# An activity-based modeling approach to assess the effects of activity-travel behavior changes and in-home activities on mobility:

## Estimations based on different stages of the COVID-19 pandemic in the Rotterdam-The Hague Metropolitan Area

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# An activity-based modeling approach to assess the effects of activity-travel behavior changes and in-home activities on mobility:

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by

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This thesis has been conducted in cooperation with TNO and Royal HaskoningDHV.

# PREFACE

This thesis is the last requirement to obtain my master's in Civil Engineering, Transport & Planning, at Delft University of Technology. It was produced between November 2020 and August 2021 in cooperation with the Netherlands Organisation for Applied Scientific Research (TNO) and Royal HaskoningDHV. During this period, I have dived into the application of activity-based modeling techniques to estimate, predict and analyze the impact of COVID-19 on mobility in the Netherlands.

Back in 2018 when I decided to come to the Netherlands from Brazil to pursue my master's degree, I tried to imagine what my life would be like after graduating. Obviously, at that time, I could not tell where my journey would end, but I knew where to start. The moment I was told that I had been selected for this degree, I remember stopping immediately what I was doing, going home, and celebrating the opportunity that life was giving me. I also remember being afraid of what was to come, as being invited to do a master's degree at one of the best civil engineering colleges in the world would not come without several challenges. More than once during this journey I felt those challenges spending long nights up finishing projects or very early Sunday mornings at the library studying for exams. I remember well the hard moments where I wondered if I was capable of going through all that. And, today, while writing the preface of my master's thesis report, I can say that those thoughts are behind me. I am proud that with a lot of dedication, discipline, and willpower, I have completed the biggest challenge of my life so far.

First, I want to express my gratitude to the members of my graduation committee. To Gonçalo Correia, for his constructive feedback, and for caring about me during the toughest times. I am honored to be the first TU Delft student you chaired. To Maaike Snelder, for providing me the opportunity to work at TNO and guiding me through this research. To Erik de Romph, for giving me the pleasure to learn from him during one and a half years through my internship and thesis project at Royal HaskoningDHV. To Henk Taale, for shedding a light during my report writing. I am delighted to have worked with you all.

Next, I want to acknowledge those who voluntarily helped me through my thesis. To my TNO colleagues Bachtijar Ashari and Reinier Sterkenburg, for their support with my most varied needs throughout this period. To my research partner Leonard Oirbans, for sharing the good and bad moments of our work and being there to support each other whenever needed. To my housemates Alexander and Pratyush, for their patience and guidance with Python programming. Your technical support and encouragement were fundamental along with this research.

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Lastly, but most importantly, I want to thank my family, especially my father José Vinicius, for giving me all the support I needed to come to the Netherlands and complete this master's degree. Dad, this degree is also yours. I love you so much!

*Vinicius Aronna Cruz*
*Delft, August 2021*

# SUMMARY

## Introduction and research approach

The outbreak of the COVID-19 pandemic and the resulting corona crisis has had a profound impact on mobility in the Netherlands and in the entire world. The measures authorities implemented against the virus since March 2020 significantly disrupted activity-travel behavior. Companies have been advised to let their employees work from home (WFH) as much as possible. Education has been held online as much as it is feasible. Sectors such as retail and horeca have been constantly changing their opening times and even providing online and delivery services to halt the spread of the virus. However, sectors considered essential cannot let their workforce out of their workplaces, for example the food and healthcare sectors. Consequently, different sectors take different measures, and a radical change in mobility patterns has been observed.

The changes in activity decisions (e.g., activity type, duration), travel decisions (e.g., mode, accompanying persons), and interacting activity/travel decisions (e.g., departure time, activity start time, location) due to the COVID-19 pandemic can significantly change the way the mobility system works. Therefore, it is essential to review policies related to the pandemic and mobility. Those policies must ensure smooth traffic flow between regions, low congestion levels within cities, proper modal usage, and, most importantly, safety against the spread of the virus. To make appropriate adjustments in policies, the expected effects in the system should be investigated and their processes understood. Travel demand models can be useful tools for estimating, exploring, and understanding these effects.

This research focuses on predicting, modeling, and analyzing changes in the activity-travel behavior of individuals in the Rotterdam-The Hague Metropolitan Area (MRDH in Dutch), the Netherlands, during the COVID-19 pandemic and assess their effects on mobility.

Nowadays, transport policy questions have become more complex and require a wider range of responses with higher levels of detail (Castiglione et al., 2014). For that reason, activity-based models (ABMs), which are the last generation and most sophisticated travel demand models, have become more widely used in practice because they work at a disaggregate person-level rather than a more aggregate zone-level such as the trip-based models. In this study, it is decided to use the activity-based modeling approach to investigate the effects of changes in activity-travel behavior on mobility. That said, the primary question to be answered by this research is the following:

*What are the effects of the changes in activity-travel behavior during events such as COVID-19 on mobility in the Rotterdam-The Hague Metropolitan Area, the Netherlands, and how can these effects be estimated, predicted, and analyzed through activity-based modeling?*

The first step in answering this question is to conduct a literature review on the topic to identify the activity-travel behavior changes that may be expected due to the COVID-19 pandemic. From this review, three major impacts of COVID-19 on activity-travel behavior are pointed out: (1) a shift from onsite to online activities, (2) re-spacing and re-timing of travel patterns, and (3) a modal shift towards the car and active modes. Second, research is done to learn and investigate how ABMs can be used (and improved) to better explain changes in activity-travel behavior in events such as the COVID-19 pandemic. From this review, it is concluded that the main improvements in ABMs should be: (1) the incorporation of in-home activity planning and (2) the collection and usage of more detailed data about planning and scheduling of in-home activities and out-home activity frequency.

The next step in this research is the development of an activity-based modeling framework that is capable of incorporating the abovementioned improvements. This framework is developed following the principles of FEATHERS, a travel demand ABM developed by Bellemans & Kochan (2016). The main goal of this framework is to provide objective assessments of changes in activity-travel behavior during emergency situations by simulating what-if scenarios that make predictions in terms of journeys and mobility density, given certain assumptions about aspects that play a role in such emergency situations. In this study, however, the framework is used to simulate stages of the COVID-19 pandemic that already happened. This is done to validate the framework's performance by comparing its outcomes with data counts and outcomes of other studies and sources.

It is important to state that the modeling framework developed in this study is not a full ABM. To be used, it requires some outputs of ABMs as inputs. For instance, it uses as a starting point the schedules generated by ABMs to estimate new schedules for the population by considering other types of data such as the weekly frequency at which agents perform different activities and modal shifts during emergency situations (e.g. during the COVID-19 pandemic).

## Model design

An overview of the modular structure of the modeling framework is presented in Figure S-1. In total, the model has four data inputs, named synthetic population, activity frequency values, modal shift values and baseline schedules. While the synthetic population and the baseline schedules are ready inputs that come from the outputs of existing ABMs, the activity frequency values and modal shift values are inputs containing activity-travel behavior data for the stages/scenarios in analysis.

