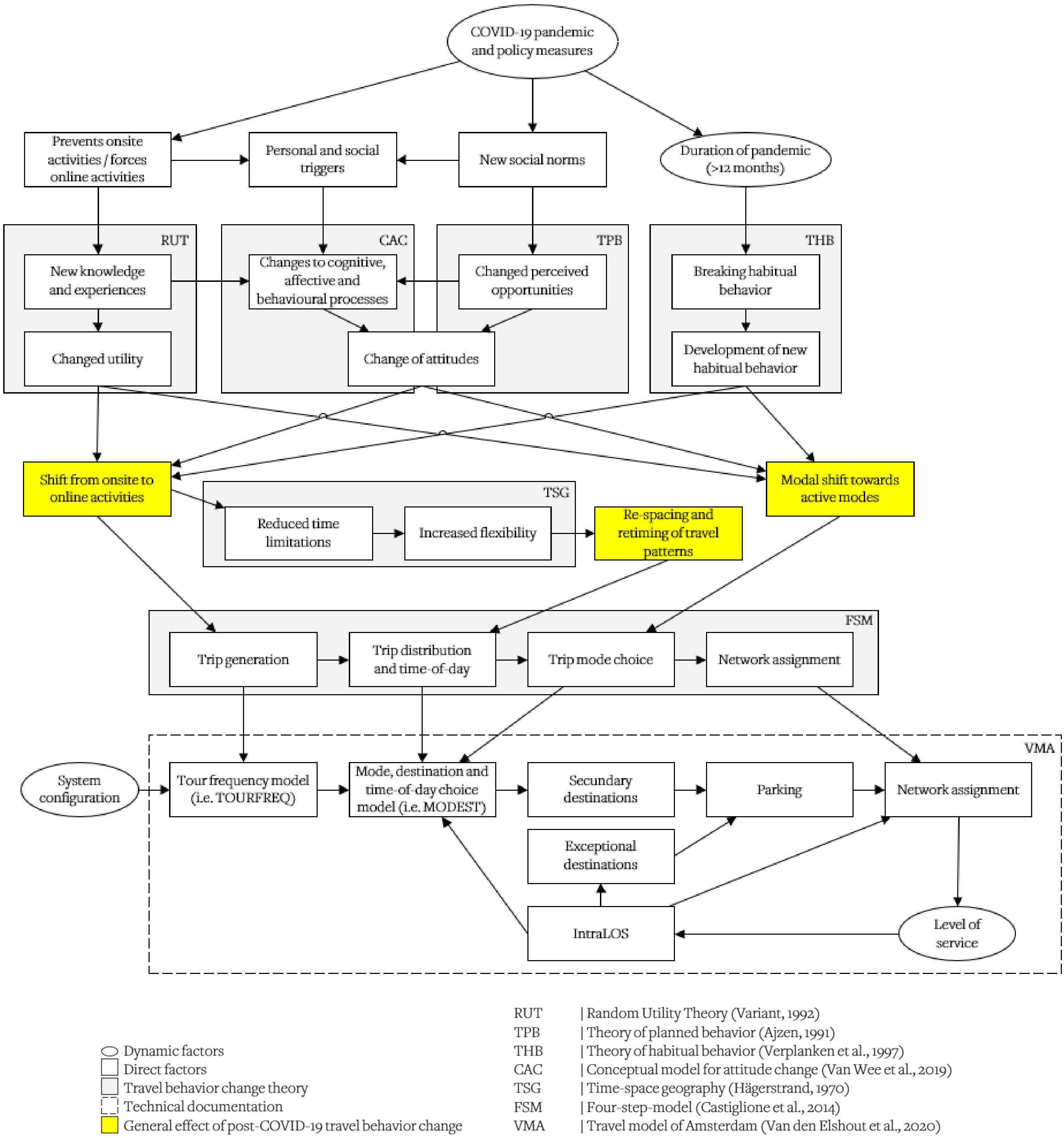


Fig. 12: Conceptualization of direct effects of the COVID-19 pandemic and policy measures on travel and activity patterns within a theoretical framework.

Cyclists in Amsterdam, the Netherlands | Photo by Dana Marin on Unsplash, edited by author

Chapter 4

Post-COVID-19 travel behavior scenarios

As concluded from the previous chapter, three general direct effects of the COVID-19 pandemic and policy measures on travel and activity patterns may be expected. These include: (1) a shift from onsite to online work-related activities, (2) the retiming and respacing of work-related travel patterns and (3) a modal shift towards active modes. With a clear view on which long term travel behavior changes may be expected post-COVID-19, the next question is what the potential future development paths could be of these general direct effects. In other words, this chapter explores how the travel behavior changes that may be expected due to the COVID-19 pandemic could develop post-COVID-19. This exploration is done through the creation of post-COVID-19 travel behavior scenarios. During four individual and identical workshops with mobility experts post-COVID-19 travel behavior scenarios are created by the mobility experts. The individual results of the four experts are presented in section 4.1. As this process resulted in a total of sixteen post-COVID-19 storylines, the individually created scenario matrices where combined within a novel scenario switchboard to result in four distinct post-COVID-19 travel behavior scenarios. Section 4.2 describes how the scenario switchboard is created and section 4.3 shows how the scenario switchboard is used to create four distinct post-COVID-19 travel behavior scenarios. Section 4.4 to 4.7 presents the different post-COVID-19 scenarios and storylines. In conclusion, section 4.8 delineates how the three general direct effects of the COVID-19 pandemic and policy measures on travel and activity patterns may develop based on the four distinct post-COVID-19 travel behavior scenarios.

4.1 Four mobility expert perspectives on post-COVID-19 travel behavior

As delineated within chapter 2, section 2,1, this thesis aims to create exploratory scenarios from the school of intuitive logic using the Wilson matrix from the standard approach and the two-by-two scenario matrices from the minimal approach. The scenarios are constructed with a participatory approach which involved identical individual workshops with four mobility experts:

1. Prof. dr. G. P. van Wee
   Professor Transport Policy within the faculty Technology, Policy, and Management at the Delft University of Technology and scientific director of TRAIL research school;

2. Dr. ir. H. Taale
   Assistant professor within the Department of Transport and Planning at the Delft University of Technology and senior consultant at Rijkswaterstaat;

3. Dr. M. Snelder
   Assistant professor Transport Networks within the Department of Transport and Planning at the Delft University of Technology and Principal Scientist at TNO;

4. Dr. J. A. Annema
   Teacher Transport Policy Analysis within the faculty Technology, Policy and Management at the Delft University of Technology.

The first methodological step when constructing the scenarios is the identification of key factors and driving forces. Key factors are variables that might explain or influence the observed travel behavior changes during the COVID-19 pandemic and are listed by the participating experts by answering the following question: "What factors might be guiding travel behavior changes during the COVID-19 pandemic?". Driving forces are comparable to theoretical principles, (sub-) systems or phenomena that may underlie the key factor and are listed by the participating experts by answering the following question: "What forces could drive these changes (i.e. key factors) during the COVID-19 pandemic?". Although it is more common to perform these steps within a grouped workshop, planning issues and time considerations only allowed for the workshops to be carried out individually. The key drivers and driving forces as identified by the mobility experts are listed in tables 1 to 4.

Table 1: Key factors and driving forces as identified by expert 1.

Key factor	Driving force
Fear of contamination, and thus no public transportation	Reduce risk of virus spreading
Increased competence with online tools	Technology
Increased positive experience with online tools	Technology
Intrinsic motivation for being mobile	Personal drivers for mobility
Less comfortable to travel by public transport because of masks	Supply and characteristics of transport system
More walking and biking to compensate need for recreation	Personal drivers for mobility
Policy employer, implementation of government policy on telecommuting	Reduce risk of virus spreading
Policy government, request to travel as little as possible	Reduce risk of virus spreading
Policy government, request to work at home as much as possible	Reduce risk of virus spreading
Public transport supply changed, less capacity in vehicles and stations	Supply and characteristics of transport system
Support of home office by employer with regards to hardware	Technology
Working from home is the norm, as is keeping one's distance	Reduce risk of virus spreading

Table 2: Key factors and driving forces as identified by expert 2.

Key factor	Driving force
Fear of contamination	Demography, information
Policy government	Policy government
Policy employer	Policy employer

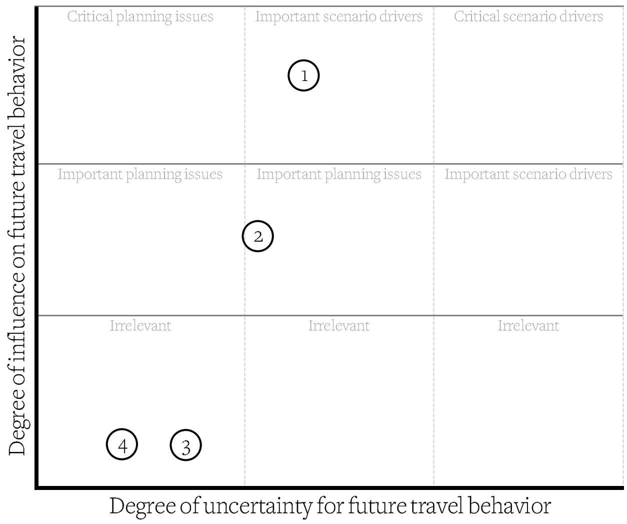
Table 3: Key factors and driving forces as identified by expert 3.

Key factor	Driving force
Decision of individuals to keep a safe distance or not	Health, reduce risk of virus spreading
Fear of contamination	Health
Companies encourage working from home	Policy employer, technology
Acquisition of private means of transportation (e.g. car, e-bike and bicycle)	Travelers' attitude
Less travel because of digitalization	Technology
Different moment of travel to avoid crowding	Health
Temporary closing of schools and universities	Policy government
Changes to the physical infrastructure (e.g. one way pedestrian paths)	Reduce risk of virus spreading
Changed attitudes (e.g. cycling is healthy)	Travelers' attitude
Economic crisis	Economy
People move out of the cities	Demography

Table 4: Key factors and driving forces as identified by expert 4.

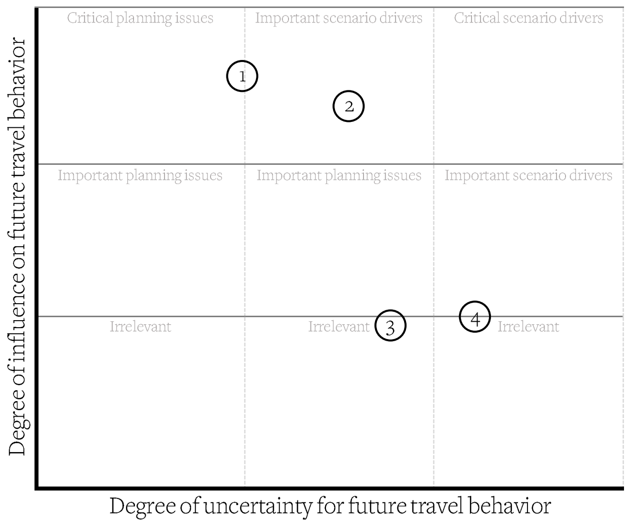
Key factor	Driving force
Following the rules	Demography
Fear of contamination	Demography
Positive experience of travel behavior change (e.g. less travel time)	Demography
Purchase of different mode of transport (e.g. car or electric bicycle)	Economy
Good experience with working from home	Demography, economy
Consciously experienced different travel behavior	Policy employer
Duration of different travel behavior (e.g. one year of non-travel)	Policy employer, policy government
Discovery of new recreational cycling routes	Demography
Breaking habitual behavior both in activity as mode of transport	Policy employer
Experiencing more comfort working-from-home by aid from employer	Technology, policy employer

The second methodological step is to identify two critical driving forces within a Wilson matrix, by evaluating all driving forces on the degree of uncertainty for, and the level of impact on post-COVID-19 travel behavior. This identification process is carried out identical in the same individual workshops. The two critical driving forces as identified by the experts are visualized in Figures 13 to 16.



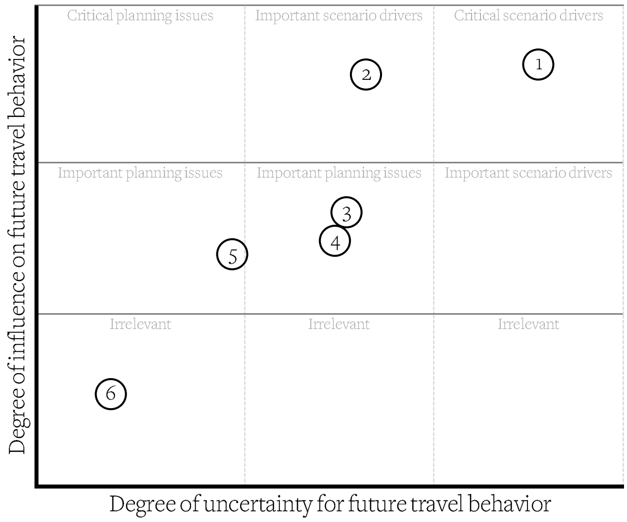
Ref.	Driving force
1	Technology
2	Personal drivers for mobility
3	Supply and characteristics of transport system
4	Reduce risk of virus spreading

Fig. 13: Wilson matrix with the uncertainty and impact of driving forces on post-COVID-19 travel behavior, as ranked by expert 1.



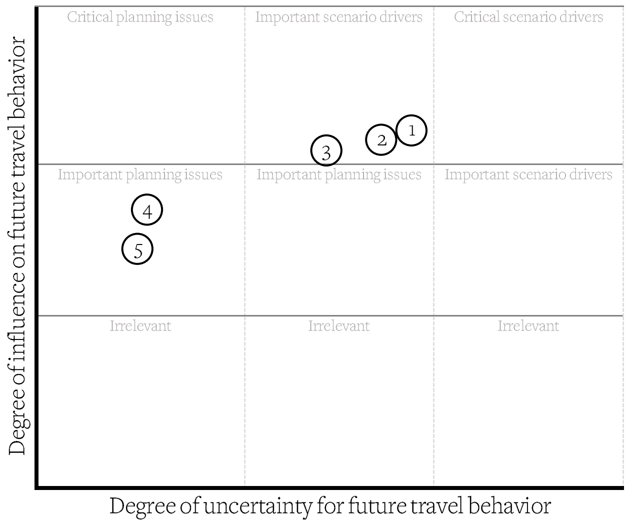
Ref.	Driving force
1	Policy employer
2	Policy government
3	Demography
4	Information

Fig. 14: Wilson matrix with the uncertainty and impact of driving forces on post-COVID-19 travel behavior, as ranked by expert 2.



Ref.	Driving force
1	Travelers' attitude
2	Technology
3	Policy employers
4	Policy government
5	Economy
6	Health

Fig. 15: Wilson matrix with the uncertainty and impact of driving forces on post-COVID-19 travel behavior, as ranked by expert 3.



Ref.	Driving force
1	Policy employer
2	Policy government
3	Economy
4	Technology
5	Demography

Fig. 16: Wilson matrix with the uncertainty and impact of driving forces on post-COVID-19 travel behavior, as ranked by expert 4.

The third methodological step is to construct a two-by-two scenario matrix where both critical driving forces are used for either the x-axis or y-axis. The scenario matrix is constructed by the participating experts by answering the following question: "What would be the extreme cases of each critical driving force?". The fourth and final methodological step is to interpret the scenario matrix by formulating four short storylines (i.e. scenarios) based on the scenario matrix quadrants. The quadrant descriptions are provided by the participating experts by answering the following question: "What would be the resulting travel behavior in the year 2030, given the extreme values of the critical driving forces associated with this quadrant?". Figures 17 to 20 depict the scenario matrices and quadrant descriptions as created by the experts.

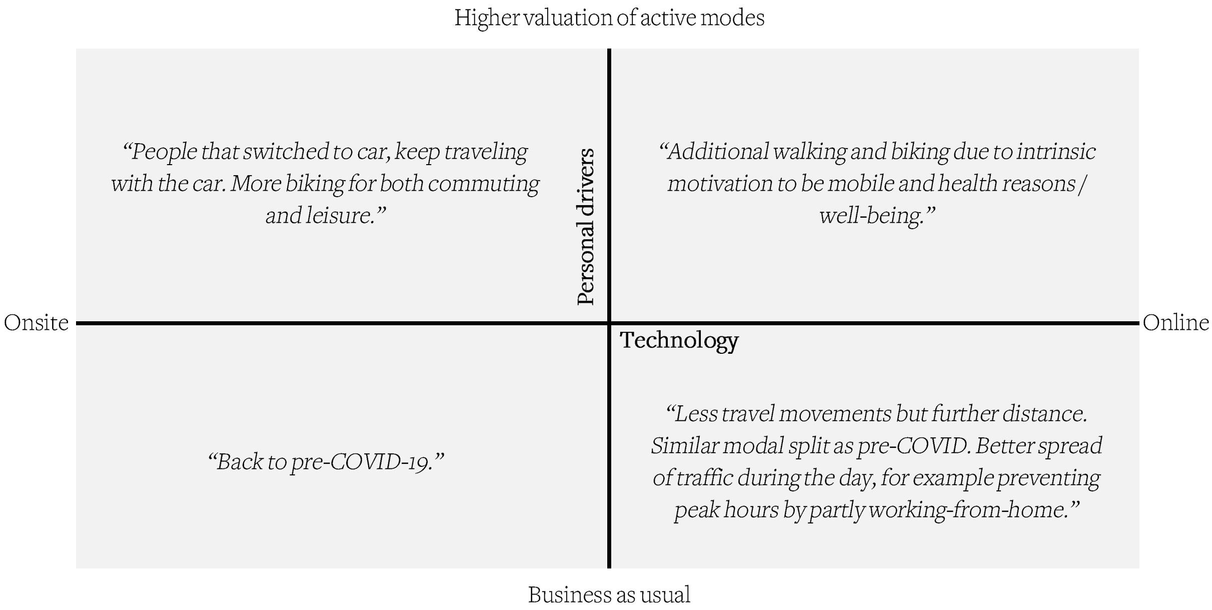


Fig. 17: Scenario matrix and post-COVID-19 storylines as formulated by expert 1.

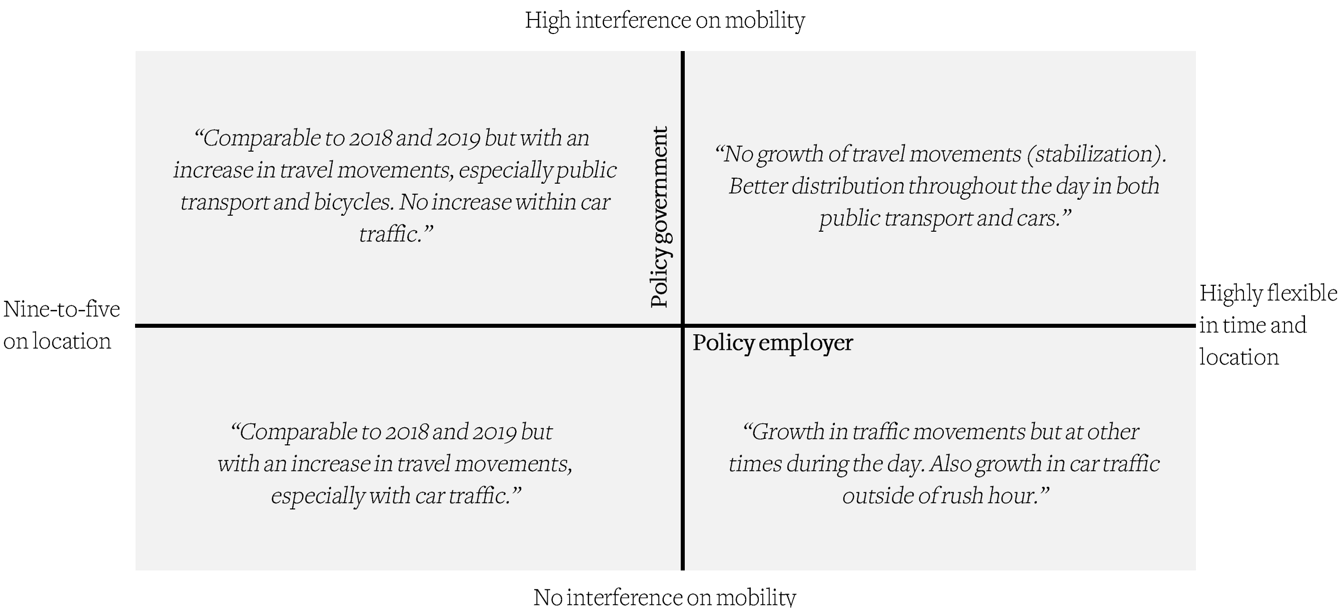


Fig. 18: Scenario matrix and post-COVID-19 storylines as formulated by expert 2.

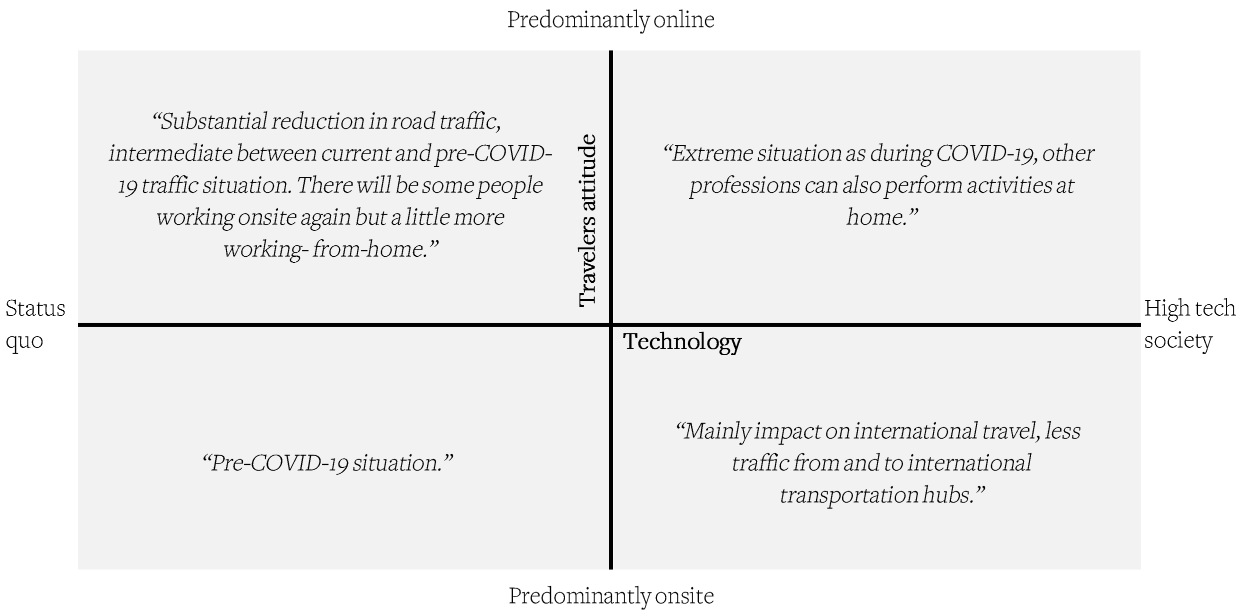


Fig. 19: Scenario matrix and post-COVID-19 storylines as formulated by expert 3.

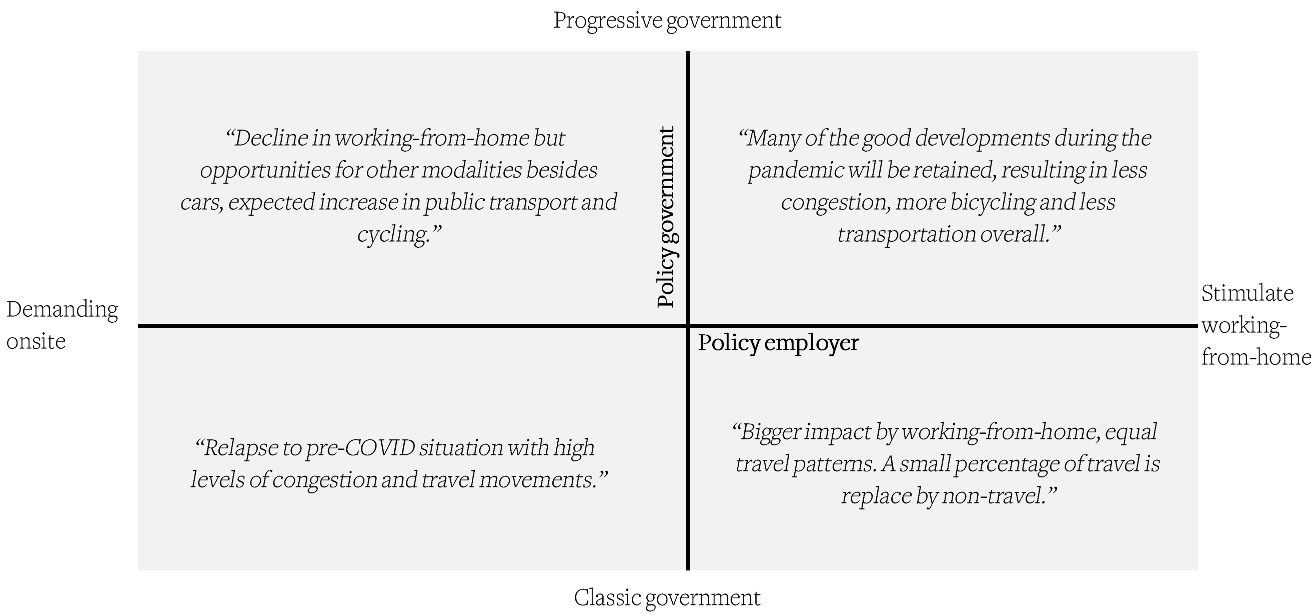


Fig. 20: Scenario matrix and post-COVID-19 storylines as formulated by expert 4.

4.2 Combining multiple mobility expert perspectives within a scenario switchboard

The scenario matrices created by the experts contain different critical drivers as matrix dimensions. To recall, the critical drivers are the most uncertain factors with the highest impact on post-COVID-19 travel behavior. Pillkahn (2008) recommends applying the standard scenario planning approach "if the number of uncertain factors cannot be reduced to two". Conventionally a morphological chart can be created within the standard scenario planning approach, based on "the variation of the individual elements of the future" (Pillkahn, 2008). This thesis applies the general concept of morphological analysis to create a novel 'scenario switchboard'. A scenario switchboard can be described as a morphological chart visualized with sliders with just two variations per element (i.e. either a neutral or alternate position). The scenario switchboard is created by (1) identifying and validating all critical driving forces, (2) setting the variation of the critical driving forces in terms of a neutral and alternate position, and (3) visualizing each critical driving force and its associated positions within a slider.

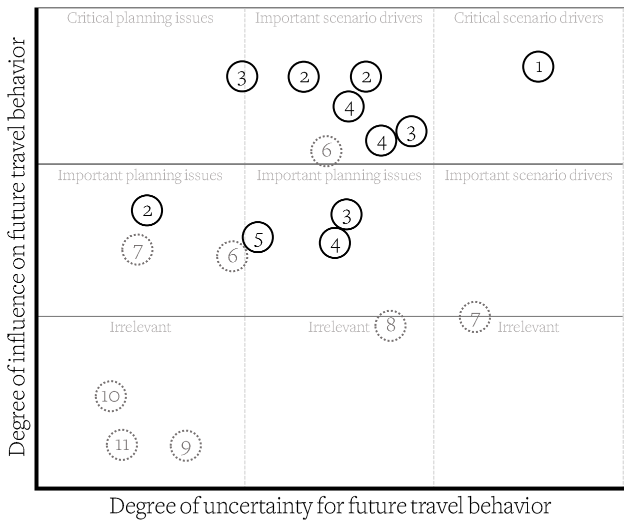
The first step is to identify and verify all critical driving forces. From the individual perspective of the participating experts the critical driving forces used as scenario dimensions within the scenario matrices, as listed within table 5, are the critical driving forces in terms of impact on, and uncertainty of future travel behavior. This is why the critical driving forces used as matrix dimensions by the experts will form the basis of the scenario switchboard.

Table 5: Overview of critical driving factors used as matrix dimensions within the experts' scenario matrices.

Expert	Driving factor x-axis	Range	Driving factor y-axis	Range
1	Technology	'Onsite' 'Online'	Personal drivers	'Business as usual' 'Changed appreciation'
2	Policy employer	'Nine-to-five on location' 'Highly flexible in time and location'	Policy government	'No interventions on mobility' 'High interference on mobility'
3	Technology	'Status quo' 'High tech society'	Travelers' attitude	'Predominantly onsite' 'Predominantly online'
4	Policy employer	'Demanding onsite' 'Stimulate working-from-home'	Policy government	'Classic government' 'Progressive government'

As the driving forces are ranked on the impact on and uncertainty of future travel behavior from an individual expert perspective it might be that, besides the two critical driving forces used as scenario matrix dimensions, other driving forces may also qualify as critical scenario drivers. This is why the individual impact and uncertainty matrices are combined as validation that the scenario switchboard includes all critical driving forces. A combined Wilson matrix is depicted in figure 20.

Based on the position within the Wilson matrix of the 'economy', represented as number 6 within figure 20, this driving force could be qualified as an important scenario driver, hence, be included within the scenario switchboard. However, as this driving force is not used as a scenario matrix dimension by any of the participating experts and the assumption within this thesis to work with a low economic forecast the economy is not included within the scenario switchboard. Any additional driving forces show to be irrelevant in terms of impact and uncertainty to include within the scenario switchboard. On this basis, it can be concluded that all critical driving forces are within the scenario switchboard, as listed in table 5.



Ref.	Driving force
1	Travelers' attitude (e.g. working-from-home)
2	Technology
3	Policy employer
4	Policy government
5	Personal drivers for mobility
6	Economy
7	Demography
8	Provision of information
9	Supply and characteristics of transport system
10	Health
11	Reduce risk of virus spreading

Fig. 21: Wilson matrix combining all driving forces as rated on impact on, and uncertainty of post-COVID-19 travel behavior by the individual expert workshops.

The second step in creating the scenario switchboard is setting the variation of the critical driving forces in terms of a neutral and alternate position which can be read off from the range of each matrix dimension as depicted within table 5. As the critical driving forces 'technology', 'policy employee' and 'policy government' are assigned multiple times as scenario matrix dimensions these will be combined within the scenario switchboard.

'Technology' is mentioned twice as a critical driving force, ranging from 'onsite' to 'online' in the scenario matrix of expert 1 and ranging from 'status quo' to 'high tech society' in the scenario matrix of expert 3. To operationalize 'technology' within the scenario switchboard it is chosen that technology will range from 'status quo' to 'high tech society'. It is assumed that the critical driving force 'technology' as used by expert 1 will be covered with the critical driving force 'travelers attitude' of expert 3, which has a similar range (i.e. predominantly onsite to predominantly online instead of onsite to online). The resulting sliders are depicted in table 6.

Table 6: Overview of sliders and variations in terms of a neutral and alternate position within the scenario switchboard.

Slider title	Neutral position	Alternate position
Personal drivers	Business as usual	Higher valuation of active modes
Travelers' attitude	Predominantly onsite	Predominantly online
Technology	Status quo	High tech society
Policy employer	Traditional onsite nine-to-five	Highly flexible in time and space
Policy government	Business as usual	Progressive with high interference

The third and final step in creating the scenario switchboard is visualizing each critical driving force and the associated neutral and alternate positions within a slider, as depicted in figure 22.

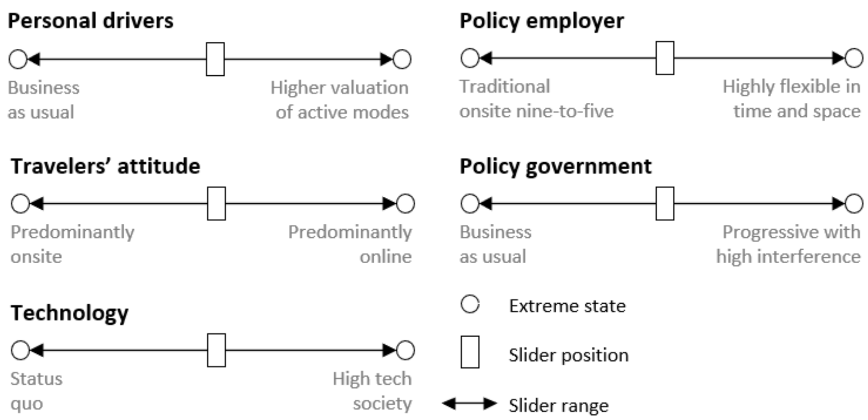


Fig. 22: The scenario switchboard: a visualization of critical driving forces and their variation as sliders.

4.3 Constructing post-COVID-19 scenarios with the scenario switchboard

Based on the two possible positions (i.e. neutral or alternate) of the five sliders within the scenario switchboard (i.e. personal drivers, travelers' attitude, technology, policy employer, and policy government) in theory a total of 32 different scenarios could be constructed. However, to keep this analysis manageable and as Stojanović et al. (2014) suggest the optimal number of scenarios is three to five, this thesis identifies four substantiated post-COVID-19 scenarios. The different scenarios are identified among dimension, range, or quadrant description similarities within the individual scenario matrices which allow some matrices to be superimposed and in this way set the position of a slider.

Both scenario matrices of experts 1 and 3, depicted within figures 17 and 19 respectively, show a similar range within a matrix dimension. The scenario matrix of expert 1 applies the range 'onsite' to 'online' for the critical driving force 'technology' whereas the scenario matrix of expert 3 applies an equal range to the critical driving force 'travelers attitude'. Based on this similarity these two scenario matrices are superimposed along the 'technology' and 'travelers attitude' matrix dimension. Expert 1 provides a quadrant description of "back to pre-COVID-19" within the quadrant where 'technology' is onsite and 'personal drivers' are business as usual. Expert 3 provides a similar quadrant description of "Pre-COVID-19 situation" where 'technology' is status quo and 'travelers attitude' is predominantly onsite. By aligning the two scenario matrices on this similar quadrant, and along the similar matrix dimension of 'technology' from the scenario matrix of expert 1 and 'travelers attitude' from the scenario matrix of expert 3 these scenario matrices can be superimposed. This process is illustrated in figure 23. The resulting scenario matrix is shown in figure 24.

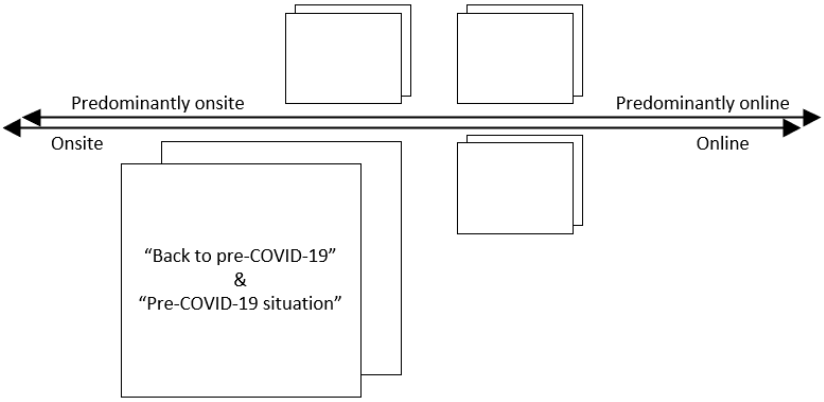


Fig. 23: Superimposing scenario matrices of experts 1 and 3 based on similarities within matrix dimensions and quadrant descriptions.

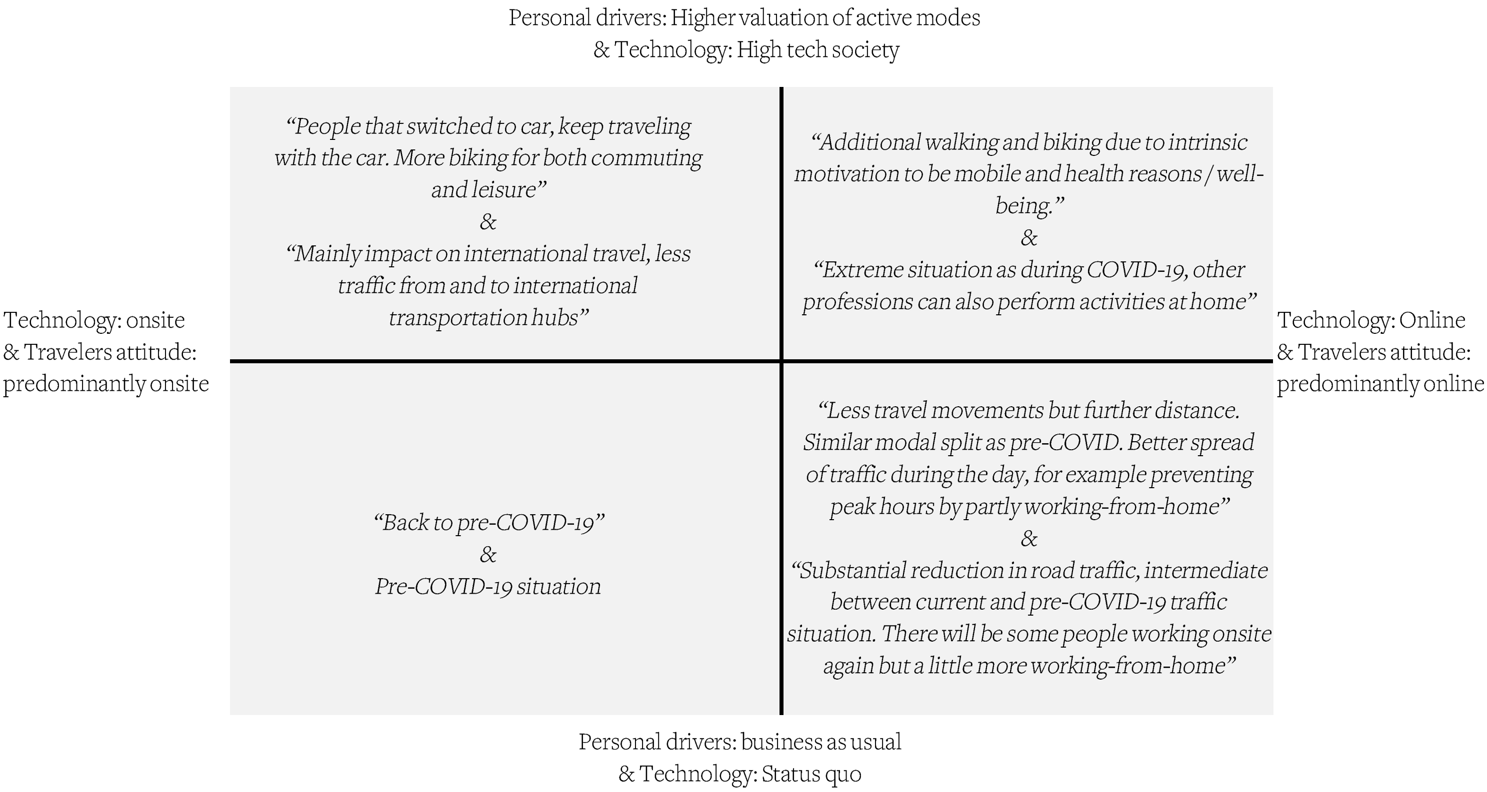
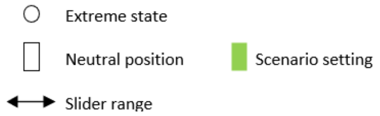


Fig. 24: Resulting scenario matrix after superimposing the scenario matrix of experts 1 and 3 based on similarities within matrix dimensions and quadrant descriptions.

With the resulting scenario matrix after superimposing the scenario matrix of experts 1 and 3 the slider position of critical driving forces 'technology', 'travelers attitude', and 'personal drivers' can be set for each quadrant (i.e. each post-COVID-19 scenario). The resulting slider positions are shown in figures 25 to 28.



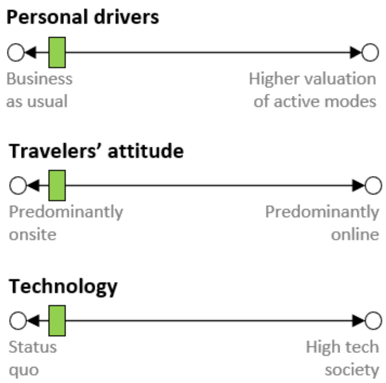


Fig. 25: Slider settings of critical forces 'personal driver', 'travelers attitudes' and 'technology' for scenario 1.

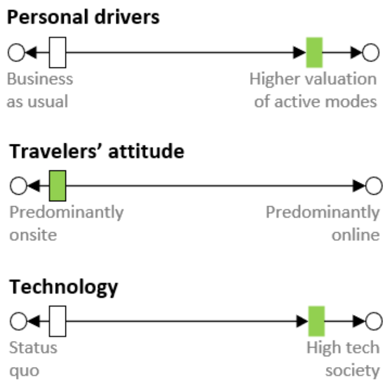


Fig. 26: Slider settings of critical forces 'personal driver', 'travelers attitudes' and 'technology' for scenario 2.

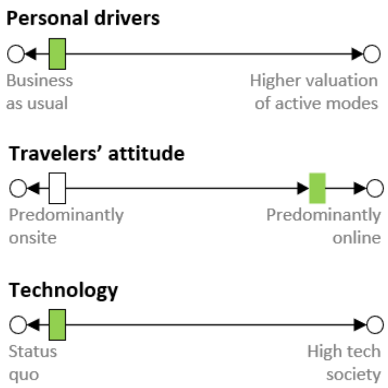


Fig. 27: Slider settings of critical forces 'personal driver', 'travelers attitudes' and 'technology' for scenario 3.

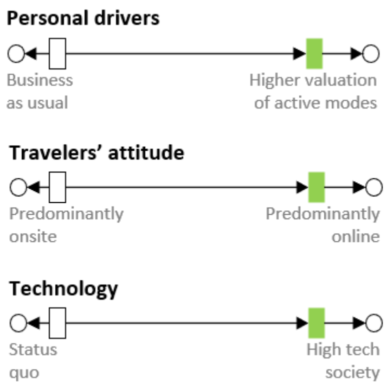


Fig. 28: Slider settings of critical forces 'personal driver', 'travelers attitudes' and 'technology' for scenario 4.