To simulate the activity-travel behavior of agents, the model takes into account different sets of variables and attributes. For instance, each agent in the population can choose between a set of six activity types to perform and seven transport modes to travel. Thus, different background characteristics such as age, gender and level of education are used to estimate these decisions for different agent types. In this study, the work sector of the population is introduced, which was not used before by FEATHERS. The work sector attribute helps to estimate which agents would work on-site and which work from home.

The modeling framework is broken down into three steps, namely Activity module, Modal shift module and Schedules adjustment module. First, the Activity module calculates the number of agents that do out-home activities taking into account the activity and agent types. For example, for a certain population, it estimates how many people are going shopping and how many people are not. That is done for all the different combinations of activity and agent types. Second, the Modal shift module estimates how many trips are performed in a certain scenario taking into account the transport modes used to travel and a modal shift between these modes. Finally, the Schedules adjustment module re-estimates the daily schedules of the population based on the estimations of the two previous modules.

The outputs of the model are new schedules, which are the baseline schedules but with adjustments. They represent the daily activity-diary of the population considering new activity-travel behavior. From these new schedules, which represent different scenarios, indicators are generated to make comparisons between scenarios and the baseline scenario.

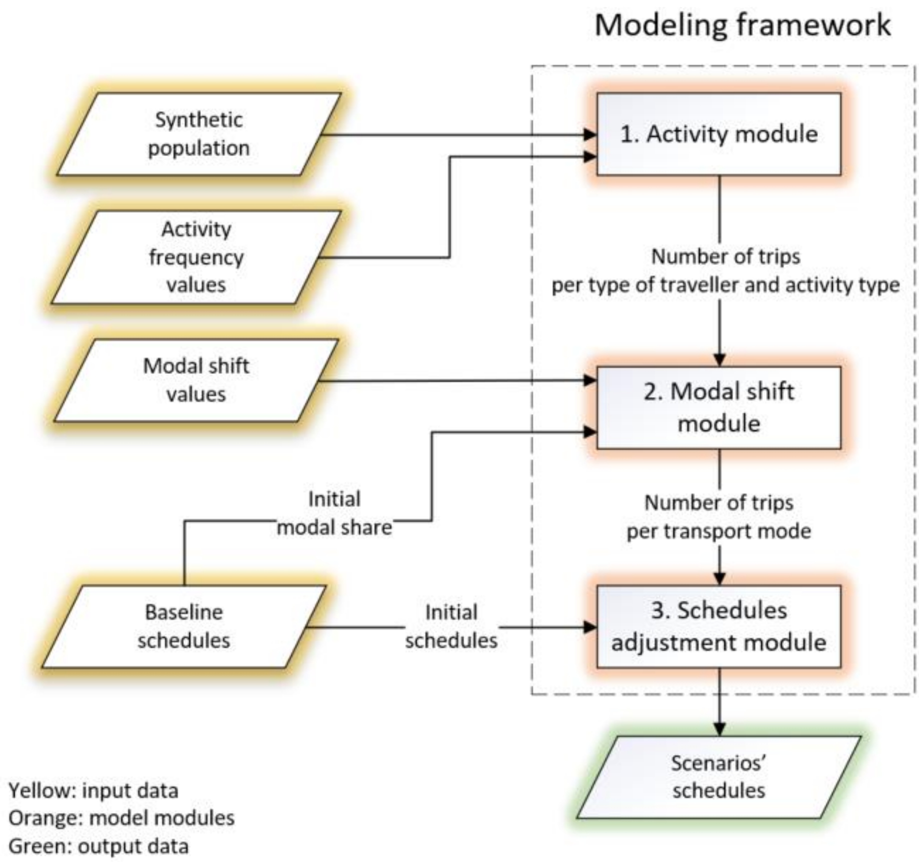


*Figure S-1 - Schematic overview of the modeling framework components, their functionalities, and their inputs*

## MRDH case study & results

The modeling framework is applied to a case study for the Rotterdam-The Hague Metropolitan Area (MRDH), the Netherlands. The motivation to use this region as a case study is because TNO, one of the companies collaborating with this work, has several ongoing projects in this region and the ABM FEATHERS was already used to estimate schedules for the MRDH population. The case study developed has as objective the estimation of changes in activity-travel behavior of travelers in the MRDH during different stages of the COVID-19 pandemic and the assessment of the effects of such changes on mobility.

In total, four stages of the COVID-19 pandemic are investigated and compared to a baseline stage, which is a period before the pandemic. These stages are presented in Table 1. The reason to select these stages is that they represent different moments of the COVID-19 pandemic and the strength of the measures applied against it, which are shown in Table 1.

*Table 1 - Stages of COVID-19 analyzed in the case study*

| Stage | Period | Description | Workplace closure measures* | School closure measures* | Stay-at-home restrictions* |
|---|---|---|---|---|---|
| **Baseline** | Sep-19 | Normal behavior | No measures | No measures | No measures |
| **1** | Mar-20 | Intelligent lockdown | Required for some | Required (all levels) | Required (except essentials) |
| **2** | Jul-20 | Summer Relaxations | Required for some | Recommended | Recommended |
| **3** | Oct-20 | Semi Lockdown | Required for some | Recommended | Recommended |
| **4** | Jan-21 | Strict lockdown | Required for all but key workers | Required (all levels) | Required (except essentials) |

*Source: COVID-19 Stringency Index in the Netherlands (Ritchie et al., 2021)

From the model outcomes, several insights about the impacts of COVID-19 on mobility in the MRDH are derived. The main insights of the case study are:

- During the pandemic, on average, there are 68% fewer tours compared to before the pandemic. The most affected age groups are elders (>65) and youngers (25-45).
- Home-Other-Home is the most frequent tour in the schedules, and walking/touring is the most preferred activity, especially during the lockdowns.
- A positive movement towards active modes is observed for all stages. On average, the share of walking increased 7.35% compared to before the pandemic.
- During the pandemic, more than half of the MRDH population is a fully home-stayer, which is six times more than before the pandemic.
- During the pandemic, on average, there are 58% fewer work trips compared to before the pandemic. In the strict lockdown (stage 4), there are 80% fewer work trips.
- The total commuting traveled distance decreased around 58%.
- Active commuting is more attractive than public transport or car. On average, its share increased more than 50% compared to before the pandemic.
- More than 60% of onsite workers worked from home. For essential sectors such as the healthcare sector, the number of on-site workers is the highest for all stages (between 74% and 99%) while for non-essential sectors such as the office sector the number of on-site workers is the lowest (between 2% and 35%).

## Conclusions

The findings of this research are used to answer the primary research question. First, the main factors that cause changes in activity-travel behavior were identified. These are the fear of infection and the policy measures regarding the closure of workplaces and schools, and stay-at-home restrictions. Second, the activity-travel behavior expected changes were identified. These are the shift from onsite to online activities, the re-spacing and re-timing of travel patterns, and the modal shift towards the car and active modes. Third, a literature review on activity-based modeling identified necessary improvements in ABMs to better model activity-travel behavior in emergency situations such as the COVID-19 pandemic. These are the incorporation of in-home activity planning and the collection and usage of more detailed data about planning and scheduling of in-home activities and out-home activity frequency.

One of the outcomes of this research is the development of an activity-based travel demand modeling framework which has been used in this study to analyze the effects of changes in activity-travel behavior on mobility in a case study for the MRDH in the Netherlands. The modeling framework provides an innovative approach to study the impacts of changes in activity-travel behavior caused by emergency situations such as the COVID-19 pandemic in a disaggregated manner. It combines the outputs of ABMs and a mix of aggregated and disaggregated data of changes in in-home and out-home activity frequencies and re-estimates the daily schedule of individuals considering factors and attributes that were not considered before, such as the weekly frequency at which agents do different activities and the sector where agents work.

With the outcomes of the case study simulations, insights about the effects on mobility were identified and compared to real data counts and results of other studies. The conclusion is that the vast majority of the model outcomes proved to be in line with the results of other sources.

From a theoretical point of view, the modulation of the modeling framework seems to be ideal, but the type of data needed is hard to obtain. Because of that, some of the input data used in the study case (e.g. modal shift values) are aggregated data, and this sometimes distorted the disaggregated outcomes. However, this imposed limited restrictions when simulating the different case study stages.

## Recommendations

Some key recommendations emerge from this research. Regarding the modeling framework and the data inputs, three main improvements are recommended. The first improvement is to enable increment the number of trips per schedule. As it is now, the model is limited to only remove trips from the baseline schedules. This limits the investigation of what-if and future scenarios, for which it is important to re-estimate the schedules of individuals' including the addition of new trips. The second improvement is to collect more data about in-home and activity frequency to better estimate changes in the daily schedule of agents. The third improvement is to collect more disaggregated data about modal shifts while considering different types of agents and the motive for traveling.

Concerning further research, it would be beneficial to assign the results of the case study to the V-MRDH 2.0 network. That linkage will enable to re-estimate individuals' routes based on feedback with network constraints, and will also generate more mobility indicators such as traffic flows and levels of congestion. Another recommendation is to use the framework to simulate what-if and future scenarios concerning the COVID-19 pandemic. For instance, the model can be used to predict mobility changes when a particular sector is fully opened/closed. To do that, one should run the model considering different sets of input assumptions such as the activity frequency and the modal shift values. Those inputs can be estimated using different sets of policy measures, for instance, using the COVID-19 stringency indexes which are estimated by Ritchie et al. (2021).

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# LIST OF ABBREVIATIONS

| Abbreviation | Reference |
|---|---|
| ABM | Activity-based model |
| CBS | Central Agency of Statistics, the Netherlands |
| COVID-19 | The novel coronavirus (SARS-CoV-2) |
| DAP | Day activity patterns |
| FEATHERS | Forecasting Evolutionary Activity-Travel of Household and their Environmental Repercussions |
| KIM | Knowledge Institute for Mobility Policy |
| KM | Kilometers |
| MRDH | Rotterdam-The Hague Metropolitan Area |
| NEA-COVID | National Survey on Working Conditions COVID-19 |
| NVP | Dutch movement panel |
| OxCGRT | Oxford Corona virus Government Response Tracker |
| PT | Public transport |
| SARS | Severe Acute Respiratory Syndrome |
| S0 | Baseline stage of the case study (Pre-pandemic period) |
| S1 | Stage 1 of the case study (Intelligent lockdown) |
| S2 | Stage 2 of the case study (Summer relaxations) |
| S3 | Stage 3 of the case study (Semi-lockdown) |
| S4 | Stage 4 of the case study (Strict lockdown) |
| TNO | Netherlands Organisation for Applied Scientific Research |
| TNO SUMS | TNO Sustainable Urban Mobility and Safety department |
| TNO W&HT | TNO Work & Health Technology department |
| ToD | Time-of-day |
| UTN | Urban Tools Next project |
| WFH | Work from home |

# 1. INTRODUCTION

## 1.1. MOTIVATION

The outbreak of the COVID-19 pandemic and the resulting corona crisis has had a profound impact on mobility in the Netherlands and in the entire world. The first measures authorities implemented against the virus around March 2020 and all those measures that followed significantly disrupted activity-travel behavior. Companies have been advised to let their employees work from home (WFH) as much as possible. Education has been being held online as much as is feasible. Sectors such as retail and horeca have been constantly changing their opening times and even providing online and delivery services to stop the spread of the virus. However, sectors considered essential cannot let their workforce out of their workplaces, for example the food and healthcare sectors. Consequently, different sectors take different measures, and a radical change in mobility patterns has been observed. This report focuses on predicting, modeling and analyzing changes in the activity-travel behavior of individuals in the Netherlands during different stages of the corona virus crisis and assess their effects on mobility.

The changes in activity decisions (e.g., activity type, duration), travel decisions (e.g., mode, accompanying persons), and interacting activity/travel decisions (e.g., departure time, activity start time, location) can change the way the mobility system works. Therefore, it is essential to review policies related to mobility. Those policies must ensure smooth traffic flow between regions, low congestion levels within cities, proper modal usage, and, most importantly, safety against the spread of the virus. To make appropriate adjustments in policies, the expected effects in the system should be investigated and their processes understood. Models can be useful tools for estimating, exploring, and understanding these effects.

Researchers worldwide have been using different types of models to analyze the impacts of COVID-19 on mobility. Epidemiological models have been used to investigate how the virus may spread in public transport systems (Krishnakumari & Cats, 2020). Metapopulation disease transmission models have been used to project the global impact of travel limitations on the spread of the pandemic (Chinazzi et al., 2020). Aggregated travel demand models have been used to explore and forecast the consequences of the pandemic on road traffic (Knoope & Francke, 2020) and public transport usage (Bakker et al., 2020). However, up to now, besides the study of Müller et al. (2021), no other studies modeling the impact of COVID-19 on mobility on an individual level have been published.

Therefore, it is of interest to investigate the impact of COVID-19 measures and changed attitudes of different groups of people, and over different periods or stages. With this, it is possible to understand travel behavior considering characteristics and aspects that cannot be seen in macroscopic analysis and that change over time. ABMs (activity-based models) are disaggregated travel demand models that can model individual behavior according to specific characteristics and conditions, and that can help make a good estimation of the changes in activity-travel patterns and traffic flows.

The main strength of ABMs is that they explain people's movements by the activities they undertake. That is consistently simulated per individual, considering preferences and combinations of motives and modes of transport within a travel chain (de Romph et al., 2019). These features make it possible to analyze, for instance, different scenarios about how the mobility of individuals from particular working sectors is affected during the pandemic or how frequently different types of travelers go shopping compared to the pre-pandemic period. These scenarios can be chosen as extreme cases and vary in different aspects, such as the change towards working from home within an entire industry sector or when shops function with limited capacity and narrower opening hours. An ABM model can provide insights in disaggregated aspects such as rates of trips and tours per activity and modal split and in more aggregated aspects such as link volumes and levels of congestion if connected to a transport network. The concept, strengths and weaknesses of travel demand models, particularly of ABMs, are presented and discussed in detail in section 2.2.

## 1.2. RESEARCH PROBLEM

As the pandemic and associated policy measures strongly influence the way people travel, it is important to understand the effects of COVID-19 on passenger mobility and what actions should policy makers take to mitigate its effects.