The same process can be applied with the scenario matrix of experts 2 and 4, which both use the same scenario matrix dimensions using the critical driving forces 'policy employer' and 'policy government'. This allows to easily superimpose both matrices. The resulting scenario matrix is displayed in figure 29.

Policy government: High interference on mobility
& Policy government: Progressive government

Policy employer: Nine-to-five on location & Policy employer: Demanding onsite			Policy employer: Highly flexible in time and location & Policy employer: Stimulate working-from-home
	"Comparable to 2018 and 2019 but with an increase in travel movements, especially public transport and bicycles. No increase within car traffic" & *"Decline in working-from-home but opportunities for other modalities besides cars, expected increase in public transport and cycling"*	*"No growth of travel movements (stabilization) better distribution throughout the day in both public transport and cars"* & *"Many of the good developments during the pandemic will be retained, resulting in less congestion, more bicycling and less transportation overall"*	
	"Comparable to 2018 and 2019 but with an increase in travel movements, especially with car traffic" & *"Relapse to pre-COVID situation with high levels of congestion and travel movements"*	*"Growth in traffic movements but at other times during the day. Also growth in car traffic outside of rush hour."* & *"Bigger impact by working-from-home, equal travel patterns. A small percentage of travel is replaced by non-travel"*	

Policy government: No interference on mobility
& Policy government: Classic government

Fig. 29: Resulting scenario matrix after superimposing the scenario matrix of experts 2 and 4 based on similarities within matrix dimensions and quadrant descriptions.

As both superimposed matrices contain a quadrant where a pre-COVID-19 situation is described this allows to identify the reference scenario (i.e. scenario 1). The diagonally opposite quadrant is assumed to resemble the most extreme scenario (i.e. scenario 4). The question remains as to which quadrants scenarios 2 and 3 should be assigned. Figuratively speaking the two superimposed matrices form two clusters, one containing the sliders 'personal drivers', 'travelers attitude' and 'technology' and another containing the sliders 'policy employer' and 'policy government'. As the superimposed scenario matrix of expert 2 and 4 contains a quadrant description mentioning "expected increase in cycling" this finds somewhat overlap with the quadrant description of the superimposed scenario matrix of expert 1 and 2 which contains a quadrant description mentioning "more biking for both commuting and leisure". This is why these two quadrants are assigned to scenario 2. However, this process remains arbitrary. An overview of the assigned quadrant descriptions to the different scenarios is depicted in table 7. The resulting slider settings for the critical forces 'policy employer' and 'policy government' are shown in Figures 30 to 33.

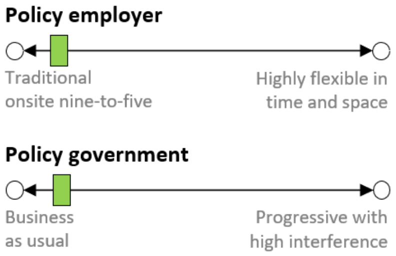


Fig. 30: Slider settings of critical forces 'policy employer' and 'policy government' for scenario 1.

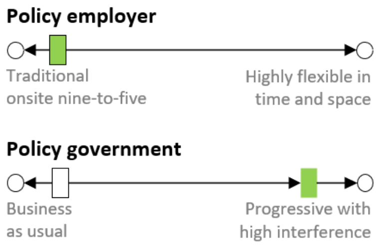


Fig. 31: Slider settings of critical forces 'policy employer' and 'policy government' for scenario 2.

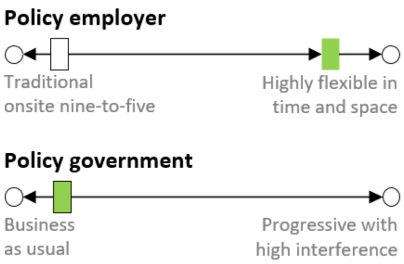


Fig. 32: Slider settings of critical forces 'policy employer' and 'policy government' for scenario 3.

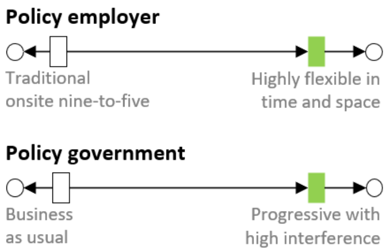


Fig. 33: Slider settings of critical forces 'policy employer' and 'policy government' for scenario 4.

Table 7: Assignment of slider positions within four post-COVID-19 travel behavior scenarios, based on an overview of all scenario matrices and quadrant descriptions as formulated during the individual workshops.

Matrix dimension	Range value	Quadrant description by experts	Assigned to…
x: Technology y: Personal drivers	Onsite Business as usual	*"Back to pre-COVID-19."*	Scenario 1
x: Technology y: Travelers' attitude	Status quo Predominantly onsite	*"Pre-COVID-19 situation."*	
x: Policy employer y: Policy government	Demanding onsite Classic government	*"Relapse to pre-COVID situation with high levels of congestion and travel movements."*	
x: Policy employer y: Policy government	Nine-to-five on location No interference on mobility	*"Comparable to 2018 and 2019 but with an increase in travel movements, especially with car traffic."*	
x: Technology y: Personal drivers	Onsite Higher valuation of active modes	*"People that switched to car, keep traveling with the car. More biking for both commuting and leisure."*	Scenario 2
x: Technology y: Travelers' attitude	High tech society Predominantly onsite	*"Mainly impact on international travel, less traffic from and to international transportation hubs."*	
x: Policy employer y: Policy government	Demanding onsite Progressive government	*"Decline in working-from-home but opportunities for other modalities besides cars, expected increase in public transport and cycling."*	
x: Policy employer y: Policy government	Nine-to-five on location High interference on mobility	*"Comparable to 2018 and 2019 but with an increase in travel movements, especially public transport and bicycles. No increase within car traffic."*	
x: Technology y: Personal drivers	Online Business as usual	*"Less travel movements but further distance. Similar modal split as pre-COVID. Better spread of traffic during the day, for example preventing peak hours by partly working-from-home."*	Scenario 3
x: Technology y: Travelers' attitude	Status quo Predominantly online	*"Substantial reduction in road traffic, intermediate between current and pre-COVID-19 traffic situation. There will be some people working onsite again but a little more working- from-home."*	
x: Policy employer y: Policy government	Stimulate working-from-home Classic government	*"Bigger impact by working-from-home, equal travel patterns. A small percentage of travel is replace by non-travel."*	
x: Policy employer y: Policy government	Highly flex. in time and location No interference on mobility	*"Growth in traffic movements but at other times during the day. Also growth in car traffic outside of rush hour."*	
x: Technology y: Personal drivers	Online Higher valuation of active modes	*"Additional walking and biking due to intrinsic motivation to be mobile and health reasons / well-being."*	Scenario 4
x: Technology y: Travelers' attitude	High tech society Predominantly online	*"Extreme situation as during COVID-19, other professions can also perform activities at home."*	
x: Policy employer y: Policy government	Stimulating working-from-home Progressive government	*"Many of the good developments during the pandemic will be retained, resulting in less congestion, more bicycling and less transportation overall."*	
x: Policy employer y: Policy government	Highly flex. in time and location High interference on mobility	*"No growth of travel movements (stabilization). Better distribution throughout the day in both public transport and cars."*	

4.4 Scenario 1: "Back to normal"

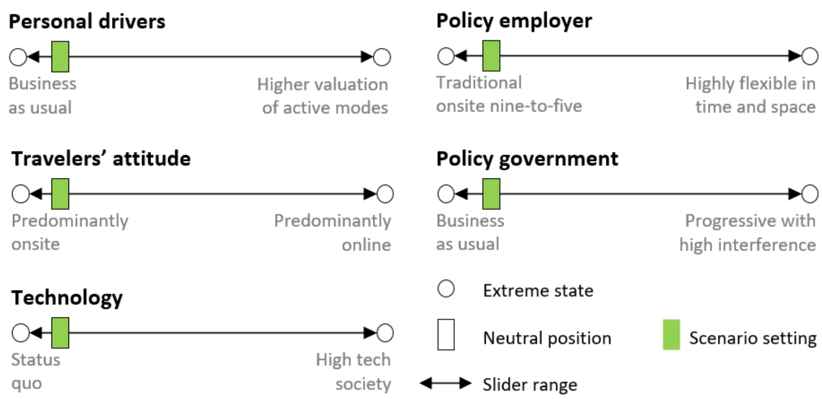


Fig. 34: Scenario switchboard of scenario 1.

The COVID-19 pandemic was just a bump on the road, in the year 2030 travelers have fallen back into old habits. Even though a lot of people experienced online activities during the COVID-19 pandemic the preference for onsite activities remains post-COVID-19. This preference of onsite activities is recognized by employers, resulting in policies that stimulate to work within traditional nine-to-five hours on location. Partially due to the absence of stimulating governmental policy travelers still prefer to travel by car for their commute. No long-term travel behavior changes occurred due to the COVID-19 pandemic.

4.5 Scenario 2: "Minor changes"

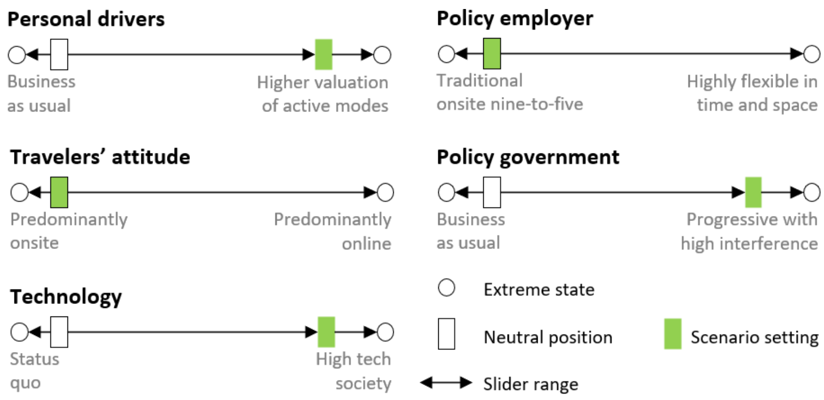


Fig. 35: Scenario switchboard of scenario 2.

The high-tech society of 2030 makes it very attractive to substitute onsite for online activities. However, most travelers prefer onsite activities which caused a decline in working-from-home when comparing to the times during the COVID-19 pandemic. The substitution of travel for nontravel by digitalization experiences the most impact on international travel, which results in less traffic from and to international transportation hubs. People who switched to a car as a mode of transportation during the COVID-19 pandemic remain traveling by car, but overall there is also more biking for both commuting and leisure. The progressive government also helps to provide opportunities for other modalities besides cars, in combination with a higher valuation of active modes a slight increase in cycling is experienced.

4.6 Scenario 3: "Working from home is here to stay"

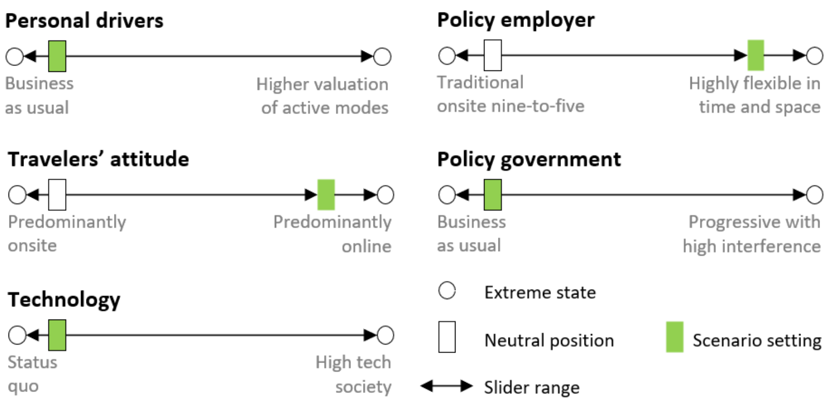


Fig. 36: Scenario switchboard of scenario 3.

Even though technology within the year 2030 is comparable to that of 2021, travelers' attitudes towards online activities and highly flexible policies from employers allow for a substantiate group of travelers to work at home. This 'new norm' to work-from-home results in the re-spacing and retiming of travel patterns, expressed in fewer travel moments but with further distances and outside peak hours. Overall there is a substantial reduction in road traffic. A modal shift towards active modes is not experienced given unchanged personal drivers and a classic governmental policy with little interference.

4.7 Scenario 4: “The cyclist paradise”

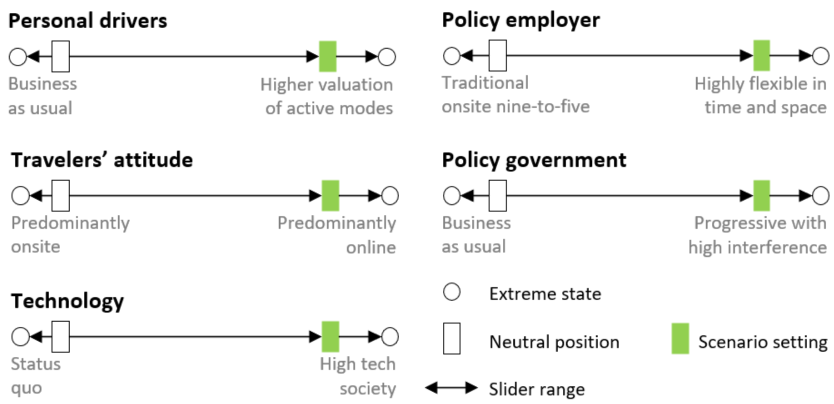


Fig. 37: Scenario switchboard of scenario 4.

The pandemic was an eye-opener for many people, post-COVID-19 travel behaviors appear to have changed permanently. The need for transportation is greatly reduced as the majority of activities are performed online. Technological developments allow people to efficiently work, study and shop from the comfort of their own home, even for professions where this was not yet possible during the COVID-19 pandemic. Employers also recognized benefits such as reduced cost regarding property and increased productivity allowing their employees to be highly flexible to work whenever and wherever they want to cause the re-timing and respacing of travel patterns. Moreover, due to the online society employers strongly support employees by providing software, hardware, and other utilities, increasing the work-from-home experience of the employees. Even though society is predominantly online, people still feel an intrinsic motivation to be mobile. Moreover, due to health reasons and wellbeing people actively choose to cycle and walk more, both for scheduled and leisure activities. Due to the provided flexibility regarding work and study hours, travel movements are distributed throughout the day for both public transportation and car traffic. Governmental policy actively nudges towards the use of public transport instead of cars.+

4.8 Implications of the post-COVID-19 travel behavior scenarios to the general direct effects of the COVID-19 pandemic and policy measures on travel and activity patterns

With the four distinct post-COVID-19 travel behavior scenarios established, these are used to project the potential development of general direct effects of the COVID-19 pandemic and policy measures on travel and activity patterns. To recall, these general direct effects are: (1) a shift from onsite to online work-related activities, (2) the respacing and retiming of work-related travel patterns and (3) a modal shift towards active modes.

The first step is to identify which configuration of sliders within the scenario switch board relates to which general effect. Reasoning from the theoretical framework as presented in chapter 3, section 3.4, figure 12, a shift from onsite to online work-related activities might be expected if (1) the utility of working from home increases, (2) attitudes towards working from home increase and (3) new habitual behavior includes working from home. As displayed in figure 38, the scenario switchboard arguably captures the utility of working from home within the technology and policy employer sliders. The attitudes towards working from home are captures within the travelers attitude slider. Habitual behavior however, is not included within the scenario switchboard. Given the direct relationship between the shift from onsite to online work-related activities and the respacing and retiming of work-related travel patterns, it is assumed that any reduced generation of work-related trips also causes the respacing and retiming of work-related travel patterns. Sliders positioned as depicted in figure 38 might cause a strong shift from onsite to online work-related activities, and as a result, also a strong respacing and retiming of work-related travel patterns.

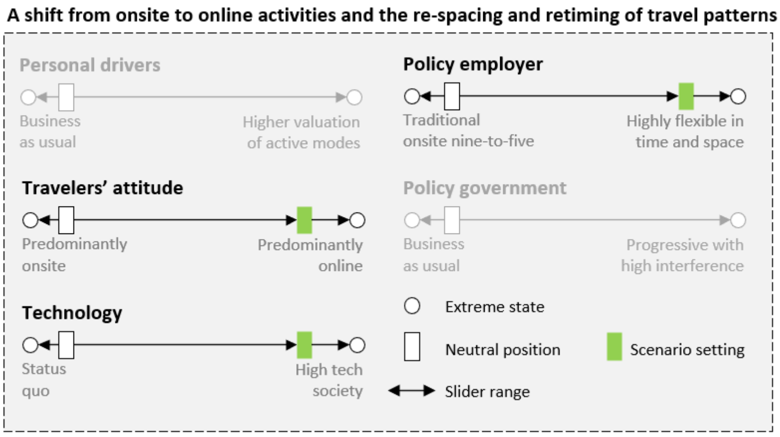


Fig. 38: Scenario switchboard with a slider configuration that causes a shift from onsite to online work-related activities and the respacing and retiming of work-related travel patterns.

Reasoning from the theoretical framework as presented in chapter 3, section 3.4, figure 12, a modal shift may be expected towards active modes if (1) utility of active modes increases, (2) attitudes towards active modes increase and (3) new habitual behavior includes active modes. As displayed in figure 39, the scenario switchboard arguably captures the utility of active modes within the policy government slider. Attitudes towards active modes are captured within the personal drivers slider. Again, habitual behavior is not included within the scenario switchboard. Sliders positioned as depicted in figure 39 might cause a strong modal shift towards active modes.

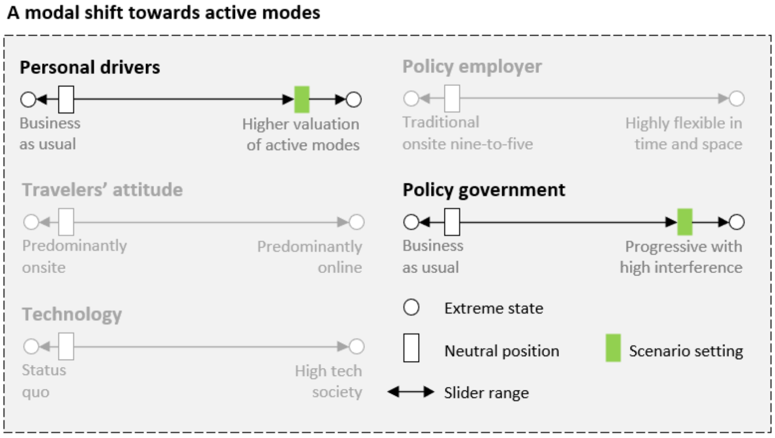


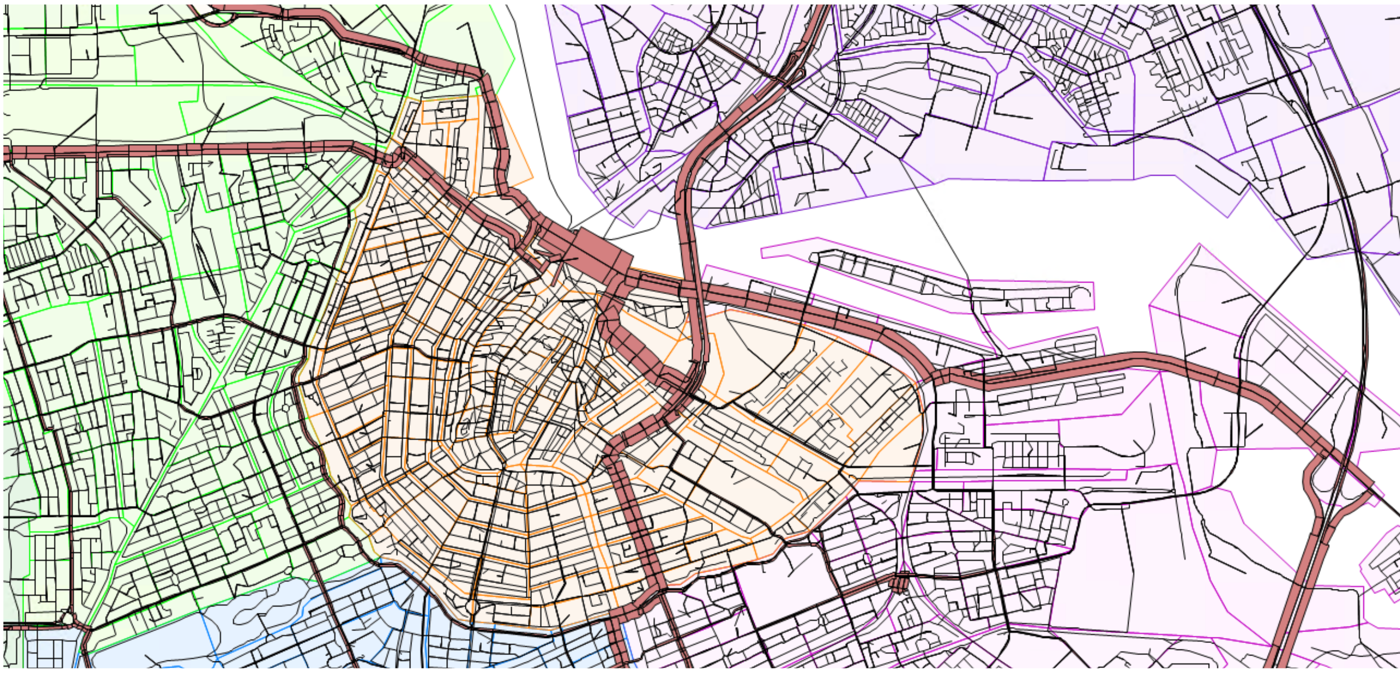
Fig. 39: Scenario switchboard with a slider configuration that causes a modal shift towards active modes.