The learning cycle developed by the Netherlands Organisation for Applied Scientific Research (TNO, 2020) and presented in Figure 1 can be used to investigate the impacts of COVID-19 on mobility by learning from experience. Measures such as physical and social distancing, lockdowns and curfews are constantly being implemented, and they are continually being strengthened or relieved based on what is observed (Ritchie et al., 2021). As a consequence, institutions and consultancy firms are continually collecting data to update information such as working conditions, the frequency of onsite and online activities, and also mobility pattern changes (Cats & Hoogendoorn, 2020). This information then is used by policymakers to adjust policies and make interventions whenever necessary. Then, as the figure suggests, the next step in this cycle would be to use models capable of predicting the impact of travel behavior changes on the transportation system and use its outcomes to help making informed decisions (TNO, 2020).

The COVID-19 pandemic is not the first time that a public health crisis has had a wide impact on the traffic system. For example, the SARS (Severe Acute Respiratory Syndrome) epidemic in 2003, which first spread in China, caused more than 50% of transit ridership reduction in major Chinese cities (Wang et al., 2020). However, tools capable of modeling individuals in such a level of detail were relatively new by that time, and scenarios such as the corona crisis were never investigated in such a way before.

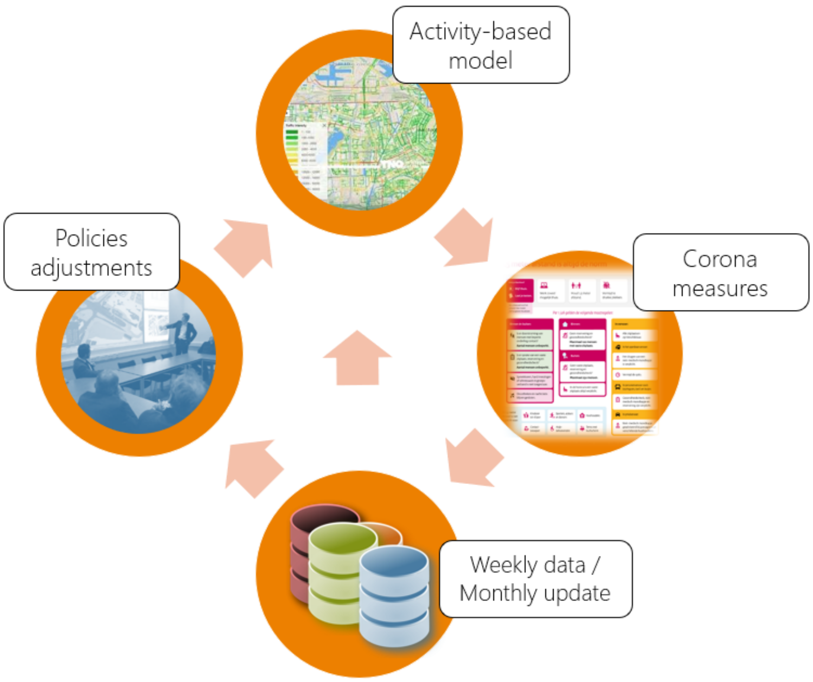


*Figure 1-1 - Learning cycle of actions taken against COVID-19 pandemic (Source: TNO, 2020)*

If the outcomes of such a situation cannot be investigated and understood, society will be severely impacted when a crisis such as the COVID-19 pandemic occurs again. Using models capable of investigating the impacts of pandemics on mobility can help to make adjustments in policies and to monitor the effectiveness of measures such as lockdowns and physical distancing. Therefore, this study aims to provide more information about the impacts of COVID-19 on mobility and to contribute to the academic research of the activity-based modeling approach.

## 1.3. Research objective and scope

Given the motivations stated in section 1.1 and the research problem of section 1.2, the objective of this research is to explore changes in activity-travel behavior during the COVID-19 pandemic and to assess their effects on mobility by using the activity-based travel modeling approach.

Due to resource constraints, in this research, no existing ABMs will be used to do estimations. Instead, a (travel demand) modeling framework which follows the principles of activity-based modeling will be developed. This framework will be used to do estimations for a case study in the Rotterdam-The Hague metropolitan area (MRDH), the Netherlands.

A common procedure in travel demand modeling is to assign the outputs of ABMs to a network to estimate indicators such as flow patterns and levels of congestion. However, due to time constraints, network assignment is out of the scope of this study. Hence, this study focuses only on modeling and analyzing travel demand.

## 1.4. Research questions

To achieve the objective of this research, the following questions are defined. The primary question is:

*What are the effects of the changes in activity-travel behavior during events such as COVID-19 on mobility in the Rotterdam-The Hague Metropolitan Area, the Netherlands, and how can these effects be estimated, predicted, and analyzed through activity-based modeling?*

The secondary questions are:

a) *What activity-travel behavior changes may be expected due to the COVID-19 pandemic?*
b) *How can activity-based models be used (and improved) to better explain changes in activity-travel behavior in events such as COVID-19?*
c) *What effects can be expected on mobility during the different stages of the pandemic and what factors influence these effects?*
d) *What is the added value of the modeling framework developed in this study to investigate the effects of changes in activity-travel behavior on mobility?*

## 1.5. Research approach

There are six main research steps in this study. Table 2 provides an overview of the research flow process, indicating the steps in which each research question is answered.

In research step 1, theories about activity-travel behavior are explored to investigate the existing literature on the factors that influence changes in activity-travel behavior, particularly in the case of the COVID-19 pandemic.

*Table 2 - Research flow overview*

| | *Research step* | *Method* | *Output* | *Referred research question* |
|---|---|---|---|---|
| *1* | Investigate how the COVID-19 pandemic might affect activity-travel behavior | Literature study; Tracked local and international media | Conceptual framework; Travel behavior theory; Effects of COVID-19 on activity-travel behavior | a) What activity-travel behavior changes may be expected due to the COVID-19 pandemic? |
| *2* | Explore activity-travel behavior during COVID-19 in the Netherlands | Data exploration; exploratory analysis | Guidelines for developing the modeling framework; Data for the case study; | |
| *3* | Investigate usage of activity-based models for the study; find resources for modeling | Literature study; Applied research; Resources allocation | Modeling framework development | b) How activity-based models can be used (and improved) to better explain changes in activity-travel behavior in events such as COVID-19? |
| *4* | Estimate the effects of changes in activity-travel behavior on mobility in the case study area | Model application; Quantitative analysis; | Quantitative analysis of COVID-19 stages | c) What effects can be expected on mobility during the different stages of the pandemic and what factors influence these effects? |
| *5* | Assess stages' indicators and discuss the results | Literature study; Qualitative analysis; | Qualitative analysis of COVID stages; discussion of results based on literature and other data sources | *What are the effects of the changes in activity-travel behavior during events such as COVID-19 on mobility in the Rotterdam-The Hague Metropolitan Area, the Netherlands, and how can these effects be estimated, predicted, and analyzed through activity-based modeling?* |
| *6* | Evaluate the performance of the model developed. Discuss future improvements | Subjective perspective | Thoughts and conclusions about the model performance and recommendations for improvement | d) What is the added value of the modeling framework developed in this study to investigate the effects of changes in activity-travel behavior on mobility? |

In research step 2, exploratory research is carried out to find the type of data that will be used in the study. This step is necessary because the type of data provides important guidelines for developing the model framework.

In research step 3, research is done about the principles of activity-based travel demand modeling and the usage of ABMs to explore activity-travel behavior changes and their effects on mobility. Then, based on the insights of research steps 1, 2, and 3, an activity-based modeling framework is developed.

In research step 4, the modeling framework is applied for a case study about the impacts of COVID-19 for different periods in the Netherlands.

In research step 5, the results of the case study are analyzed and compared to a pre-pandemic period. This study refers to existing publications to validate these results.

Finally, in research step 6 the performance of the modeling framework developed for this study is evaluated and recommendations for improvements are provided.

## 1.6. Reading guide

This report is organized as follows. Chapter 2 presents a literature review about the impacts of COVID-19 in activity-travel behavior, as well as an overview of the activity-based modeling approach and their usage to assess the impacts of changes in activity-travel behavior on mobility. Chapter 3 provides a discussion about the methods chosen to be used in this study. Chapter 4 presents and explains the modeling framework developed for this study. Chapter 5 introduces the case study and describes in detail the data that is used. Chapter 6 presents and analyzes the results of the case study. Finally, chapter 7 answers the research questions, presents recommendations for model improvement and policy-makers, and suggestions for future research.

# 2. LITERATURE REVIEW

This chapter presents the literature review. Section 2.1 discusses the potential changes in activity-travel behavior caused by COVID-19. Section 2.2 gives an overview of the activity-based modeling approach. Section 2.3 discusses the usage of ABMs to study activity-travel behavior and discusses possible model improvements to better investigate activity-travel behavior in events such as the corona virus pandemic. After the discussion of these subjects, section 2.4 defines the scientific gaps to be filled by this research.

## 2.1. UNDERSTANDING ACTIVITY-TRAVEL BEHAVIOR CHANGES CAUSED BY COVID-19

As defined by Koppelman & Wen (2000), activity-travel behavior refers to the complicated decision-making process of travelers before starting and during a trip, regarding choices in travel mode, route, departure time, destination, and the type of activity. Throughout the years, activity-travel behavior has been extensively studied to tackle urban issues such as social inequalities (Scheiner, 2010) and traffic congestions (Kim & Kwan, 2019). However, since 2020 a special focus has been given to COVID-19 since it has been reshaping activity-travel behavior and drastically changing our daily routines.

Van Wee (2020) explores the various theories and conceptual models that explain how displacement behavior comes about. He also defines important determinants for activity and travel behavior changes and uses them to explore the possible long-term influences of COVID-19 on activity-travel behavior. He concludes that long-term effects of COVID-19 are likely for a variety of reasons, ranging from breaking habitual behavior, changing attitudes, and increasing the commute distance through relocation or job changes, to the emergence of a new balance in costs and benefits of travel versus online activities.

In another study exploring the potential travel behavior changes due to the COVID-19 pandemic, Oirbans (2021) highlights three major impacts of COVID-19 on travel behavior: a shift from onsite to online activities, re-spacing and re-timing of travel patterns, and modal shift towards active modes. Indeed, the spread of the COVID-19 virus has resulted in unprecedented measures restricting travel and activity participation in many countries (de Vos, 2020). Avoiding social contact and the fear of contamination completely changed the number and types of onsite activities people perform and how people reach these activities (de Haas et al., 2020). It also led to short-term changes in people's lifestyles, amount of teleworking and teleshopping, mode choice preference, the value of time, among others (de Palma & Vosough, 2021). As a result, the demand for travel reduced considerably and a significant shift from public transport (PT) to cars and active modes was also noticed (Taale et al., 2021).

The COVID-19 crisis has a major impact on working life too. People lost their jobs during the pandemic but there were significant changes also for those who continued to work. Various COVID-19 measures were taken by companies, but the extent to which this was done differs according to the type of work and sector. Field research conducted by Rod et al. (2021) about working conditions during the corona crisis in the Netherlands indicates that temporary workers, younger workers, and workers of lower and intermediate education levels more often worked on location, while elders and workers of higher education levels more often worked from home. Thus, employees in the healthcare, retail, construction and transport sectors more often worked on location, while employees in the education and office sectors more often worked from home. Those observations indicate that it is important to consider different groups of people when studying the impacts of COVID-19 on daily routines.

The abovementioned changes in activity-travel behavior and their effects on mobility can be studied using travel demand models. Trip-based and tour-based models are travel demand models that have been used for a long time to assess mobility changes, but their inability to work at a disaggregate person-level is an issue (Castiglione et al., 2014). To analyze changes at a disaggregated level, ABMs are the most prominent travel demand models. In the next section, the concepts of travel demand models, particularly ABMs, are introduced and their functionalities are explained.

## 2.2. UNDERSTANDING ACTIVITY-BASED MODELING

Activity-based models are the last generation of travel demand models. Travel demand models use current travel behavior to predict future travel patterns from a sample of behavior data. In general, they assist decision-makers in making informed transportation planning decisions.

The first generation of travel demand models consists of trip-based models, which use the individual person trip as the fundamental unit of analysis and assume that all trips are made independently (Castiglione et al., 2014). An ABM differs from a trip-based model because it introduces the notion of activity and not trip, and considers tours[1] as the unit to model instead of isolated trips (Kochan, 2013). Thus, it can represent each person's activity and travel choices across the entire day, considering the types of activities the individual needs to participate in and setting the priorities for scheduling these activities (Castiglione et al., 2014).

The type of travel model that is appropriate to use is dependent on the particular questions being asked by decision-makers. Nowadays, transport policy questions became more complex and require a wider range of responses with higher levels of detail (Castiglione et al., 2014). For that reason, ABMs have become more widely used in practice because they work at a disaggregate person-level rather than a more aggregate zone-level such as trip-based models.

The central focus of the ABMs is whether, when, and where to participate in activities and for how long. They are based on behavioral theories about how people make decisions about activity participation in the presence of constraints. Because they represent decisions and the resulting behavior more realistically, they are often better at representing how policies or other changes will affect people's travel behavior (Castiglione et al., 2014).

The structure and components of the majority of ABMs are similar, but they may differ according to the study purposes. Figure 2-1 depicts the typical component sections of ABMs and these components are explained in this section.

The inputs to develop and apply ABMs include household travel survey information, economic and demographic information about the spatial distribution of employment and households, and representations of transportation networks (Castiglione et al., 2014). Household travel surveys contain detailed information about whether, where, how, and when individuals and households travel. For ABMs, all the survey data must be internally consistent across all the individuals in each household.

In the ABM system, households and persons are used as the core decision-making units, making choices about key considerations such as the type and amount of activities that occur or the location of key destinations such as work or school. Population synthesis is used to create the lists of households and persons, or synthetic populations, that are the basis for simulating these choices (Castiglione et al., 2014).