With the implication of slider positions to the general direct effects of the COVID-19 pandemic and policy measures on travel and activity patterns, the post-COVID-19 travel behavior scenarios are evaluated in the following paragraphs in regards of these general direct effects.

In regards to the development of technology, the high tech society within scenario 2; 'minor changes', might nudge the working population to work from home due to increased utility of online tools. However, given the attitude towards working from home within this scenario the working population prefers to predominantly work onsite. Moreover, as employers guide to work onsite with traditional onsite nine-to-five policies, the reduced generation of work-related trips in this scenario might be low. To recall from the theoretical framework as presented in chapter 3, section 3.4, figure 12, the direct effects of respacing and retiming of work-related travel patterns might also be low as this is directly related to the shift from onsite to online work-related activities. With regards to the third general direct effect of the COVID-19 pandemic and policy measures on travel and activity patterns, a modal shift towards active modes may be expected within this scenario as personal drivers show a higher valuation of active modes and governmental policies are progressive with a high interference on mobility. These might increase the utility and attitudes towards active modes, hence, cause a modal shift towards active modes.

In scenario 3; 'working from home is here to stay', travelers preferably work from home given the attitude implies predominantly online activities. In combination with employer policies that encourage high flexibility in time and space, compared to scenario 2; 'minor changes', a bigger reduction of generated work-related trips may be expected within scenario 3; 'working from home is here to stay'. As this directly relates to the respacing and retiming of work-related travel patterns also in this regard a bigger effect might be expected compared to the previous scenario. A modal shift may not be expected within scenario 3; 'working from home is here to stay', given personal drivers towards active modes and governmental policies are both business as usual. In other words, within this scenario no changes to the utility and attitudes towards active modes are expected.

Finally, scenario 4; 'the cyclist paradise' has it all. A strong shift from onsite to online work-related activities may be expected in this scenario given travelers attitudes towards working from home shift towards predominantly online activities, technology enables a high utility of online activities and employer policies enable high flexibility in time and space. Given the strong shift from onsite to online work-related activities, also a strong retiming and respacing of work-related travel patterns may be expected within this scenario. Furthermore, a strong modal shift towards active modes may be expected in this scenario given personal drivers towards active modes show a higher valuation of active modes and progressive governmental policy show high interference on mobility.



Screenshot from the city center of Amsterdam within the VMA travel model | Image by author.

Chapter 5

Exploring post-COVID-19 travel behavior scenarios with a traditional travel model

The results of the previous chapter (i.e. chapter 4) provide insights in the potential development paths of three general direct effects of the COVID-19 pandemic and policy measures on travel and activity patterns. Scenario 1; 'back to normal' shows no travel behavior changes. Scenario 2; 'minor changes' indicates both a low shift from onsite to online work-related activities, a low respacing and retiming of work-related travel patterns and a slight modal shift towards active modes. Scenario 3; 'working from home is here to stay' indicates a medium shift from onsite to online work-related activities, a medium respacing and retiming of work-related travel patterns and no modal shift towards active modes. Scenario 4; 'the cyclist paradise' indicates both a high shift from onsite to online work-related activities, a high respacing and retiming of work-related travel patterns and a strong shift towards active modes. With these qualitative descriptions in place, the next objective is to quantify the post-COVID-19 travel behavior scenarios. In other words, the question this chapter aims to answer is what the magnitude of the three general direct effects could be within each post-COVID-19 travel behavior scenario. To recall, the theoretical framework as presented in chapter 3, section 3.4, figure 12, identified two submodels within the VMA travel model that could be used to simulate the three general effects. The TOURFREQ model enables to simulate the shift from onsite to online work-related activities by altering the trip generation for work-related travel motives. The MODEST model enables to simulate the respacing and retiming of work-related travel patterns and a modal shift towards active modes. Section 5.1 continues on these insights and further explores the TOURFREQ and MODEST submodels to identify which parameters can be used to simulate (1) a shift from onsite to online work-related activities, (2) the respacing and retiming of work-related travel patterns and (3) a modal shift towards active modes. Section 5.2 aims to estimate a bandwidth for each identified parameter by analyzing COVID-19 travel data and providing corrections to match the post-COVID-19 travel behavior scenarios.

5.1 Translating the scenario switchboard to parameters of the VMA travel model

To recall, FSMs such as the VMA travel model do not allow to dynamically change travel behavior, but statically models the way people travel through the four main modelling steps (1) trip generation, (2) trip distribution and time-of-day, (3) trip mode choices (i.e. modal split) and (4) network assignment (i.e. rout choice) (Banister, 2003; Castiglione et al., 2014). In other words, the sliders of the scenario switchboard aren't represented in a similar fashion within the VMA travel model. This is why the general effects as delineated within chapter 4, section 4.8 are replicated within the VMA travel model. Reasoning from the theoretical framework as presented in chapter 3, section 3.4, figure 12, it is assumed the shift from onsite to online work-related activities will cause less work related trips to be generated. Note that the general effects are described as 'trips' where the VMA travel model generates 'tours'. Tours can be considered as journeys, composed of trips. For example, as illustrated in figure 40, a tour could include two trips if a secondary destination is visited. Moreover, a single tour between a origin and destination always includes both a trip towards the destination and a trip back to the origin (Van den Elshout et al., 2020).

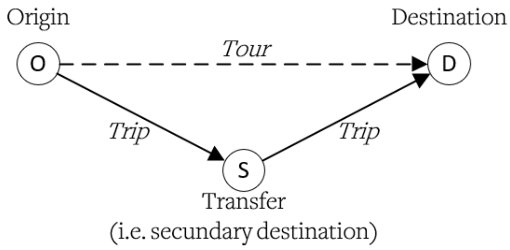


Fig. 40: Conceptual illustration of tours and trips within the VMA travel model, adapted from (Van den Elshout et al., 2020)

Based on person and household characteristics, the tour frequency model (i.e. TOURFREQ) predicts, for each motive the probability that individuals will take a certain number of tours on an average working day (Van den Elshout et al., 2020). The VMA travel model distinguishes various travel motives as depicted within table 8.

Table 8: Travel motives as distinguished by the TOURFREQ model within the VMA travel model (Van den Elshout et al., 2020)

Motive	Definition	Description
1	Home - work	Tours from home to the office
2	Home - business	Tours from home to a client, work-related
3	Home - education	Tours from home to educational facilities, secondary education, and higher
4	Home - shopping	Tours from home to shopping facilities
5	Home - other	Other tours from home
6	Nonresidential - business	Tours from other locations but home with work-related purposes
7	Nonresidential - other	Other tours from other locations but home
8	Child - education	Tours of children to educational facilities
9	Child - shopping	Tours of children to shopping facilities
10	Child - other	Other tours of children

The TOURFREQ model consists of two simultaneously estimated choice models: (1) the 0/1+ model predicts the probability that a person will or will not make a tour, if at least one tour is taken

(2) the stop/repeat model predicts the probability that additional tours will be added on an average weekday (Van den Elshout et al., 2020).

The utility (U) of choosing not to take a (or any additional) tour(s) consists of the sum of a constant (C) and the value (X) of several people- and household characteristics (K) multiplied by the to be estimated coefficient (β) (Van den Elshout et al., 2020):

$$U(0) = C_0 + \sum_k \beta_k^0 * X_k \tag{5.1}$$

$$U(1,2) = C_{stop} + \sum_k \beta_k^{stop} * X_k \tag{5.2}$$

$$U(1+,2+,3+) = 0 \tag{5.3}$$

To simulate the potential implications of working-from-home, the constants (i.e. c-value) for both the 0/1+ model (b_const) and stop/repeat model (s_const) are changed for the motive home-work. To verify if raising the c-values of these two parameters will indeed result in fewer work-related tours, the c-values are doubled and the resulting tours generated by the TOURFREQ model are examined. The c-values used for this process are listed in table 9.

Table 9: Parameter value increase of constants within the 0/1+ and stop/repeat model within the VMA travel model general parameters.

Parameter	Reference	C+10%	C+20%	C+40%	C+80%	C+160%	C+320%
b_const	-0.5545	-0.4991	-0.4436	-0.3327	-0.1109	0.3327	1.0979
s_const	2.846	3.131	3.415	3.984	5.123	7.400	13.149

Based on the resulting tours, as listed in table 10, as generated by the TOURFREQ model it can be observed that by raising the c-values of both the b_const and s_const TOURFREQ parameters the total number of work-related tours can be decreased to simulate the effects of working-from-home, hence, simulate a shift from onsite to online work-related activities.

Table 10: Resulting change in the number of tours by changing 0/1+ and stop/repeat constants parameter values within the 'home-work' travel motive. *Work-related trips are considered motives 1, 2, 6, and 7.

Motive	Reference	C+10%	C+20%	C+40%	C+80%	C+160%	C+320%
1. Home - work	5,392,054	5,192,182	5,012,714	4,695,405	4,150,603	3,205,615	1,884,217
2. Home - business	411,002	411,002	411,002	411,002	411,002	411,002	411,002
3. Home - education	1,586,025	1,586,025	1,586,025	1,586,025	1,586,025	1,586,025	1,586,025
4. Home - shopping	3,405,915	3,405,915	3,405,915	3,405,915	3,405,915	3,405,915	3,405,915
5. Home - other	5,850,288	5,850,288	5,850,288	5,850,288	5,850,288	5,850,288	5,850,288
6. Nonresidential - business	32,179	31,053	30,040	28,248	25,147	19,652	11,689
7. Nonresidential - other	104,101	100,110	96,539	90,259	79,562	61,200	35,757
8. Child - education	1,393,511	1,393,511	1,393,511	1,393,511	1,393,511	1,393,511	1,393,511
9. Child - shopping	232,581	232,581	232,581	232,581	232,581	232,581	232,581
10. Child - other	820,997	820,997	820,997	820,997	820,997	820,997	820,997
Total work-related tours*	5,939,336	5,734,346	5,550,295	5,224,914	4,666,315	3,697,468	2,342,666
Change work-related tours		-3.5%	-6.6%	-12.0%	-21.4%	-37.7%	-60.6%
Grand total tours	19,228,653	19,023,664	18,839,613	18,514,232	17,955,632	16,986,786	15,631,984
Change total tours		-1.1%	-2.0%	-3.7%	-6.6%	-11.7%	-18.7%

Reasoning from the theoretical framework as presented in chapter 3, section 3.4, figure 12, it is assumed that the respacing and retiming of work-related travel patterns will directly relate to the reduced work-related trips as generated by the TOURFREQ model.

The MODEST model within the VMA travel model simultaneously predicts the mode choice, destination choice, and time-of-day choices of travelers based on zone-, person and household-specific characteristics, and the level-of-service (e.g. time and costs). Car infrastructure is dependent on capacity, which means that increased use of a certain road by cars will result in congestion, hence, a lower level-of-service. Infrastructure for other modes however is not dependent on capacity. Reasoning from the theoretical framework as presented in chapter 3, section 3.4, figure 12, it is assumed that to simulate a modal shift towards active modes within the MODEST model the utility of slow modes needs to be increased.

The utility of a certain mode within the MODEST model is used to predict the probability of choosing an alternative mode. Utility (U) of an alternative (a) consists of the sum of one or more constants (C) of that alternative, the value (x) of some level-of-service, zonal-, person- and household characteristics (k) multiplied by estimated coefficients (β) and an unknown error term (ε) (Van den Elshout et al., 2020):

$$U_a = C_a + \sum_k \beta_k * X_k + \varepsilon_{a,r} \tag{5.4}$$

This means the utility as modeled by the MODEST model is constructed in two parts: (1) the observed utility and (2) an error term (i.e. unobserved perceptions, preferences, and knowledge). Reasoning from the theoretical framework as presented in chapter 3, section 3.4, figure 12, the modal shift towards active modes can be explained by a change in utility, attitudes, and/or the development of new habitual behavior. In the post-COVID-19 scenarios nor travel time and costs are projected to change, instead, a more subjective concept is suggested to change which is the attitude towards a certain mode. It is assumed that the attitude towards a mode translates to its attractiveness compared to other modes, this attractiveness of a certain mode is captured within the MODEST model in a mode-specific constant (C_a within equation 5.4). The value of a mode-specific constant of an alternative mode is related to walking. In other words, a higher mode-specific constant would mean the alternative mode has a higher attractiveness compared to walking. Due to this mechanism within the MODEST model, combined with time limitations, this thesis only experiments with a higher attractiveness of cycling. To simulate a model shift towards cycling, this attractiveness of the bicycle as a mode of transport is increased for the motives home-work, home-education, home-shopping, and home-other. The c-values used for this process are listed in table 11.

Table 11: Parameter value increase of mode-specific constants related to cycling for different motives within the VMA travel model' general model parameters.

Parameter	Reference	C+20%	C+40%	C+80%
C_bike woon-werk	3.189	3.827	4.465	5.740
C_bike woon-educ	0.9235	1.1082	1.2929	1.6623
C_bike woon-wink	-2.615	-2.092	-1.569	-0.523
C_bike woon-overig	0.00203	0.00244	0.00284	0.00365

The resulting model split per c-value is shown in table 12. It can be observed that by raising the c-values of both the C_bike woon-werk, C_bike woon-educ, C_bike woon-wink and C_bike woon-overig parameters the share of cyclists within the model split can be increased to simulate a modal shift.

Table 12: Resulting change in mode shares by increasing the attractiveness of bicycles within the MODEST model.

Mode	Reference	C+20%	δ	C+40%	δ	C+80%	δ
Car	27%	26%	-4%	25%	-7%	24%	-14%
Public transport	15%	14%	-8%	13%	-16%	11%	-29%
Cycling	39%	41%	+8%	44%	+15%	50%	+29%
Walking	19%	18%	-4%	17%	-8%	16%	-16%
Total trips	1,975,036	1,984,711	+0.5%	2,003,584	+1.4%	2,049,806	+3.8%

5.2 Estimating VMA travel model parameter bandwidth with insights from COVID-19 travel data

With the identification of parameters within the VMA travel model that could simulate a shift from onsite to online work-related activities and a modal shift towards cycling, the question remains what the parameter values should be to simulate the desired magnitude of the general post-COVID-19 effects as projected by the post-COVID-19 travel behavior scenarios. For this, a bandwidth is estimated where the original parameter value used to create the reference projection for the year 2030 within the VMA travel model will serve as a base value, hence, these parameter values will be used to simulate scenario 1; 'back to normal' (i.e. the reference scenario). The other end of the bandwidth is the situation as observed during the COVID-19 pandemic.

As post-COVID-19 the fear of contamination arguably doesn't play a role, and social distancing policy is probably not in effect, the bandwidth will be estimated based on the moment during the COVID-19 pandemic where COVID-19 infections were low and policy measures were maximally eased. As delineated within appendix 2, the moment where COVID-19 infections were relatively low and policy measures where maximally eased can be set to week 29 to 33 of the year 2020.

As described in appendix 3 and 4, between weeks 28 to 33 on average -11.5% fewer trips were made with on average -42% fewer trips to the office. As shown in tables 9 and 10 within section 5.1, similar results can be achieved by setting the c-values of both the b_const and s_const parameters for home-work related trips to a value of 0.3327 and 7.400 respectively. This means the bandwidth for the b_const parameter will range from -0.5545 to 0.3327 and for the s_const will range from 2.846 to 7.400. The lowest range will be assigned to scenario 1; 'back to normal', as this is the reference scenario. The highest range will be assigned to scenario 4; 'the cyclist paradise' as this is the most extreme scenario.

To estimate the b_constant (b) and s_constant (s) parameter values for scenarios 2 and 3, respectively one and two-thirds of the difference between the maximal c-value (C) and the reference c-value (C_{ref}) will be added to the reference value:

$$Senario\ 2\ constant\ value_{(b,s)} = C_{ref\,(b,s)} + \frac{1}{3} * \left(C_{(b,s)} - C_{ref\,(b,s)}\right) \tag{5.5}$$

$$Senario\ 3\ constant\ value_{(b,s)} = C_{ref\,(b,s)} + \frac{2}{3} * \left(C_{(b,s)} - C_{ref\,(b,s)}\right) \tag{5.6}$$

In this way, each scenario shows a proportional change which enables to explore different implications by the potentially reduced trip demand in the year 2030. The resulting parameter values are listed in table 13.

Table 13: TOURFREQ 0/1+ and stop/repeat model parameter values for each post-COVID-19 scenario.

Parameter	Scenario 1: 'Back to normal'	Scenario 2: 'Minor changes'	Scenario 3: 'Working from home is here to stay'	Scenario 4 'The cyclist paradise'
b_const	-0,5545	-0,2588	0,0370	0,3327
s_const	2,846	4,364	5,882	7,400

As described in appendix VIII a modal shift can be observed on all travel movements within the Netherlands of -2% car, -61% public transportation, +15% cycling, and +4% walking. When assuming in the most extreme case the modal split in 2030 will have the same magnitude towards active modes of transportation, a +15% increase in the share of cyclists and a +4% share in walking can be projected to the model split as generated by scenario 1. As depicted within tables 11 and 12 of section 5.1, a +15% increase in the share of cyclists can be achieved by increasing the parameters C_bike woon-werk, C_bike woon-educ, C_bike woon-wink and C_bike woon-overig respectively to a value of 4.465; 1.2929; -1.569 and 0.00284. This means the bandwidth for the C_bike woon-werk parameter will range from 3.189 to 4.465; for the C_bike woon-educ will range from 0.9235 to 1.2929; for the C_bike woon-wink from -2.615 to -1.569 and for the C_bike overig from 0.00203 to 0.00284. The lowest range will be assigned to scenario 1; 'back to normal', as this is the reference scenario. The highest range will be assigned to scenario 4; 'the cyclist paradise' as this is the most extreme scenario. As only a modal shift is expected in scenario 2; 'minor changes' and scenario 4; 'the cyclist paradise', the parameter value for scenario 2; 'minor changes' is set by dividing the c-value (C) by two and subtracting the result from the reference c-value (C_{ref}) for every variant from the set of travel motives (M):

$$M = \{c\_cardr\ woonwerk, c\_cardr\ wooneduc, c\_cardr\ woonwink, c\_cardr\ woonoverig\}$$

$$Senario\ 2\ constant\ value_{(M)} = C_{ref\,(M)} - \frac{C_{ref\,(M)} - C_{(M)}}{2} \tag{5.7}$$

The resulting scenario parameter values per post-COVID-19 travel behavior scenario are listed in table 14.

Table 14: MODEST model parameter values for each post-COVID-19 scenario.

Parameter	Scenario 1: 'Back to normal'	Scenario 2: 'Minor changes'	Scenario 3: 'Working from home is here to stay'	Scenario 4 'The cyclist paradise'
C_bike woon-werk	3.189	3.827	3.189	4.465
C_bike woon-educ	0.9235	1.1082	0.9235	1.2929
C_bike woon-wink	-2.615	-2.092	-2.615	-1.569
C_bike woon-overig	0.00203	0.00244	0.00203	0.00284

Chapter 6

Results

With the quantified post-COVID-19 travel behavior scenarios in place, this allows exploring in which way potential long-term travel behavior changes due to the COVID-19 pandemic could impact the accessibility and the allocation of public space within the city of Amsterdam. Scenario 1; 'back to normal', represents the projection of Amsterdam in the year 2030 without any changes. For scenario 2; 'minor changes', scenario 3; 'working from home is here to stay' and scenario 4; 'the cyclist paradise', a reduced work-related trip generation is simulated by reducing work-related tours in the TOURFREQ model. In addition, for scenario 2; 'minor changes' and scenario 4; 'the cyclist paradise' also a modal shift towards cycling is simulated by increasing the attractiveness of bicycles as a mode of transport within the MODEST model. Section 6.1 presents the implications of the different post-COVID-19 travel behavior scenarios on the accessibility by reflecting on congestion within the city and resulting travel time savings from the city center to all other zones within Amsterdam. Section 6.2 presents the implications of post-COVID-19 travel behavior scenarios on the allocation of public space by reflecting on the modal split for every district in Amsterdam.