[1] A tour is a series of trips beginning and ending at home (Kochan, 2013).

Long-term choices are choices that influence day-to-day travel behavior but are not made daily, like for example the decision of where to live or the possession of a car. These decisions are considered because they can significantly influence the availability and attractiveness of different scheduling choices that create the daily activity and travel pattern (Castiglione et al., 2014).

The day activity patterns (DAP) component is where the model system designs vary most widely across practical implementations (Castiglione et al., 2014). The common feature of all those designs, however, is that the main focus of the day-pattern models is tour generation. Regardless of the exact sequence and specification of choices that are simulated, the main output is the number of tours that each individual makes for several different activities and tour purposes.

The tour & trip details component is where the choices of location, time-of-day (ToD), and transport mode of trips and tours are estimated. For this component, it is necessary to have information about the land use and the transport network (Bellemans & Kochan, 2016).

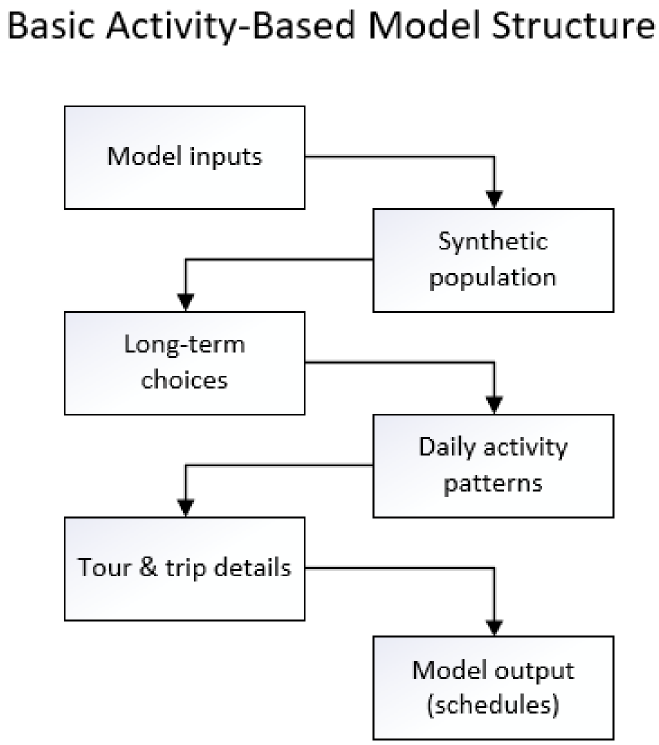


*Figure 2-1 - Typical activity-based model structures (adapted from* Castiglione et al., 2014)

The outputs of an ABM are the so-called predicted schedules. The predicted schedules are sets of activity-trip diaries estimated per agent. Figure 2-2 exemplifies the schedule of an individual for a full day. In total, there are 5 trips between 4 locations. The arrows represent the trips and the rectangles, the locations. The 1$^{st}$ trip starts at home and has the work location as a destination. Then, after work has finished, the 2$^{nd}$ trip is to a shopping mall and after that the 3$^{rd}$ trip is to return home. From home, there is a 4$^{th}$ trip to the gym and then a 5$^{th}$ trip returning home. The block on the bottom of the figure shows the timeline of the schedule. It shows the activity start time and duration, the trip start time and duration, and the transport mode used. The agent uses a different transport mode for the different tours. In this example, the agent uses a car for the 1$^{st}$ tour and a bike for the 2$^{nd}$.

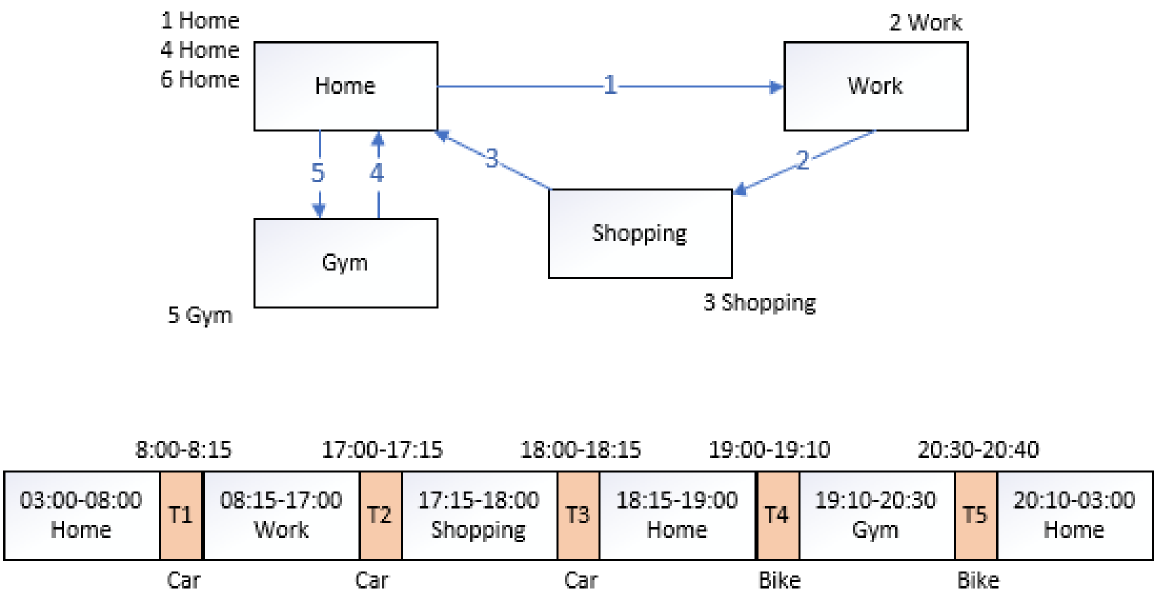


*Figure 2-2 - Example of the predicted schedule of an agent*

Once there is a series of predicted schedules that contain activities and trips for all agents in the study area, then these outputs can be used to create some indicators such as transport mode shares, distances traveled, and the number of trips per person. This is possible because ABMs are always embedded within an integrated model system in which there is an interaction between the demand model, which predicts the demand for travel, and network models, which predict how this demand affects the performance of the transportation network supply (Castiglione et al., 2014). It is also possible to determine the patterns of flow and levels of congestion in the network using a traffic assignment or to use the outputs as input to other specialized models, such as emissions (Kochan, 2013) or transport safety models (Bellemans & Kochan, 2016). Thus, it can make any kind of segmentation in the population to determine indicators for specific groups of persons. For example, it is possible to tabulate commuter rail riders by income, by age, by gender, by the number of trips on a tour, or by any other category included in the synthetic population or the results. The ability to tabulate the results in this way enhances the analyst's ability to understand how projects and policies affect different categories of people (Travel Forecasting Resource, 2014).

## 2.3. Studying Activity-Travel Behavior Using ABMs

Some of the major impacts of COVID-19 on activity-travel behavior have been discussed in section 2.1. Home reclusion due to the fear of infection, the acceleration of teleworking and the shift from onsite to online activities are some of the most notable changes. With exception of the fear of infection, these changes in activity-travel behavior are not exclusive to the COVID-19 situation. They have already been studied over time, and the pandemic has been working as a trigger in their acceleration (Van Wee, 2020).