6.1 General implications of a shift from onsite to online work-related activity and travel patterns, and a modal shift towards cycling

When simulating the different scenarios within the VMA travel model the results, as listed show that the total number of trips gradually reduces from scenario 1; 'back to normal', to scenario 4; 'the cyclist paradise' as a result of reduced work-related trip generation. The time of day of the trips also shifts as a result of the reduced work-related trip generation, from the morning and evening rush hours to the rest-of-day. This dynamic is the same in each scenario and gradually increases from scenario 1; 'back to normal', to scenario 4; 'the cyclist paradise'.

Regarding the modal split, the scenarios show different results. The attractiveness of the bicycle is increased for scenarios 2; 'minor changes', and scenario 4; 'the cyclist paradise', and the share of bicycles also gradually increased within these scenarios. Interestingly, this shift is mainly gained from public transport. Within scenario 3; 'working from home is here to stay', the attractiveness of the bike is not altered. This means that the modal shift as observed within scenario 3 is directly related to the shift from onsite to online work-related activity and travel patterns. Within scenario 3, the share of cars and walking increased at the expense of public transport and cycling. Again, it is noticeable that public transportation experience a reduced share in all scenarios.

Table 15: Modal split and total trips as generated by the VMA travel model within the different post-COVID-19 travel behavior scenarios.

Model split	Scenario 1: 'Back to normal'	Scenario 2: 'Minor changes'	δ	Scenario 3: 'Working from home is here to stay'	δ	Scenario 4: 'The cyclist paradise'	δ
Car	27%	27%	-2.4%	28%	+1.5%	27%	-1.6%
Public transport	15%	14%	-9.4%	15%	-4.2%	13%	-17.3%
Cycling	39%	41%	+5.9%	38%	-2.0%	42%	+8.3%
Walking	19%	19%	-0.8%	20%	+5.4%	19%	-0.6%
Total trips	1,975,036	1,896,981	-4.0%	1,813,192	-8.2%	1,790,551	-9.3%

Table 16: Time-of-day of trips as generated by the VMA travel model within the different post-COVID-19 travel behavior scenarios.

Time-of-day	Scenario 1: 'Back to normal'	Scenario 2: 'Minor changes'	δ	Scenario 3: 'Working from home is here to stay'	δ	Scenario 4: 'The cyclist paradise'	δ
Morning rush	14%	14%	-2.5%	13%	-5.5%	13%	-6.1%
Rest-of-day	69%	70%	+0.9%	71%	+1.9%	71%	+2.1%
Evening rush	16%	16%	-1.5%	16%	-3.2%	16%	-3.7%

6.2 Implications of post-COVID-19 travel behavior scenarios on congestion rates by car within the city of Amsterdam

As described within chapter 2, section 2.7, accessibility within the field of transportation can be described as "the ease of reaching a destination from an origin by utilizing the available travel mode options with inherent impeding properties of the route-generally time, speed, distance, and mode of transport" (Ahuja & Tiwari, 2021). Given travel time is chosen within this thesis as an indicator of accessibility, and congestion is arguably an important contributor to longer travel times when traveling by car, this section explores the implications of post-COVID-19 travel behavior scenarios on congestion rates. As addressed in chapter 5, section 5.1, only car traffic experiences congestion within the VMA travel model as the infrastructure of other modes does not account for capacity. Furthermore, the VMA travel model deviates between a morning rush hour from 7:00 am to 9:00 am, an evening rush hour from 4:00 pm to 6:00 pm, and the rest-of-day including the other twenty hours of the day (Van den Elshout et al., 2020). When comparing the bandwidth plots that illustrate the level of congestion generated within the different post-COVID-19 travel behavior scenarios, it can be concluded that most differences (i.e. congestion reduction) can be observed within the morning and evening rush hours. The differences with regards to congestion rates (i.e. intensity divided by capacity) as generated within the different post-COVID-19 travel behavior scenarios are illustrated within figure 41 to 44. These figures show bandwidth plots which resembles the congestion during the morning rush hour on the road network of Amsterdam. The width of sections of road resemble the intensity of car traffic and the color indicates the congestion rate.

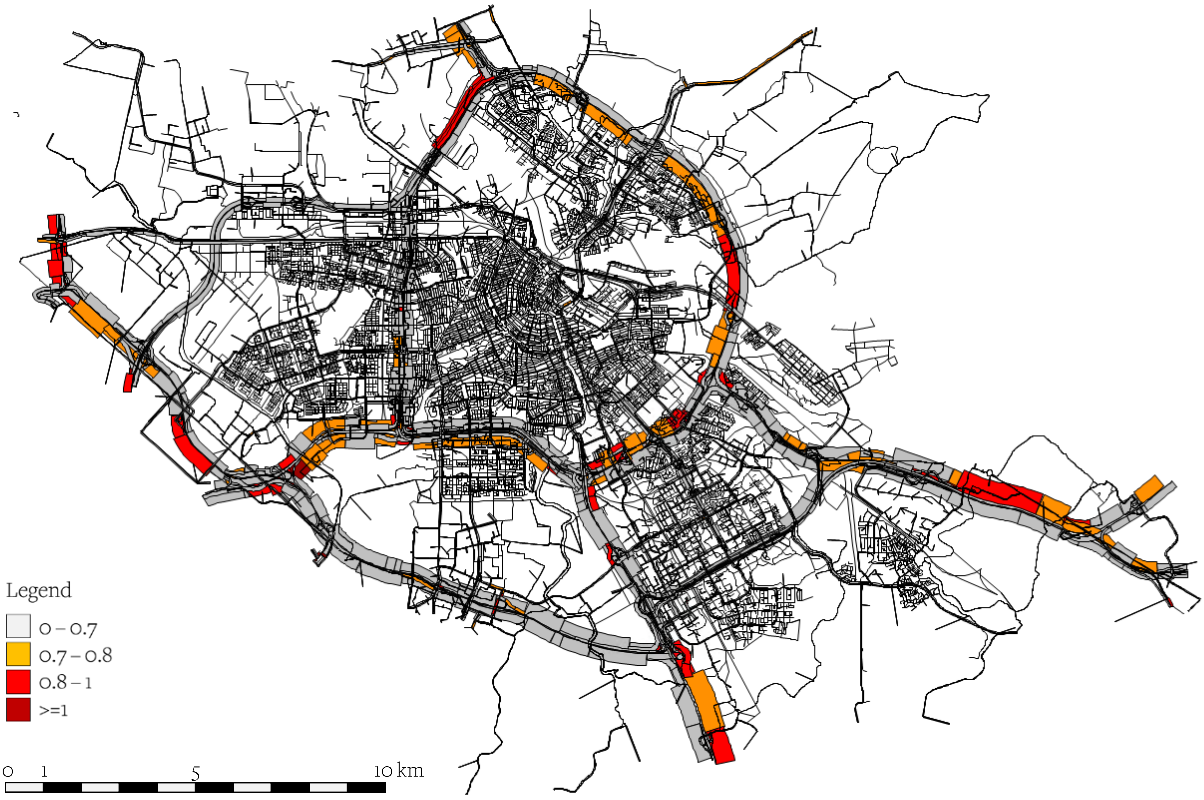


Fig. 41: Congestion rates during the morning rush hour in Amsterdam within scenario 1: 'Back to normal'.

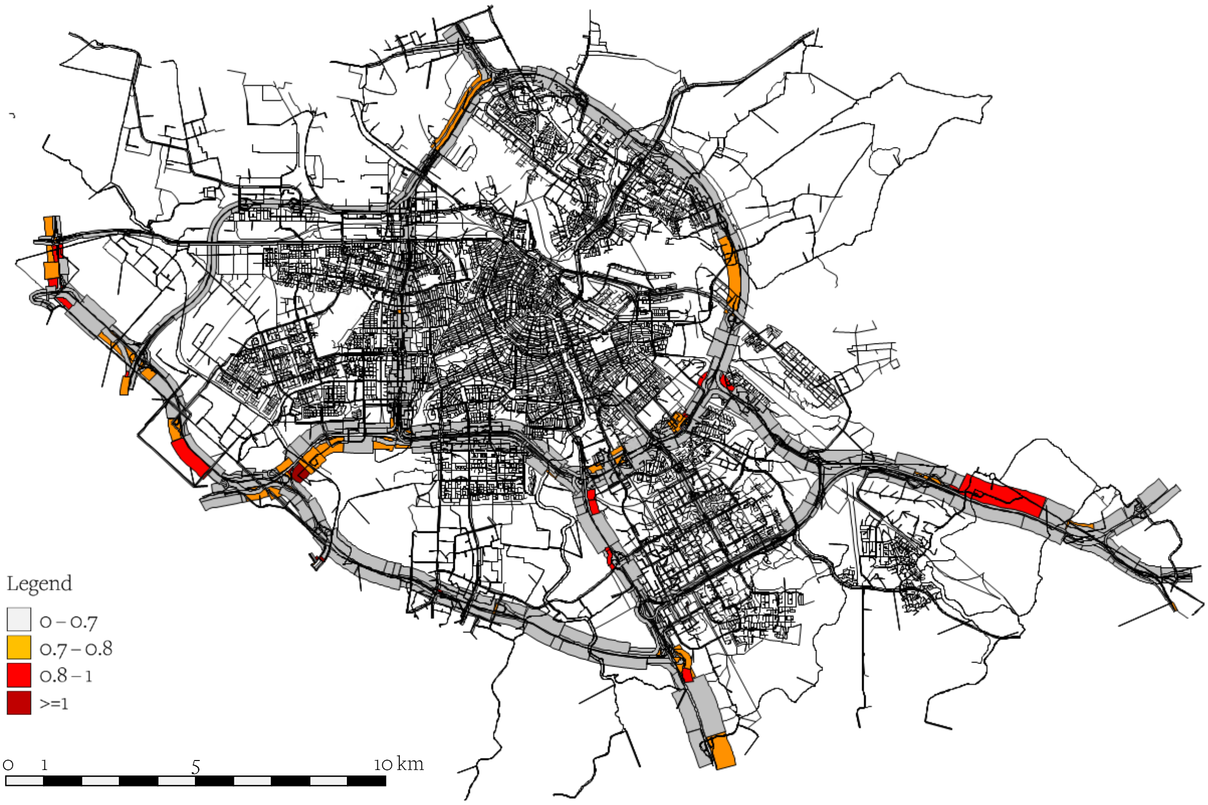


Fig. 42: Congestion rates during the morning rush hour in Amsterdam within scenario 2: 'Minor changes'.

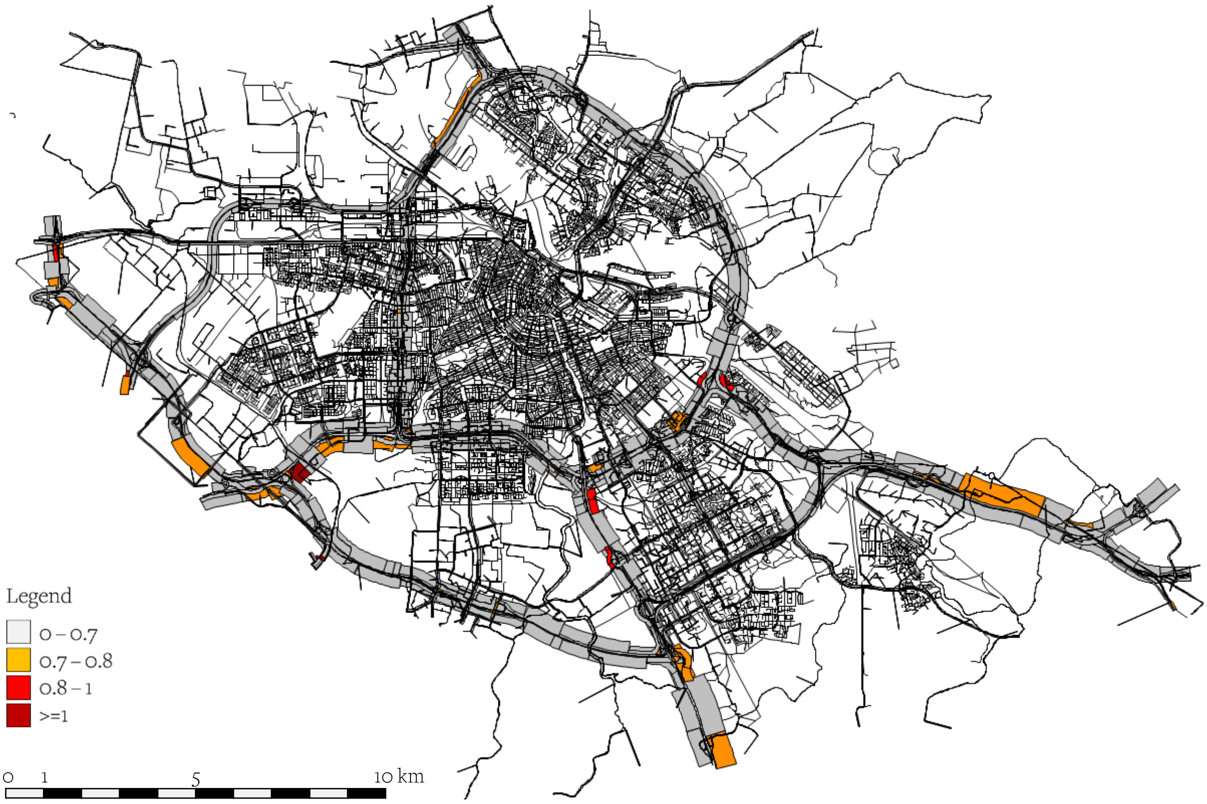


Fig. 43: Congestion rates during the morning rush hour in Amsterdam within scenario 3: 'Working from home is here to stay'.

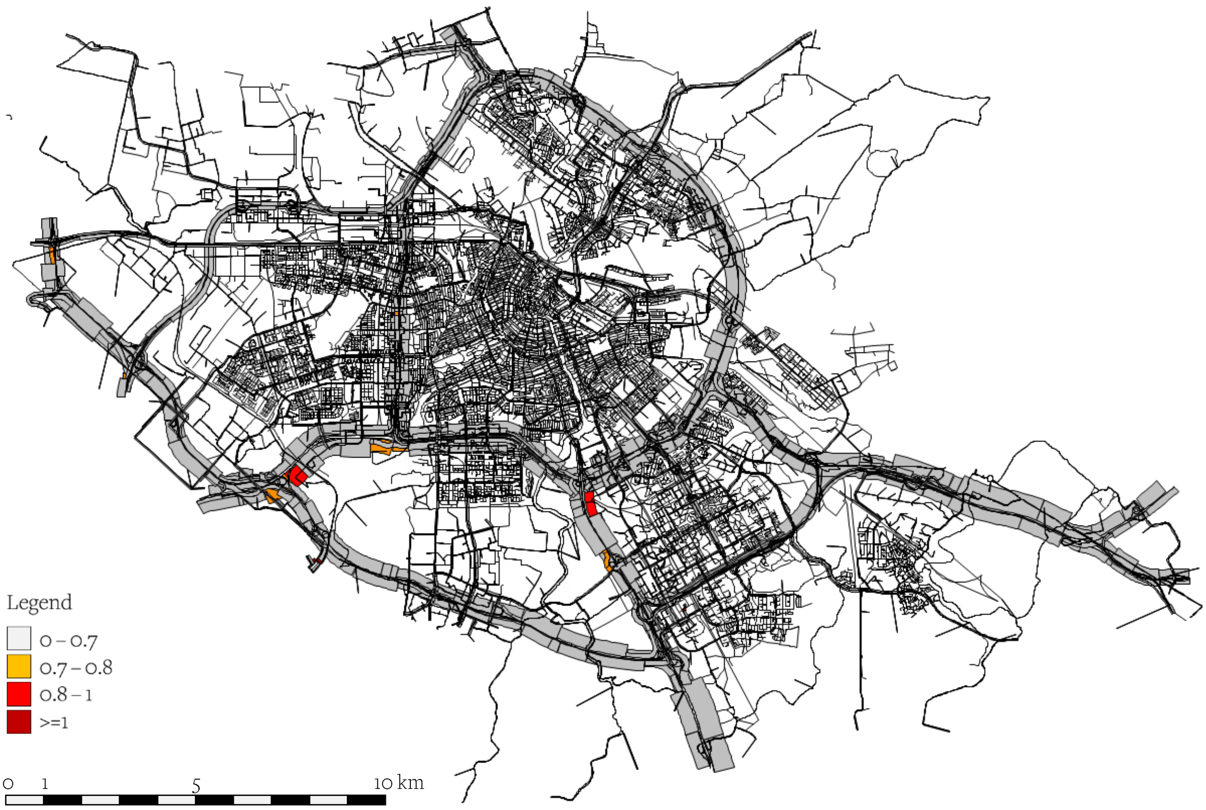


Fig. 44: Congestion rates during the morning rush hour in Amsterdam within scenario 4: 'The cyclist paradise'.

When comparing the different bandwidth plots (i.e. figure 41 to 44) it can be observed that congestion within the morning rush hour alleviates within scenario 2; 'minor changes' and scenario 3; 'working from home is here to stay' compared to scenario 1; 'back to normal'. The biggest change is observed within scenario 4; 'the cyclist paradise' where the majority of congestion in the morning rush hour seems to have disappeared.

6.3 Implications of post-COVID-19 travel behavior scenarios on travel times by car within the city of Amsterdam

Given the reduction of congestion, this section explores the implications on travel times by car. To recall, only travel times by car are influenced by congestion within the VMA travel model as the network for other modes of transportation does not include a capacity, hence, does not experience congestion (Van den Elshout et al., 2020). Figure 45 indicates the travel times in minutes from a zone within the city center to any other zone within Amsterdam, this particular zone is chosen as within the city center this zone produces the most trips by car to all other zones in Amsterdam. Although travel times to other zones by car may greatly differ based on the chosen origin within the city center, time limitations did not allow to analyze any additional zones. As shown in figure 45 the relative highest travel times for this particular zone are mainly from the city center to the south-eastern parts of the city and have a duration of around 30 minutes.

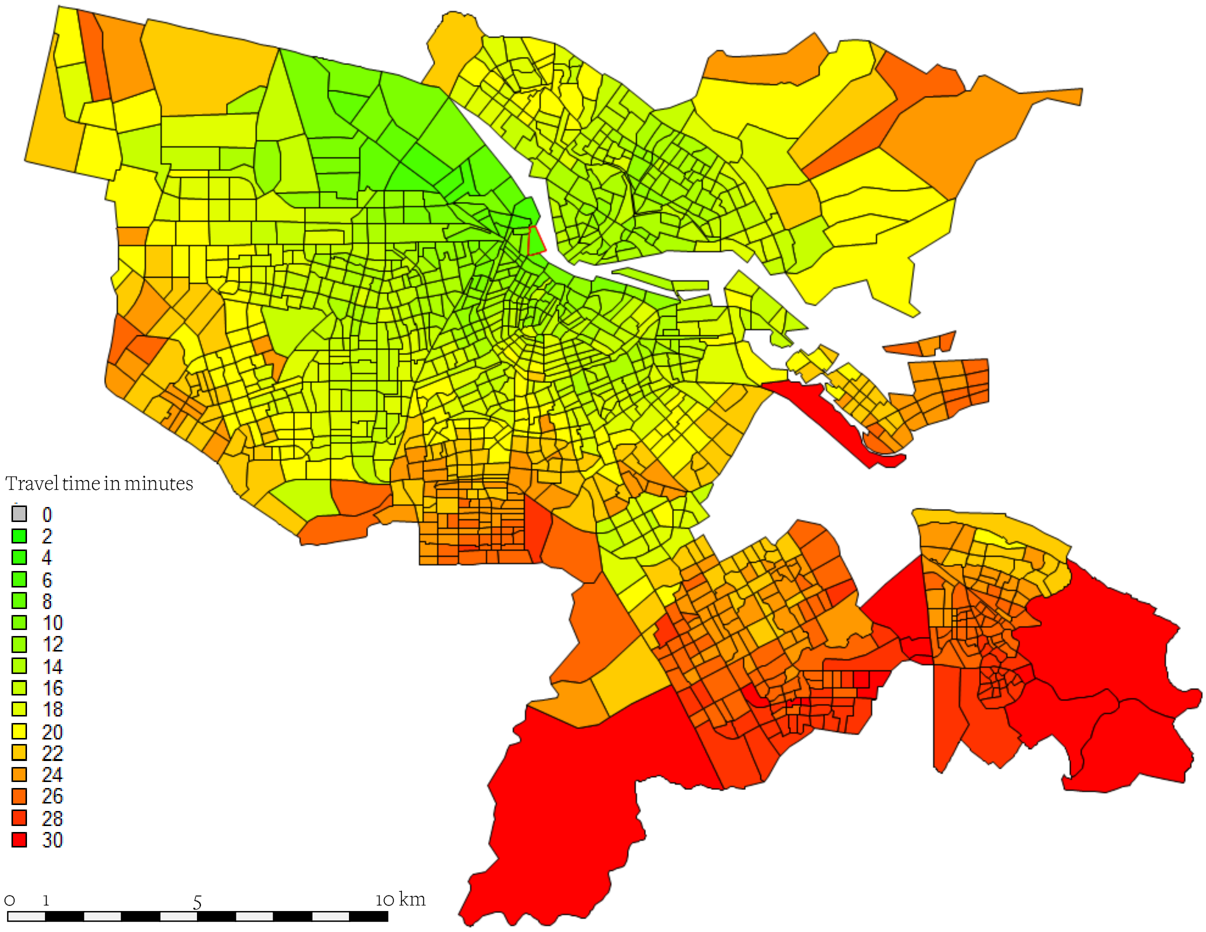


Fig. 45: Travel times from a zone within the city center to any other zones within Amsterdam by car in the morning rush hour, as generated within scenario 1: 'Back to normal'.