Some of these changes in activity-travel behavior have also been studied using activity-based modeling. Concerning teleworking, for instance, Pirdavani et al. (2014) assessed the road safety impacts of teleworking policies by using an activity-based transportation model framework to produce detailed exposure metrics. The results of their research show a traffic safety benefit of teleworking since they reduced the total vehicle kilometers traveled by 3.15%. Acknowledging remote and in-home activities, Shabanpour et al. (2018) enhanced their ABM to plan and schedule a joint model of in-home and out-of-home activities. Their results indicated that the estimated joint models outperformed the independent models in terms of goodness-of-fit and prediction accuracy.

The number of studies using ABMs that include in-home activities, however, is limited. As discussed by Shabanpour et al. (2018), the role of in-home activities in the process of planning and scheduling of individuals’ daily activities has been traditionally ignored because of two reasons: (1) in-home activities are not directly involved with trips; and (2) data sources that provide required details on planning and scheduling these activities are scarce. However, considering the interchangeable nature of out-of-home and in-home activities, and the significant effects that they have on each other, ignoring in-home activities may result in an overestimated frequency and duration of out-of-home activities, which may lead to inconsistent and unrealistic activity schedules (Shabanpour et al., 2018).

Another common issue in activity-based modeling is the lack of usage of multiple-day travel datasets. Applying one-day observation data in travel demand modeling provides an inadequate basis for an understanding of complex travel behavior to predict the impact of travel demand management strategies (Tajaddini et al., 2020). Multiple-day data are needed to refine this process. For example, the study of Medina (2018) used smart cards of public transport to identify temporal weekly patterns of primary activities performed by public transport users in Singapore, and as continuous travel data from the same user during a week could be extracted, work-leisure cycles could be recognized. To better estimate the daily activity patterns, it is important to investigate the capacity of a typical week in capturing rhythms in activity-travel behavior (Nurul Habib et al., 2008).

In conclusion, with the increase of in-home and online activities summed up to the fear of infection caused by the corona virus crisis, it is of great importance to incorporate in-home activities in studies of planning and scheduling individuals’ daily activities. Thus, multiple-day travel datasets might be better options to explain the frequency in which agents perform activities. And to do so, it is also necessary to collect data that can better explain such behaviors. For instance, by creating surveys that ask the frequency that individuals telework (Hooftman, et al., 2020), or how often they do out-home activities (KiM, 2020).

## 2.4. Scientific gap

This research is related to the novel corona virus, a pandemic that is changing the world in many aspects. There is a growing number of studies on the impacts of the pandemic on the transportation sector (e.g. Knoope & Francke, 2020; Zhang & Hayashi, 2020; Kuiper et al., 2020; Tirachini & Cats, 2020; Hendrickson & Rilett, 2020; Beck et al., 2020) – and more specifically, travel behavior (e.g. Shakibaei et al., 2021; Huang et al., 2020; Pandey, 2020; Williamson et al., 2020, Shamshiripour et al., 2020). However, at the time of writing this report, there is a lack of studies using travel demand models to study the effects on passenger mobility on the individual level. The only study found is from Müller et al. (2021), which combined the principles of activity-based modeling with an epidemiological model to understand the contributions of different activity types to the infection dynamics over time.

As discussed in the previous sections, ABMs are useful tools to analyze changes in activity-travel behavior and assess its effects on mobility. However, to model the changes in activity-travel behavior discussed in the literature review using ABMs, some adjustments are needed. The most notable conclusions that arise from the literature overview of changes in activity-travel behavior during COVID-19 and the usage of ABMs to study these changes are: (1) the need to incorporate in-home activity planning in the modeling; and (2) to collect and use more detailed data on planning and scheduling of in-home activities and out-home activity frequency.

Given the necessity of understanding the impacts of COVID-19 on mobility and the degree of detail that ABMs can work, this study aims at using the activity-based modeling approach to estimate changes in activity-travel behavior, particularly in activity frequency and in-home activities, and assess their effects on mobility.

# 3. METHODOLOGY

From the previous chapter, it has been concluded that ABMs are useful tools to estimate changes in activity-travel behavior and their effects on mobility. That is because nowadays, transport policy questions became more complex and require a wider range of responses with higher levels of detail (Castiglione et al., 2014). For that reason, activity-based models (ABMs), which are the last generation and most sophisticated travel demand models, have become more widely used in practice because they work at a disaggregate person-level rather than a more aggregate zone-level such as the trip-based models.

However, it has also been discussed that to use ABMs to model the changes in activity-travel behavior discussed in the literature review, some model and input adjustments are needed. The approach presented in chapter 2, section 2.3, discusses the necessity of ABMs to incorporate in-home activities in the process of planning and scheduling individuals' daily activities (Shabanpour et al., 2018).

For this study, however, no ABMs were available for usage, only their outputs. Therefore, it has been decided to build a new (specialized) travel demand activity-based modeling framework.

This new modeling framework (or just 'model') uses the outputs of ABMs as input. Thus, it is specialized because it is capable of analyzing changes in activity-travel behavior and assess their effects on mobility by estimating the frequency that individuals perform on-site activities and teleworking during events such as the COVID-19 pandemic. To calibrate the model, the estimates of travel demand and related choices output by the model will be compared to observed real-world data. To validate the model, keys metrics will be identified, and comparisons between model estimates and observed data that have not been used in the model estimation will be made. Furthermore, it is important to mention that the modeling framework has been built to study the impacts of COVID-19 as an initial purpose. Therefore, the methods and the data (formats) were designed taking into account the data availability and the limitations imposed by it in the Netherlands.

In the next chapter, the modeling framework is presented and described in detail.

# 4. MODEL DESIGN

In order to answer the research questions formulated in chapter 1, section 1.3, and explore the scientific gaps discovered in chapter 2, section 2.4, a modeling framework has been developed. This framework is used to estimate changes in the daily schedules of agents of a determined study area and assess the effect of these changes on mobility both at an aggregated and disaggregated level. It uses as a starting point the predicted schedules (outputs) of ABMs to estimate new schedules. The model has been written using the programming language Python.

In this chapter, the modeling framework is presented. Section 4.1 discusses the applicability of the model. Section 4.2 presents the modeling framework and introduces its modules, inputs and outputs. Section 4.3 describes the model inputs in great detail. Section 4.4 explains each of the model components. Finally, section 4.5 provides considerations about the model and also describes its limitations.

## 4.1. APPLICABILITY

The goal of the model is to provide objective assessments of changes in activity-travel behavior during emergency situations. Thus, it should be able to evaluate alternative policies that are difficult to test using aggregated travel demand models. For example, the model should provide more robust capabilities and sensitivities for assessing the impact of the increase of in-home activities or changes in the frequency of out-home activities on individuals' daily schedules.