To explore travel time savings due to the reduction of congestion within the different post-COVID-19 travel behavior scenarios, travel times from the same zone within the city center as used within figure 45 to any other zone within Amsterdam are compared with the results as generated by the other scenarios. The travel time savings per zone are given by subtracting the travel time by car in the morning rush hour from the zone in the city center to all other zones within Amsterdam of scenario 1 by those of scenario 2, 3, or 4. Travel time savings, in minutes, are shown in figures 46 to 48. From these zonal plots, it can be observed that the reduction of congestion during the morning rush hour results in travel time savings from 1 to 2 minutes from the chosen zone within the city center to all other zones within Amsterdam. Furthermore, also some zones can be identified where the different scenarios result in a longer travel time, these zones are located especially in the northern part of the city and experience around one minute longer travel times.

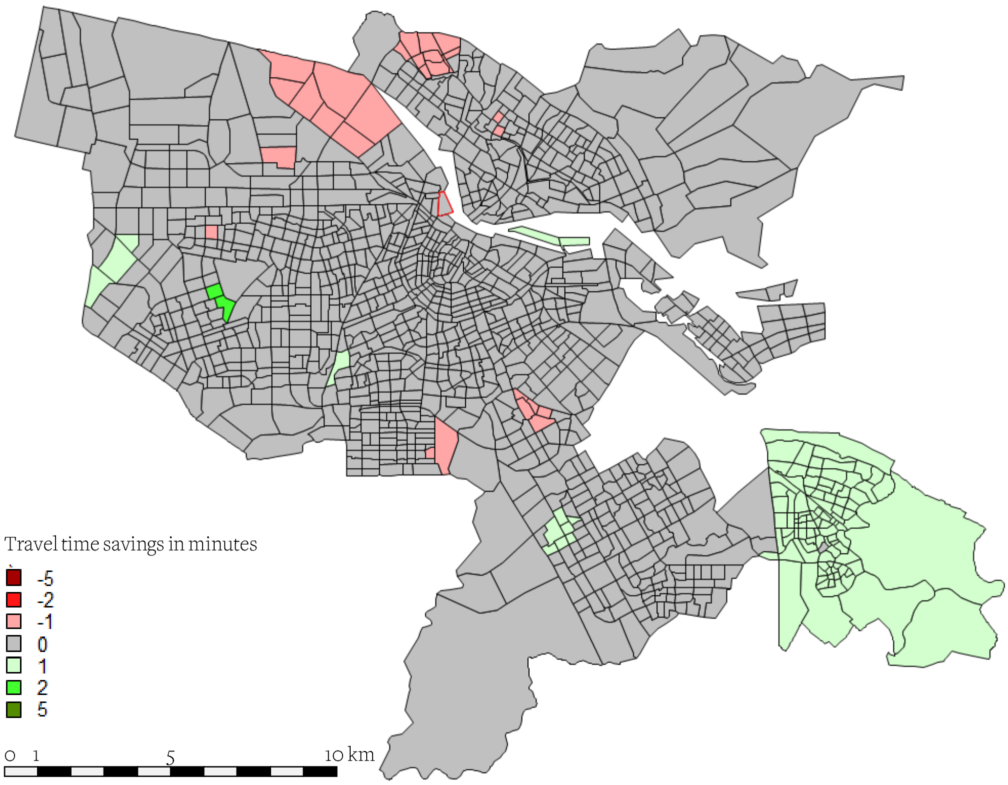


Fig. 46: Resulting travel time savings in minutes in scenario 2: 'Minor changes' compared to scenario 1: 'Back to normal' when traveling from a zone within the city center to all other zones within Amsterdam.

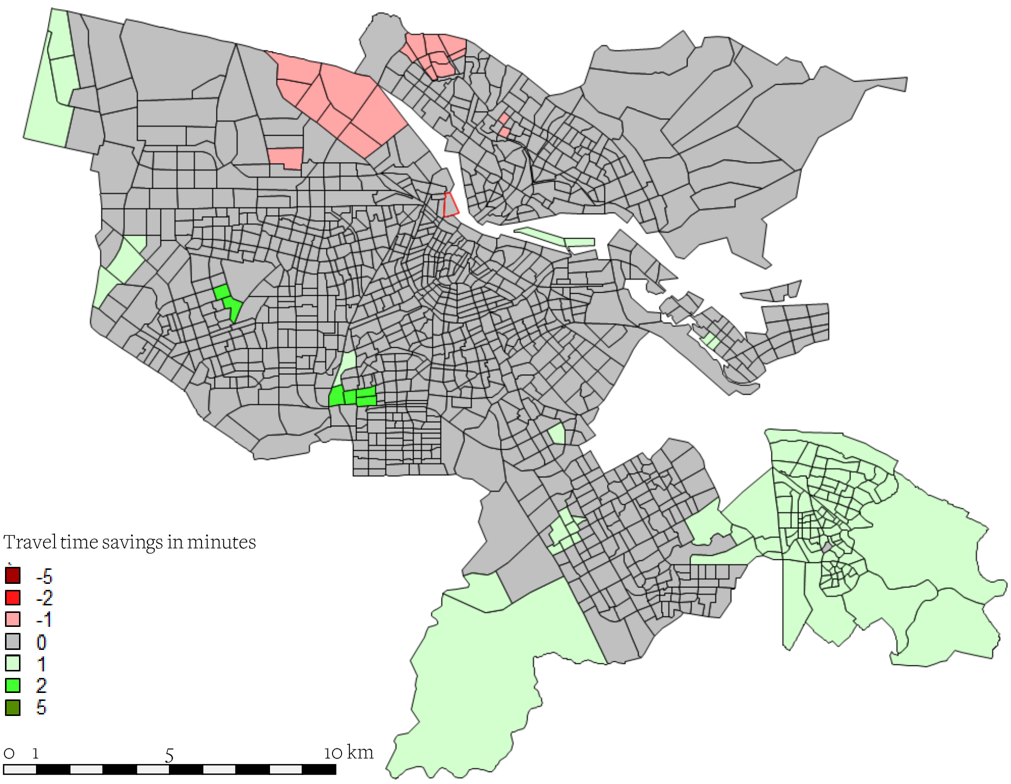


Fig. 47: Resulting travel time savings in minutes in scenario 3: 'working from home is here to stay' compared to scenario 1: 'Back to normal' when traveling from a zone within the city center to all other zones within Amsterdam.

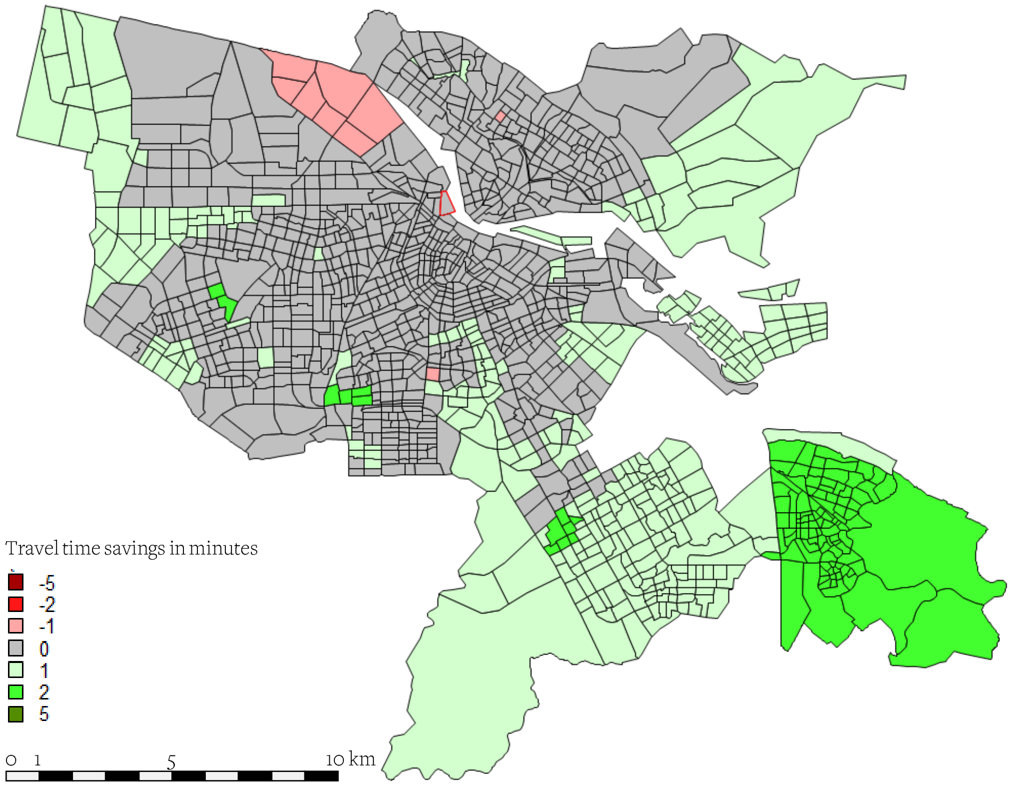


Fig. 48: Resulting travel time savings in minutes in scenario 4: 'The cyclist paradise' compared to scenario 1: 'Back to normal' when traveling from a zone within the city center to all other zones within Amsterdam.

6.4 Implications of post-COVID-19 travel behavior scenarios on the allocation of public space

An altered model split within a district in the city could suggest that a different allocation of public space might be possible. To assess in which districts a different allocation of public space from cars to cyclists might be needed the number of trips by cars and bicycle is analyzed for every district and compared between the different post-COVID-19 travel behavior scenarios. These results are listed in table 17. When analyzing the number of trips, in absolute terms only growth in the number of bicycle trips is experienced within scenario 2; 'Minor changes', in all districts except Westpoort.

When assuming a modal split with just cars and bicycles, as listed in table 18, it can be observed that within scenario 2; 'Minor changes' and scenario 4; 'The cyclist paradise' the share of cyclists in all districts increases while simultaneously the share of cars decreases. This combination would argue in favor of a different allocation of public space where more space could be allocated towards cycling infrastructure at the cost of car infrastructure. Especially within the districts of Centrum, Zuid, Oost, and Nieuw West given the relatively high absolute number of trips made by bicycle from these districts. However, scenario 3; 'Working from home is here to stay', shows the opposite as in the districts Centrum, Westpoort, West, Zuid, and Oost show an increase in the share of cars and a decrease in the share of bicycles. Interestingly, the modal split of cars and bicycles within the district Nieuw West shows to be consistent over all scenarios in regards of a larger share of bicycles and a lower share of cars.

Table 17: Number of trips per district as generated by the VMA travel model in each post-COVID-19 travel behavior scenario.

District		Scenario 1: 'Back to normal'	Scenario 2: 'Minor changes'	δ	Scenario 3: 'Working from home is here to stay'	δ	Scenario 4: 'The cyclist paradise'	δ
Centrum	Car	68,166	65,034	-5%	64,681	-5%	62,930	-8%
	Bicycle	209,327	212,519	2%	182,752	-13%	20,1811	-4%
Westpoort	Car	30,269	27,061	-11%	26,258	-13%	23,849	-21%
	Bicycle	10,641	10,648	0%	8,816	-17%	9,697	-9%
West	Car	101,759	95,245	-6%	94,499	-7%	89,878	-12%
	Bicycle	199,525	201,944	1%	177,800	-11%	193,167	-3%
Zuid	Car	144,678	134,913	-7%	133,699	-8%	126,975	-12%
	Bicycle	263,549	267,467	1%	233,935	-11%	255,740	-3%
Oost	Car	127,199	117,765	-7%	116,413	-8%	110,247	-13%
	Bicycle	203,404	206,868	2%	183,071	-10%	199,721	-2%
Noord	Car	113,866	106,164	-7%	104,773	-8%	98,532	-13%
	Bicycle	117,974	120,654	2%	107,506	-9%	117,929	-0%
Zuidoost	Car	126,284	115,735	-8%	113,566	-10%	105,455	-16%
	Bicycle	125,549	128,057	2%	112,294	-11%	123,801	-1%
Nieuw west	Car	188,133	171,838	-9%	169,170	-10%	155,317	-17%
	Bicycle	210,173	213,048	1%	189,652	-10%	205,524	-2%

Table 18: Relative modal split comparing car and bicycle shares per district as generated by the VMA travel model in each post-COVID-19 travel behavior scenario.

District		Scenario 1: 'Back to normal'	Scenario 2: 'Minor changes'	δ	Scenario 3: 'Working from home is here to stay'	δ	Scenario 4: 'The cyclist paradise'	δ
Centrum	Car	25%	23%	-5%	26%	6%	24%	-3%
	Bicycle	75%	77%	2%	74%	-2%	76%	1%
Westpoort	Car	74%	72%	-3%	75%	1%	71%	-4%
	Bicycle	26%	28%	9%	25%	-3%	29%	11%
West	Car	34%	32%	-5%	35%	3%	32%	-6%
	Bicycle	66%	68%	3%	65%	-1%	68%	3%
Zuid	Car	35%	34%	-5%	36%	3%	33%	-6%
	Bicycle	65%	66%	3%	64%	-1%	67%	4%
Oost	Car	38%	36%	-6%	39%	1%	36%	-8%
	Bicycle	62%	64%	4%	61%	-1%	64%	5%
Noord	Car	49%	47%	-5%	49%	0,5%	46%	-7%
	Bicycle	51%	53%	5%	51%	-0,5%	54%	7%
Zuidoost	Car	50%	47%	-5%	50%	0,3%	46%	-8%
	Bicycle	50%	53%	5%	50%	-0,3%	54%	8%
Nieuw west	Car	47%	45%	-5%	47%	-0,2%	43%	-9%
	Bicycle	53%	55%	5%	53%	0,2%	57%	8%

Chapter 7

Conclusion

This research aimed to provide insight into the potential implications of long-term travel behavior changes caused by the COVID-19 pandemic on accessibility and the allocation of public space within the city of Amsterdam. Based on a literature review it can be concluded that post-COVID-19 three general direct effects of the COVID-19 pandemic and policy measures on travel and activity patterns may be expected: (1) a shift from onsite to online activities, (2) the respacing and retiming of travel patterns and (3) a modal shift towards active modes of transport such as walking and cycling. This thesis particularly addresses a shift from onsite to online work-related activities which show to be dependent on (1) the utility towards working-from-home, (2) attitudes towards working-from-home and (3) habitual behavior including working-from-home. Furthermore, the respacing and retiming of work-related travel patterns show to be a direct result of the increased flexibility due to a shift from onsite to online work-related activities. A modal shift towards active modes within this thesis addresses as a modal shift towards cycling, which shows to be dependent on (1) the utility of cycling, (2) attitudes towards cycling, and (3) the development of new habitual behavior including cycling.

Based on exploratory scenario planning from which four post-COVID-19 travel behavior scenarios were created with the input of four mobility experts from an intuitive logic approach, potential future development paths of post-COVID-19 travel behavior show to depend on five critical uncertainties: (1) the valuation of active modes of transportation through personal drivers of travelers, (2) travelers' attitude towards online activities, (3) technological developments to enable the substitution of onsite for online activities, (4) policy of employers with regards to flexibility in both working location and office hours as well as supporting working-from-home and (5) governmental policies. Based on these critical uncertainties four post-COVID-19 travel behavior scenarios were created and analyzed within the FSM, tour based, VMA travel model:

1. Scenario 1: 'Back to normal', where no long-term travel behavior changes post-COVID-19 are expected. This reference scenario is used to relate changes as observed within the other scenarios.

2. Scenario 2: 'Minor changes', where a slight shift from onsite to online work-related activities and a slight modal shift towards cycling are expected. Analysis of this scenario within the VMA travel model results in a -4,0% reduction of total trips within the city of Amsterdam. Trips within the morning and evening rush hour within Amsterdam are reduced by -2,5% and -1,5% respectively, while trips during the rest-of-day increase by 0,9%. A modal shift is observed within Amsterdam with an increase of +5,9% cycling, primarily at the expense of public transport which share is reduced by -9,4%.

3. Scenario 3: 'Working from home is here to stay', featuring a medium shift from onsite to online work-related activities and no modal shift. Analysis of this scenario within the VMA travel model results in a -8,2% reduction of total trips within the city of Amsterdam. Trips within the morning and evening rush hour within Amsterdam are reduced by -5,5% and -3,2% respectively, while trips during the rest-of-day increase by 1,9%. A modal shift is

observed within Amsterdam with an increase of +1,5% in the share of cars and +5,4% in the share of walking, primarily at the expense of public transport which share is reduced by -4,2%.

4. Scenario 4: 'The cyclist paradise', featuring a large shift from onsite to online work-related activities and a strong modal shift towards cycling. Analysis of this scenario within the VMA travel model results in a -9,3% reduction of total trips within the city of Amsterdam. Trips within the morning and evening rush hour within Amsterdam are reduced by -6,1% and -3,7% respectively, while trips during the rest-of-day increase by 2,1%. A modal shift is observed within Amsterdam with an increase of +8,3% cycling, primarily at the expense of public transport which share is reduced by -17,3%.

Based on the results of the four post-COVID-19 travel behavior as calculated within the VMA travel model, it can be concluded that the reduced work-related activities and its consequential changes to work-related travel patterns: (1) strongly alleviates congestion rates during the morning and evening rush hours, (2) decreases travel time from the city center of Amsterdam to certain zones with 1 to 2 minutes per person per trip, and (3) provides arguments to allocate more public space towards cycling infrastructure, especially within the district of Nieuw West.

Chapter 8

Discussion

Chapter 8 provides a discussion by reflecting on the choice of Amsterdam as case study in section 8.1, the unique execution of the scenario planning process which includes the novel scenario switchboard in section 8.2. A reflection on the usefulness of exploratory scenarios when investigating future travel behavior is provided in section 8.3. Choices that directly influence the results of this thesis are addressed in section 8.4, and suggestions for future research are provided in section 8.5.

8.1 Choosing an atypical case study: the city of Amsterdam

This thesis explicitly addresses the potential implications of long-term travel behavior changes caused by the COVID-19 pandemic on accessibility and the allocation of public space within the city of Amsterdam. Amsterdam is by far a regular city given the high degree of bicycle ownership (the average number of bicycles per household was 1.98 in the year 2017 in Amsterdam, and growing), its relatively high share of cyclists within the modal split for trips within Amsterdam (35% in the year 2017) and unique cycling infrastructure (containing 736 km of isolated cycling paths (i.e. separated from other traffic) and 1,600 km of shared roads containing cycling paths.) (Gemeente Amsterdam, 2019). By assessing the potential implications of long-term travel behavior changes in the unique city of Amsterdam has two expected advantages. Firstly, given contemporary challenges such as congestion are predominantly present within urban areas and Amsterdam already faces high congestion rates, the city of Amsterdam could magnify any implications of long term travel behavior changes due to the COVID-19 pandemic within this regard (Brůhová Foltýnová et al., 2020; Gemeente Amsterdam, 2019). Secondly, given the high share of cyclists in Amsterdam and the projected modal shift towards active modes of transportation the city of Amsterdam could also magnify potential implications to this effect. As this research is a first exploration into the magnitude of long term travel behavior effects caused by the COVID-19 pandemic, the results from this atypical case study could also be useful to provide insights for more typical Dutch and European cities as this thesis does not aim to predict the future, but provides a reflection on the potential direction, magnitude and general implications of post-COVID-19 travel behavior. It could be that magnitude of these implications differ for more, or less urbanized areas, however, it is reasonable to believe that the general effects of the COVID-19 pandemic and policy measures on travel and activity patterns will be similar as these are delineated from (universally applicable) travel behavior change theories. Furthermore, this thesis specifically addresses the accessibility and the allocation of public space. However, many more effects could be analyzed such as environmental or safety implications. Due to time considerations, these effects are not taken into account in this research.

8.2 Unique execution of the scenario planning process including a novel scenario switchboard

As presented within chapter 2, section 2.4, the scenario planning process of this thesis consists of two general phases. Within the first phase, four mobility experts individually create a scenario matrix through conventional steps from the standard scenario planning approach, including (1) the identification of key factors and driving forces, (2) the identification of two critical driving forces by ranking these in a Wilson matrix on uncertainty and impact, and (3) constructing a two-by-two scenario matrix where each quadrant is used to formulate a potential storyline of the future (Dean, 2019; Pillkahn, 2008). The unconventional part of the approach within this thesis is that these expert workshops are not carried out in one or multiple shared expert workshops but in individual workshops. The effect of this step (which was at the time practically made due to the difficulty to plan a grouped meeting, hence, time limitations) was that four different scenario matrices were constructed, each containing four storylines on post-COVID-19 travel behavior. Given the optimal number of scenarios is around 3 to 5, this created the necessity to reduce this number of potential post-COVID-19 travel behavior scenarios down to four (Stojanović et al., 2014). Usually, when there are more than two uncertain factors, a morphological chart can be used to create different scenarios (Pillkahn, 2008). A morphological chart in this case would show the critical driving forces and all possible future states. However, as the scenario matrices (i.e. post-COVID-19 storylines) created by the mobility experts already included the critical driving forces of post-COVID-19 travel behavior and in this way already suggest a preset for these critical driving forces the 'design space' for the scenarios was more limited than what a morphological chart would present. Based on the general concept of the morphological chart a novel scenario switchboard is created with sliders with just two variations per element (i.e. either a neutral or alternate position). Based on travel behavior change theories these elements, such as travelers' attitudes towards active modes, arguably know two directions; either an increase of attitudes towards active modes or a decrease of attitudes towards active modes. The scenario switchboard however just includes a neutral and a positive (i.e. increasing attitudes) direction. These positions are shaped by the scenario matrices as individually created by the four mobility experts. It could be that, with a different set of experts, other ranges or even other critical driving forces would be identified which in turn shape the storylines, hence, the post-COVID-19 travel behavior scenarios and their results. The design of the scenario switchboard as a tool can include as many critical driving forces as needed. Moreover, if needed the scenario switchboard can include a negative, neutral and positive position where the neutral position would be drawn in the middle of the slider. This enables the scenario switchboard to be a high flexibility tool when constructing scenarios that include more than two critical driving forces or when these driving forces know extensive ranges. The major challenge when using the scenario switchboard would be to assign the slider positions within a scenario. This can be arbitrarily chosen or, like in this research, be shaped by individual scenario matrices as created within expert workshops. To superimpose different scenario matrices to set the position of particular sliders there need to be similarities between these scenario matrices. If there are none, these scenario matrices could not be superimposed which will result in more sliders (and even more uncertainty in how to position them). It would be preferable to have a more standardized and robust approach to superimpose different scenario matrices, even when no similarities would occur. More suggestions for future research are described in section 8.2.

8.3 The usefulness of exploratory scenarios when investigating future travel behavior

Even though the future cannot be predicted, scenario planning enables to systematically think about alternative future states of a system and its components. Travel behavior can be arguably considered a variable component within the transportation system. Even though travel behavior change theories extensively conceptualize the different aspects of travel behavior and their direct and indirect influential factors the high uncertainty and disruptive influence of the COVID-19 pandemic on future travel behavior makes it arguably unfeasible to create predictive scenarios; the uncertainty is simply too big. This means that exploratory and anticipatory (i.e. normative) scenarios are arguably most applicable when addressing future travel behavior. Anticipatory scenarios would provide valuable insights when assessing post-COVID-19 travel behavior, especially given the projection by Hattrup-Silberberg et al. (2020) and Van Audenhove et al. (2020) that the pandemic provides opportunities for policymakers to shape mobility's future. This means that, with anticipatory scenarios, valuable insights could be created for policymakers on how to shape the desired mobility's future. However, given no substantiated post-COVID-19 travel behavior scenarios were present within scientific literature it is hard to create anticipatory scenarios when it is unknown what to expect, hence, on what to anticipate as a policymaker and which policy levers to pull to shape the desired mobility's future. The construction of exploratory scenarios, therefore, is arguably the only logical first step when facing such high uncertainty as this provides critical insights into what to expect and to which magnitude of change potential parts of the system are confronted. The rich scenario planning literature allows for highly flexible approaches when creating explorative scenarios and, as shown by the results from this thesis, are well applicable to explore high uncertain future developments of travel behavior.

8.4 Choices that directly influence the results of this thesis

The exploratory scenario approach as used in this thesis includes some choices that are very influential to the outcomes. First of all, the use of the projection of the transportation system of Amsterdam in the year 2030, which was already present within the VMA travel model, is the most influential choice that shapes the outcome of this research as all other scenarios as calculated within the VMA travel model are variants to this 2030 projection. This means that the modeling choices of Van den Elshout et al. (2020) in the creation of the VMA travel model and the 2030 projection directly influence the results produced by the model.

Secondly, by only accounting for the direct effects of the COVID-19 pandemic and policy measures on travel and activity patterns many indirect effects are out of scope. As described within chapter 3, section 3.4, many indirect effects could be expected due to the COVID-19 pandemic and policy measures.

Thirdly, by only accounting for a shift from onsite to online work-related activities this simplifies reality as also other travel motives could be influential. For example, it is reasonable to assume that digital education could provide a shift from onsite to online educational-related activities and travel patterns, e-commerce could provide a shift from onsite to online shopping-related activities and travel patterns, biological gadgets such as a smartwatch could provide a shift from onsite to online health-related activities and digital social events could provide a shift from onsite to online leisure-related activities.

Fourth, by only accounting for a modal shift towards cycling, this deviates from expert expectations about future travel behavior and observations made during the COVID-19 pandemic. These indicate a modal shift towards active modes, which include both cycling and walking. As delineated within chapter 5, section 5.1, the way utility is calculated within the VMA travel model, in combination with time considerations, did not allow to match the modal split with the, to be expected, shares of walking. Instead, a modal shift from walking towards cycling occurs, which arguably would not happen as a result of the COVID-19 pandemic. Moreover, scenario 3; 'working from home is here to stay' does not include parameter changes that force a modal shift towards cycling, and as the results show this provides a very different modal split with increased car use and increase walking. This shows that the inclusion of parameters within each scenario highly influences the outcome.

Finally, observations during the COVID-19 pandemic (as shown in appendix 3 and appendix 7) show that public transportation is almost entirely avoided by travelers. This is not incorporated within the scenarios as it is assumed that this is merely the result of the fear of contamination, which will arguably not play a role when the COVID-19 pandemic is over. It is however interesting to see that, no matter which scenario, public transportation always loses share in the modal split. This could be a signal for policymakers and public transportation operators to research the potential implication to public transportation services or the cost- and benefit ratio of public transport (infrastructure) projects.

8.5 Suggestions for future research

Future research that could be done fairly easily and quickly are further explorations of post-COVID-19 travel behavior implications within the VMA travel model. As is, included with the post-COVID-19 travel behavior scenarios as created within this research, the model allows to:

1. Explore potential implications on a wider scale (e.g. between Dutch cities) by setting the research area to a wider network or zones within the model;

2. Explore potential implications on a smaller scale (e.g. within a specific district in Amsterdam) by adjusting the selected research area to be only the district or an even smaller selection of zones;

3. Explore other implications besides congestion, travel time savings, and modal shift such as environmental implications, or assess the implications on accessibility and the allocation of public space by using different indicators. For accessibility this could for example be travel costs, while the allocation of public space could be explored by locating parts of the network where the intensity of one mode (e.g. bicycles) increases while

another (e.g. cars) decreases; this would indicate that part of the network could be allocated differently;

4. Experiment with (a combination of) different parameter and associated values to see how this would influence the results;

Future research that is not to be considered 'low hanging fruit' but could be very interesting is listed in the following suggestions:

1. It could be interesting to perform identical research with a different set of mobility experts, or with a different (type of) city and compare the results with this thesis;

2. This research provides examples of potential indirect effects that may be expected post-COVID-19 within chapter 3, section 3.4. It would be interesting to explore these potential indirect effects of the COVID-19 pandemic on activity and travel patterns by continuing on the theoretical framework as presented in figure 12 and include them in the post-COVID-19 scenarios.

3. As described in section 8.4, this research addresses work-related activity pattern changes while there are many more motives that might change due to the COVID-19 pandemic. It would be interesting to investigate these potential long-term travel behavior effects for different activities and add them to the post-COVID-19 scenarios within the VMA travel model to investigate its influence on the results of this thesis.

4. As described within section 8.3, a decision within this research was to model a modal shift towards cycling without correcting for the share of pedestrians in the modal split. It would be interesting to see if any corrections to the share of pedestrians in the modal split would change the results.

5. As the VMA travel model does not include capacity for cycling paths it could be very interesting to see if the increased number of cyclists as projected within scenario 2; 'minor changes' also cause capacity problems within the cycling infrastructure of Amsterdam. Results could provide an argument to either allocate more space to cyclists or not if there are no issues with capacity.

6. When creating scenarios with the novel scenario switchboard, presented within this research as a methodological tool for the creation of scenarios, it can be challenging to combine (i.e. superimpose) individually created scenario matrices into equivalent and consistent scenarios. Even though this could be easily overcome by arranging a grouped expert workshop instead of individual workshops, it could be interesting to improve on this tool as it provides an alternative that overcomes planning issues given individual workshops are much easier to plan as it only involves one (or two) agendas. The scenario switchboard could be improved by the creation of a more standardized and robust approach when superimposing different individually created scenario matrices.

Appendix 1: Calculating stringency indices for activity and travel limitations

The policy measures as displayed within appendix 2 figure 50, are calculated with the equation displayed below, "where k is the number of component indicators in an index and Ij is the sub-index score for an individual indicator" Roser et al. (2020). The sub-index scores are displayed within table 20.

$$index = \frac{1}{k}\sum_{j=1}^{k} I_j \tag{A1}$$

Table 19: Overview of stringency indices and indicator composition.

Index name	k	C1	C2	C3	C4	C5	C6	C7	C8
Activity limitation	5	x	x	x	x		x		
Travel limitation	3					x		x	x

Table 20: Overview of indicators used to construct stringency indices Roser et al. (2020).

Indicator	Max. value (N_j)	Name	Possible values
C1	3 (0, 1, 2, 3)	School closure	0 - no measures 1 - recommend closing 2 - require closing 3 - require closing all levels
C2	3 (0, 1, 2, 3)	Workplace closure	0 - no measures 1 - recommend closing 2 - require closing 3 - require closing all levels
C3	2 (0, 1, 2)	Cancellation of public events	0 - no measures 1 - recommend cancelling 2 - require cancelling
C4	4 (0, 1, 2, 3, 4)	Restrictions on public gatherings	0 - no restrictions 1 - restrictions on very large gatherings (>1000 people) 2 - restrictions on gatherings between 101-1000 people 3 - restrictions on gatherings between 11-100 people 4 - restrictions on gatherings between 10 or less
C5	2 (0, 1, 2)	Public transport closure	0 - no measures 1 - recommend closing (or significantly reduce volume) 2 - require closing (or prohibit most citizens using it)
C6	3 (0, 1, 2, 3)	Stay-at-home restrictions	0 - no measures 1 - recommend not leaving house 2 - require not leaving house with exceptions 3 - require not leaving house with minimal exceptions
C7	2 (0, 1, 2)	Internal movement restrictions	0 - no measures 1 - recommend not to travel between regions/cities 2 - internal movement restrictions in place
C8	4 (0, 1, 2, 3, 4)	International travel controls	0 - no restrictions 1 - screening arrivals 2 -quarantine arrivals from some or all nations 3 - ban arrivals from some regions 4 - ban on all regions or total border closure

As the data retrieved from Roser et al. (2020) contains day-to-day values, the resulting stringency indicis are translated into a weekly average.

Appendix 2: Course of the COVID-19 pandemic and related policy measures within the Netherlands

The first COVID-19 case within the Netherlands is reported on February 27th 2020, the Dutch government responded with an 'intelligent' lockdown from the 12th of March until the 10th of May 2020 (i.e. weeks 11 to 19) (Rijksoverheid, 2020d, 2020a). From the 14th of October 2020 (i.e. week 41) a 'partially lockdown' was initiated which transformed into a 'hard lockdown' from the 15th of December 2020 (i.e. week 50) (Nu.nl, 2020; Rijksoverheid, 2020b). During the three different types of lockdowns, only the 'hard lockdown' enforced an evening curfew, preventing people from leaving their homes from 9:00 pm until 4:30 am (Rijksoverheid, 2021).

COVID-19 policy measures aim to limit the movement of people, which consequently impacts the field of urban mobility and travel behavior. Even though the fear of contamination most likely plays a dominant role in travel behavior during the pandemic, analyzing moments where COVID-19 policy measures are lifted could indicate to what extent travel behavior will return to the mobility patterns before the COVID-19 pandemic. Especially the moment between the intelligent and partial lockdown (i.e. between week 19 and 42) provides a window without any lockdown policies and arguably low fear of contamination given the relatively low number of new confirmed COVID-19 cases as displayed within figure 49. The period between the intelligent and partial lockdown (i.e. week 19 to 42) will be referred to as the 'societal restart'.

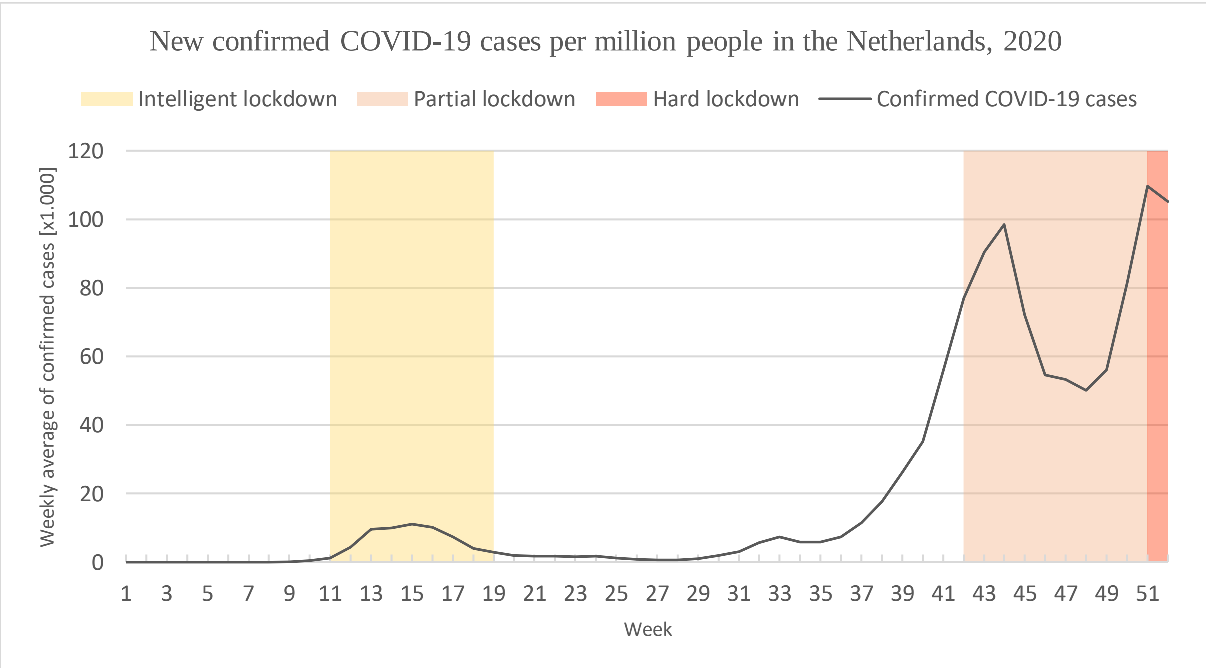


Fig. 49: Weekly average of new confirmed COVID-19 cases per million people and lockdown variants, COVID-19 data retrieved from Roser et al. (2020).

To identify a moment when COVID-19 policy measures were maximally eased, the policy measures are translated to two stringency indices using a similar methodology as proposed by Roser et al. (2020). The equations and indices used are clarified within appendix 1. The different policy measures have been categorized into activity limitations (i.e. closure of schools and workplaces, cancellation of public events, restrictions on public gatherings, and stay-at-home restrictions) and travel limitations (i.e. public transport closure, internal movement restrictions, and international travel controls). Other policy measures such as public information campaigns, testing, tracking, vaccination, and financial policy (e.g. income support and debt relief) are not taken into account as these are out of the scope of this research.

Even though the recommendation of face coverings could potentially influence travel behavior choices, these policy measure is not taken into account as the policy did not fluctuate for the duration of the pandemic; it just moved from the category 'no policy' to 'required in some public spaces' from June 1st 2019 (Roser et al., 2020).

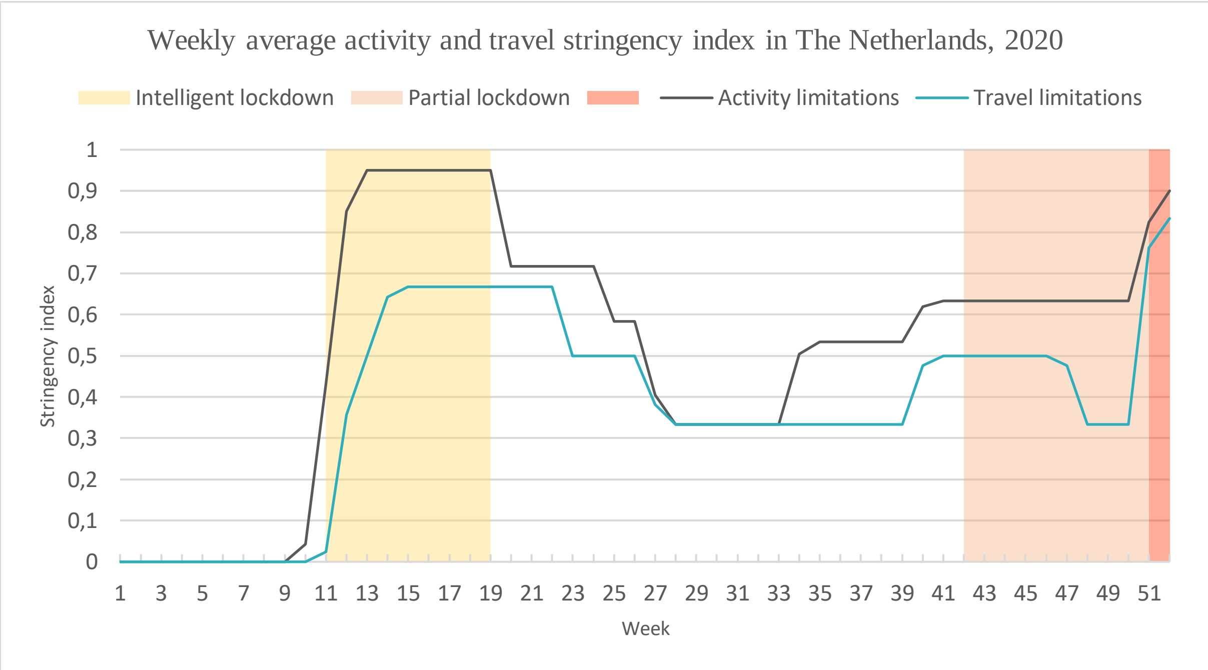


Fig. 50: Weekly average activity and travel stringency index in The Netherlands, data retrieved from Roser et al. (2020).

Based on the stringency indices depicted in figure 50, it can be determined that the policy measures started to ease from week 19 and were maximally eased between weeks 28 and 33. This timeframe will be particularly used to analyze to what extent society bounced back to travel patterns as they were before the COVID-19 pandemic.

Appendix 3: Trip changes as observed during the COVID-19 pandemic

Due to the COVID-19 pandemic and associated policy measures the number of trips within Dutch cities, such as Amsterdam, experienced a rapid decline during the intelligent lockdown. As shown in figure 51, during the societal restart phase the average number of trips increased, but remains throughout 2020 below pre-pandemic patterns as indicated with the baseline. When policy measures where maximally eased (i.e. between week 28 and 33) on average -11,5% fewer trips where made compared to pre-COVID-19. Ranging from -9% to -15% less trips within week 29 and 33 respectively.

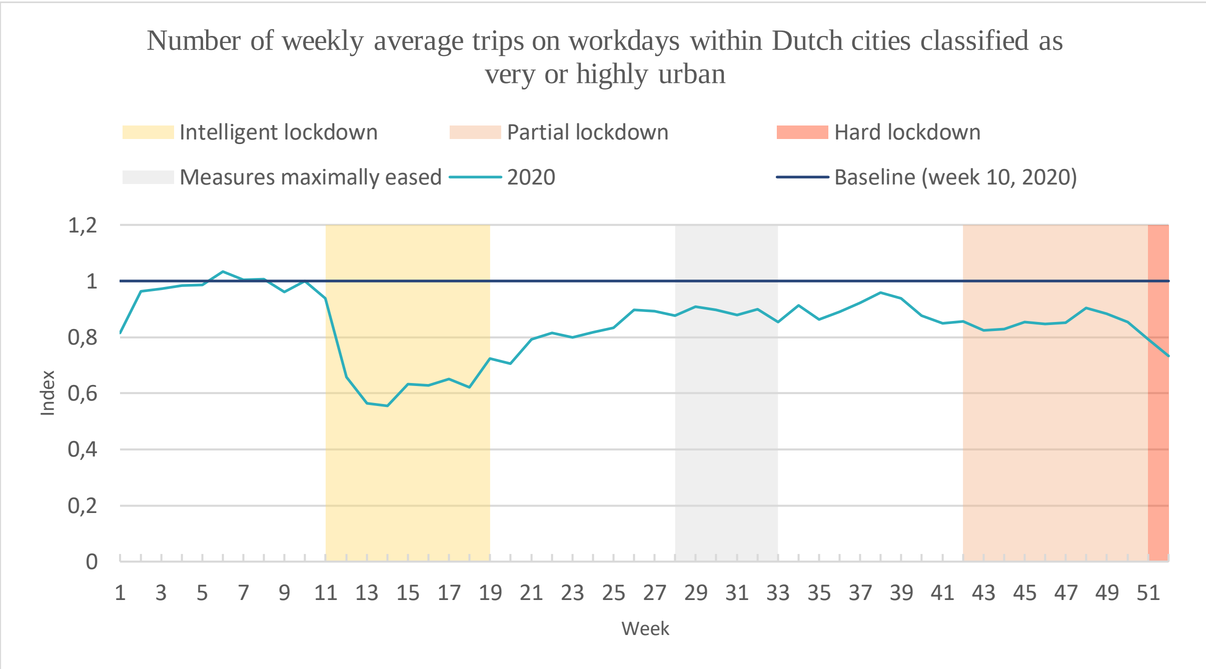


Fig. 51: Change of trips within Dutch cities during the year 2020. Data retrieved from (NVP) Dat.mobility (2021).

When this decrease in trips is set out in trips by mode, it is notable that especially trips with public transportation are hit hard by the pandemic. Where every mode of transportation tends to recover towards its pre-pandemic level, trips by public transportation stay persistently low. On average -0,6% fewer trips by car, -65,5% fewer trips by public transportation, -2,0% fewer trips by bicycle, and -8,8% fewer walking trips were made when policy measures were maximally eased compared to pre-pandemic.

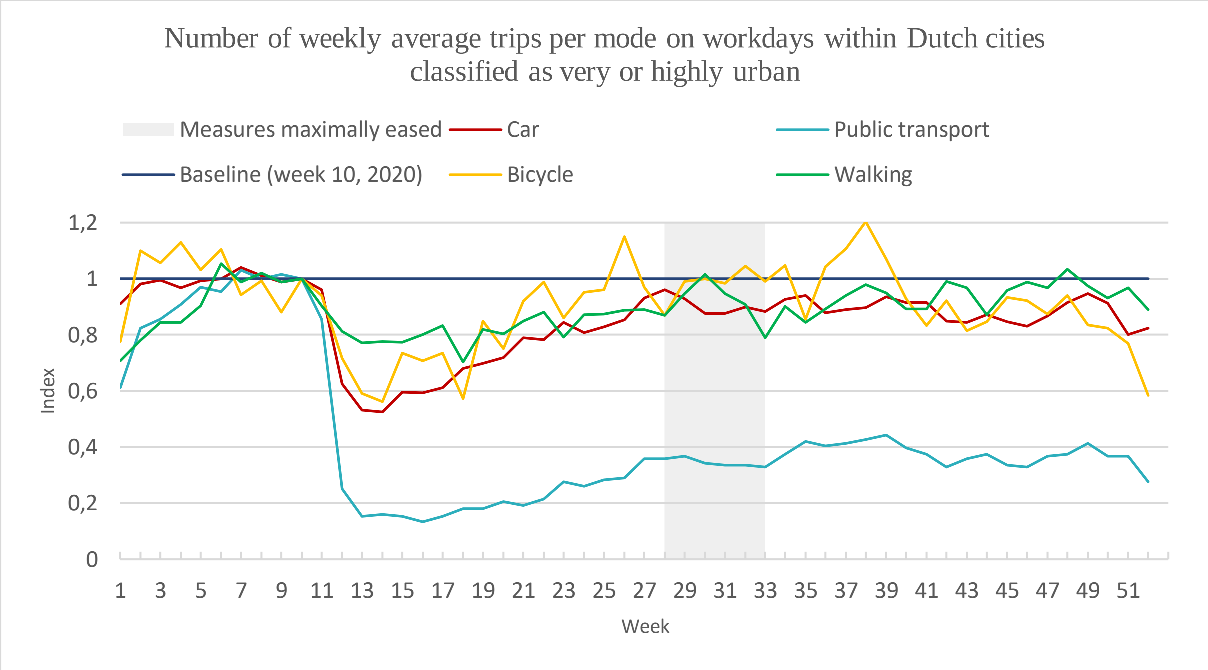


Fig. 52: Change of trips per mode within Dutch cities during the year 2020. Data retrieved from NVP Dat.mobility (2021).

Appendix 4: Activity changes as observed during the COVID-19 pandemic

Both from a trip- as an activity-based modeling approach, activities form the basis for travel movements (Castiglione et al., 2014). When comparing trips to the office and education institutes, as depicted in figure 53, it is noticeable that when COVID-19 policy measures are eased the number of trips to education institutes recovers towards a pre-pandemic level. The decline in trips towards educational institutes between weeks 27 and 37 can be explained by the summer break. In contrast to the recovering trend of trips to educational institutions, trips to the office are persistently low. On average, trips to the office are down by -38% within the societal restart between week 19 and 42, ranging from a minimum change of -29% within week 39 to a maximum change of -48% within week 19. When COVID-19 policy measures were maximally eased (i.e. between week 28 and 33) and most likely influenced by the summer break, on average -42% fewer trips were made to the office, ranging from -34% to -46% fewer trips.

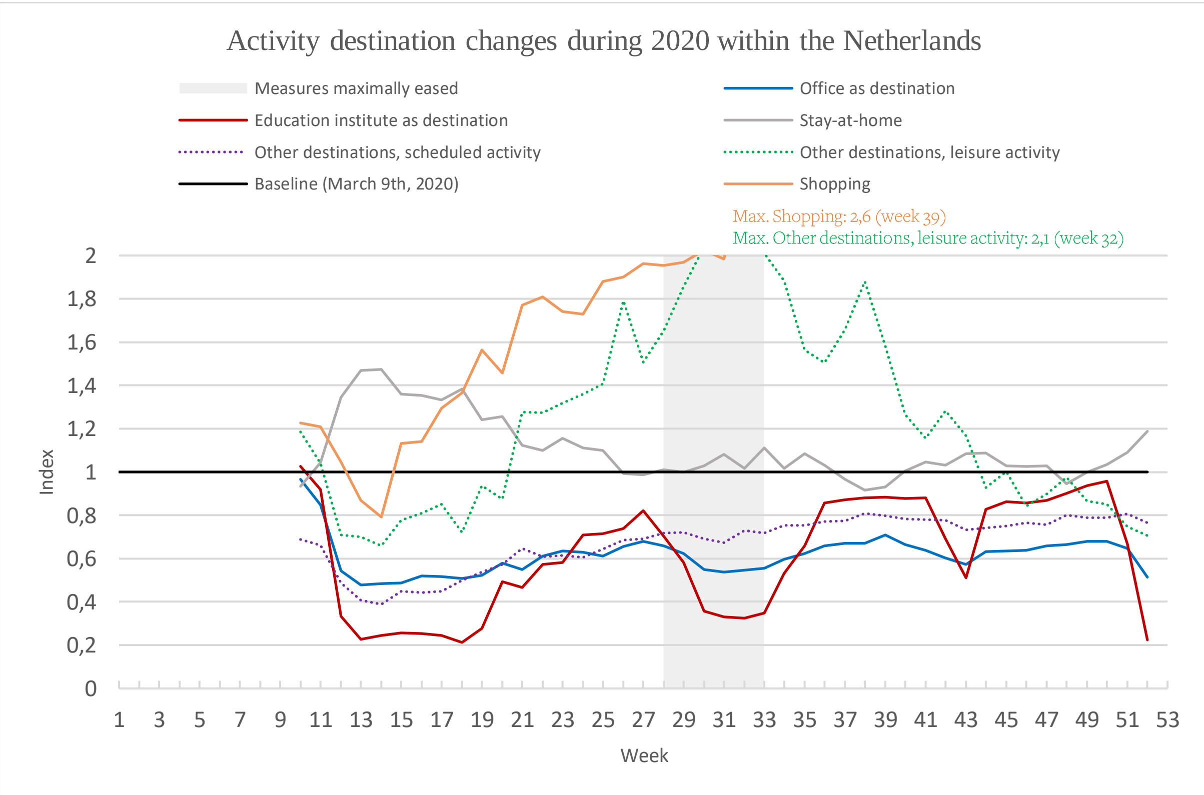


Fig. 53: Change of trip destination within the Netherlands during the year 2020. Data retrieved from NVP Dat.mobility (2021).

Also trips to scheduled activity destinations (i.e. visiting a supermarket or healthcare) shows to slightly recover towards the baseline value. Trips to leisure activity destinations (i.e. taking a stroll, visiting a café, restaurant, sports facility, hotel, camping, nature or amusement park) doubled when COVID-19 policy measures were maximally eased as did trips to shopping destinations. However, if these trends within leisure activities are unusual is unknown given the baseline of 9 March 2020. In other words, although unknown, these trends could be explained by weather influences.

The trends as displayed within figure 53 might indicate that during the beginning of the pandemic, activities were replaced by staying home. Soon after the initial intelligent lockdown, fewer and fewer people stayed home and went on trips again. Given the high number of people working-, studying- and doing groceries online it may be that the reduced time otherwise spend on commuting, is spend on shopping and other leisure activities.

Research of De Haas et al. (2020) indicates that a large group of people (45%) expect to work from home more, the majority (60%) of which expects to work from home for two or three days in the week when the COVID-19 pandemic is over and a small group (10%) expects to work from home more than 25 hours a week. Given these projections a reduced demand may be most expected for work related activities. Studying-from-home on the other hand, will be less likely to persist on the long-term as scholars and students have significantly less positive experiences with virtual (i.e. online) education (De Haas et al., 2020).

Appendix 5: The respacing of trip patterns as observed during the COVID-19 pandemic

To assess the respacing of trip patterns during the COVID-19 pandemic, the change within travel distance during the COVID-19 pandemic is analyzed. Notably, long-distance travel (i.e. ≥50km) is particularly influenced due to the COVID-19 pandemic, but recovers when policy measures are relaxed, suggesting a potential correlation with the policy measures. As the depicted change in figure 54 is relative to the baseline value (i.e. week 10) it is unknown if and to what extent the observed changes of travel distances are truly different, it might be for example that it is very usual to have more long distanced trips (i.e. ≥50km) during the holiday period.

As all depicted travel distances tend to recover to their baseline value when policy measures are eased (i.e. weeks 28 to 33) the expectation of respacing of trip patterns in terms of travel distances becomes questionable. On the other hand, this does not refute the argument that increased flexibility might lead to longer travel distances as delineated within chapter 3, but observations during the COVID-19 pandemic do not provide enough insight into the magnitude of potential respacing of trip patterns post-COVID-19.

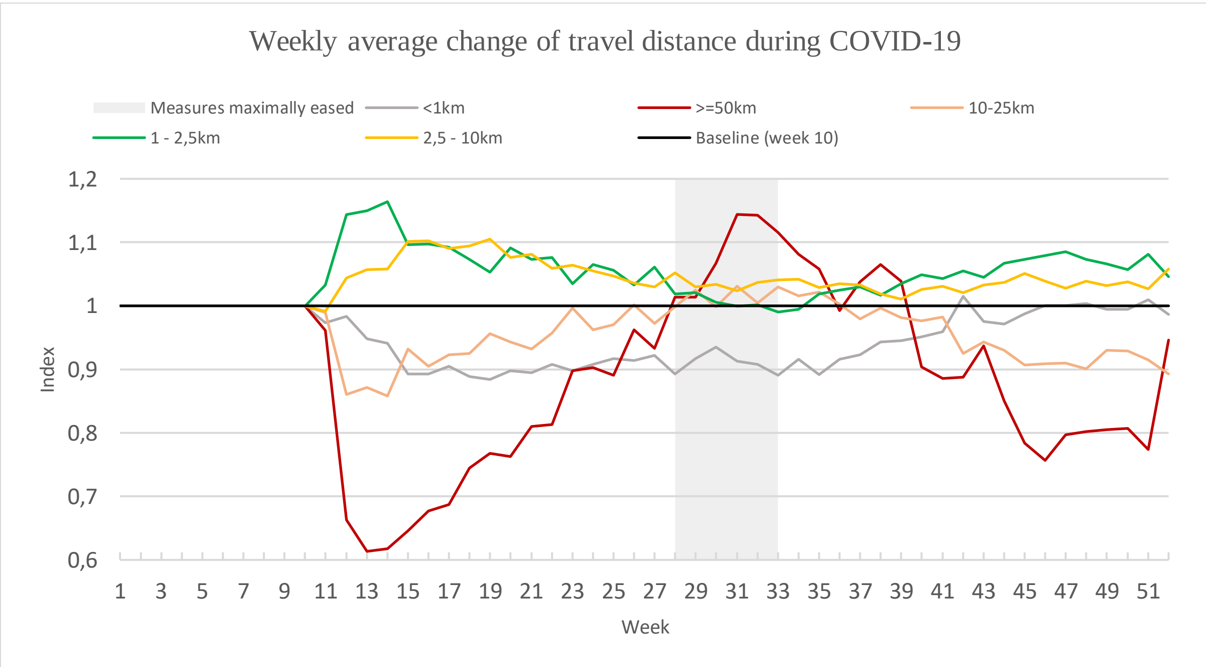


Fig. 54: Change of trip distances within the Netherlands during the year 2020. Data retrieved from NVP Dat.mobility (2021).

Appendix 6: The retiming of trip patterns as observed during the COVID-19 pandemic

When analyzing the retiming of trip patterns as depicted within figure 55, it becomes apparent that the morning and evening rush hour, respectively from 7:00 to 9:00 am and 4:00 to 6:00 pm, for both car and public transportation are nearly rendered unrecognizable when comparing the intelligent lockdown (i.e. week 12) to regular traffic pre-pandemic (i.e. week 9). Interestingly, based on this comparison pedestrians (i.e. walking) show to increase in representation both on workdays and during the weekend, where all other modes show a decrease in use.

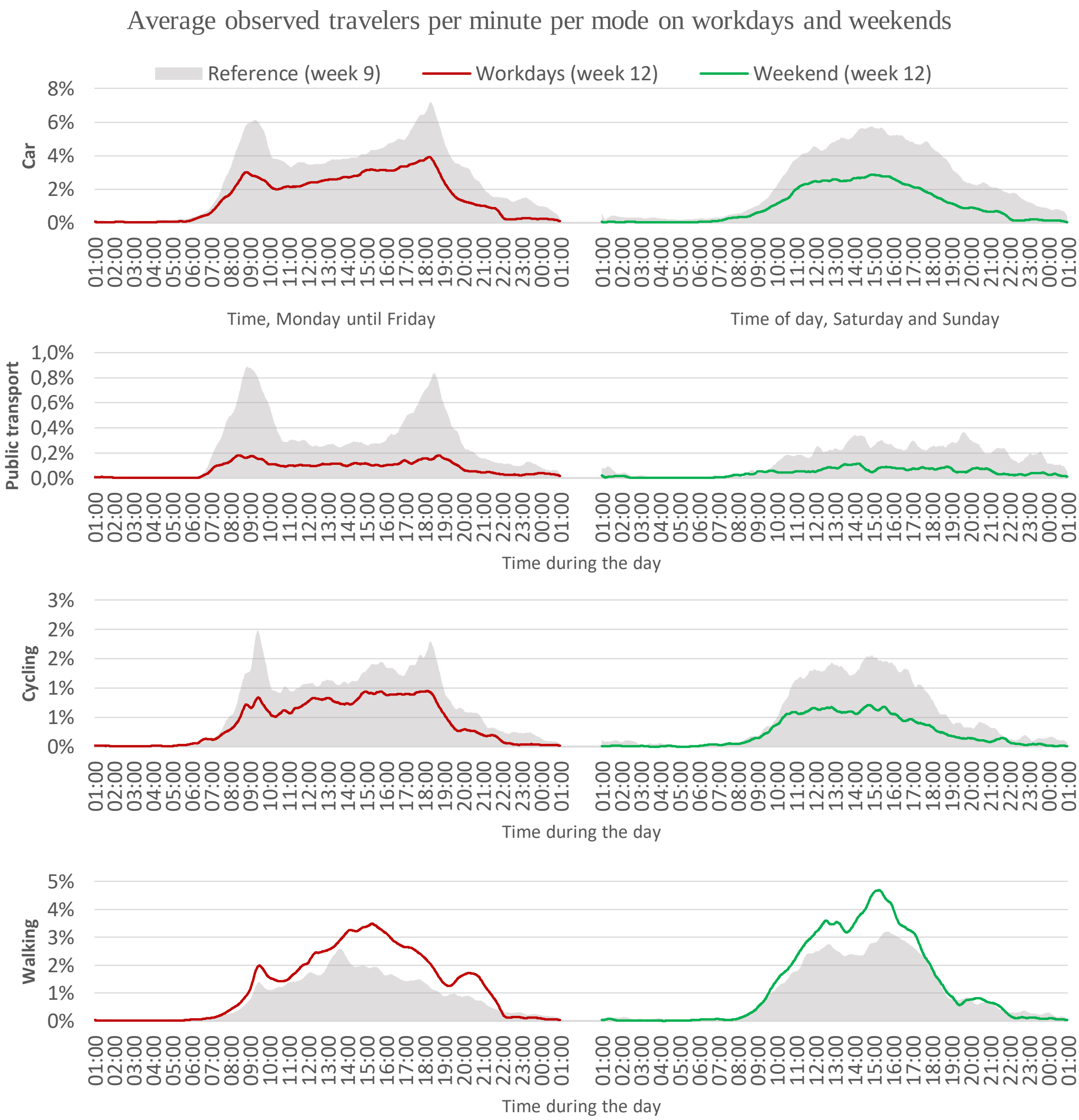


Fig. 55: Retiming of trips per mode on workdays and the weekend in the Netherlands during week 12 of the year 2020. Data retrieved from NVP Dat.mobility (2021).

Figure 56 shows the progression of change in the observed number of traveling panelists during the morning and evening rush hours. It becomes clear that even when both the morning and evening rush hours stay below the baseline value with respectively -37% and -13% on average when policy measures were maximally eased. As the number of traveling panelists stays relatively consistently low during the pandemic this could indicate a lasting change, potentially as a result of the reduced visits to office locations as delineated within appendix 4.

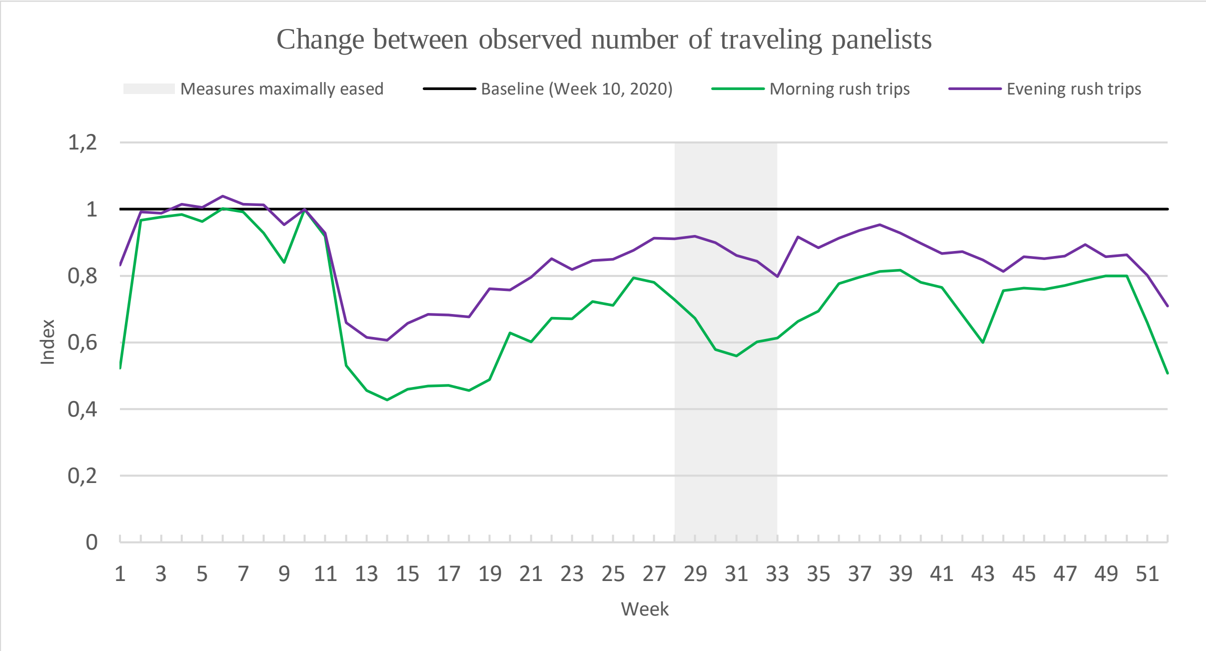


Fig. 56: Retiming of trips on workdays in the Netherlands within the year 2020. Data retrieved from NVP Dat.mobility (2021).

Appendix 7: A modal shift as observed during the COVID-19 pandemic

The change in mode shares is depicted in table 21.

Table 21: Modal shift as observed during the COVID-19 pandemic. Data retrieved from NVP Dat.mobility (2021).

Week	Car	PT	Bike	Walking
Week 10	55%	5%	23%	16%
Avg. weeks 28 to 33	54%	2%	27%	17%
Difference	-2%	-61%	+15%	+17%

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