The application of the model is meant to be wide. By running the model with different sets of input assumptions representing different scenarios, analysts should be able to predict and evaluate differences between these scenarios using a broad range of metrics and answer decision makers' key questions such as

- What mobility changes can be expected when opening/closing a particular sector?
- What is the effect of spreading physical (work/study) meetings over the week?
- What mobility changes can be expected with the incorporation of in-home activities in the schedule generation?
- Where are bottlenecks expected under the influence of (corona) measures?

The modeling framework should be used to estimate what-if scenarios that make predictions in terms of journeys and mobility density, given certain assumptions about aspects that play a role in emergency situations such as the COVID-19 pandemic. These scenarios can be defined and calculated by considering the severity of policy measures for different sectors and during different periods. For instance, the COVID-19 stringency indexes created by Ritchie et al. (2021) are used to predict and analyze the outcomes of the case study developed in this report. These stringency indexes are measures of the severity of policy measures such as school and workplace closures, restrictions on public transport, and stay-at-home requirements. The values are scaled to a value from 0 to 100 (100 = strictest) and can be used to estimate the model inputs to define and predict future scenarios. Recommendations for the development of future scenarios are further discussed in chapter 7, section 7.4.

## 4.2. MODELING FRAMEWORK

An overview of the modular structure of the proposed model is presented in Figure 4-1. In the remainder of this section, the functionality of the modules with their inputs and outputs are introduced.

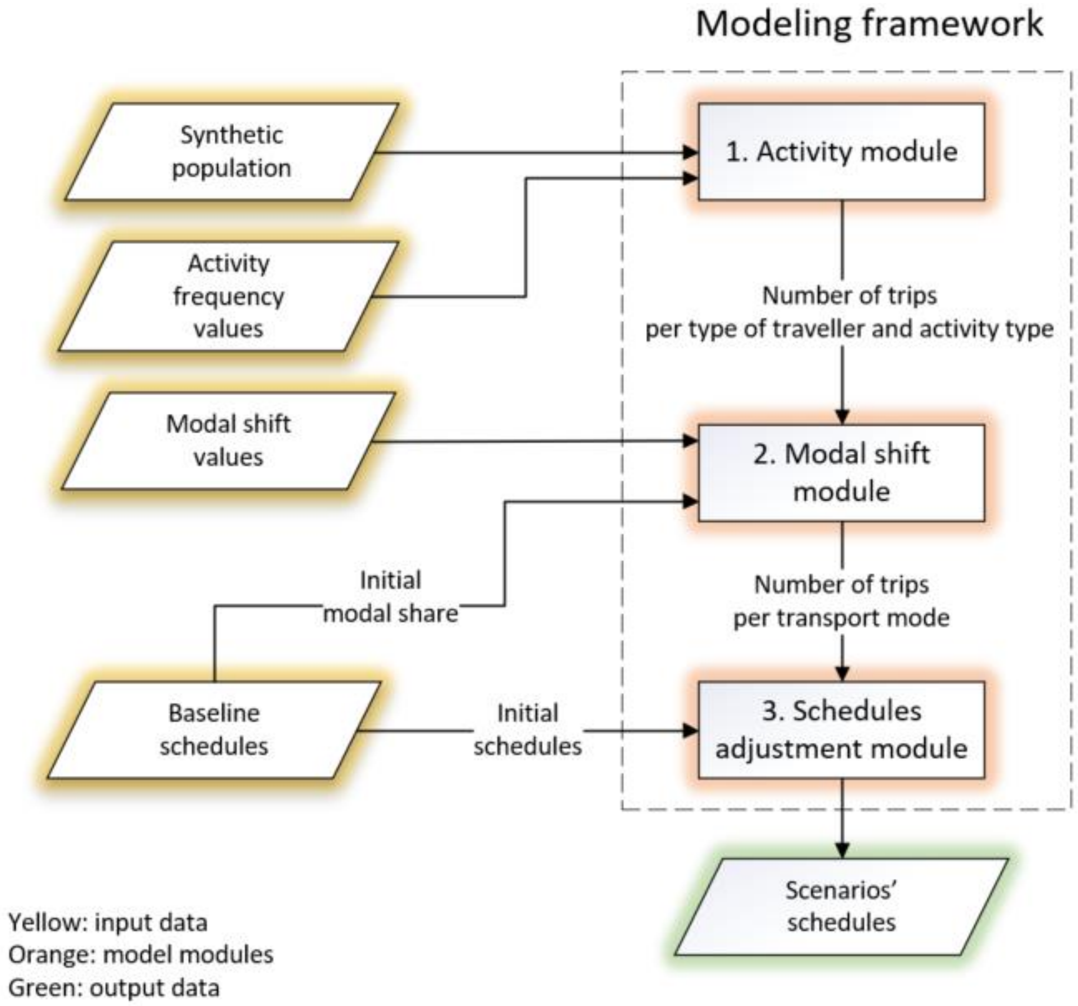


*Figure 4-1 – Schematic overview of the modeling framework components, their functionalities, and their inputs*

ABMs require assembling a diverse set of data. These data reflect travel behavior, regional demographics, land use, network configuration, and network performance (Castiglione et al., 2014). In total, the model has four data inputs:

**Input 1**: Synthetic population is the population of the study area. It contains information about every agent, for example their age, gender, and level of education. This input is explained in greater detail in section 4.3.1.

**Input 2**: Activity frequency values are data about the frequency in which agents do out-home activities, broken down by activity type and by type of agent. This is a data format created especially for the model. This input is explained in greater detail in section 4.3.2.

**Input 3**: Modal shift values are data about the change of mode of transport. For example, switching from public transport to bike trips. This input is explained in greater detail in section 4.3.3.

**Input 4:** The baseline schedules are the outputs of ABMs that are used as input for the model. These outputs are schedules predicted for the same synthetic population, but using other data. They are used as baseline to create scenarios because they provide the initial information about individuals' trips and tours, such as the activity locations, start and end time, duration, transport mode, etc. They also provide the initial modal share that is used to estimate modal shift. This input is explained in greater detail in section 4.3.4.

The modeling framework is broken down into three steps:

**Step 1**: the Activity module estimates how many trips are performed taking into account the type of agent and activity type. Detailed explanation in section 4.4.1.

**Step 2**: the Modal shift module estimates how many trips are performed taking into account the transport mode. Detailed explanation in section 4.4.2.

**Step 3**: the Schedules adjustment module removes or adds from the tours the trips that are (not) performed and adjusts the schedules based on the new set of trips. Detailed explanation in section 4.4.3.

The outputs of the model are new schedules, or adjusted schedules, which represent the daily activity-diary of the population considering activity-travel behavior for different periods or situations. From these new schedules, indicators are generated to compare scenarios and provide insights into the results.

## 4.3. INPUTS

The data required for the development of the model come from exogenous sources. Exogenous information includes demographic assumptions, household travel surveys, and processed travel behavior data. Thus, this model has been built primarily to study the impacts of COVID-19. Therefore, the data formats of the model were designed taking into account the type of data available at the time.

When data were sought for the research, COVID-19 was relatively new and little microdata was publicly available. There was an attempt to get access to some mobility microdata from private organizations, but mainly aggregated data were shared. Hence, due to these circumstances, the idea for the research turned out to be a mix of aggregated and disaggregated data to make estimations at an individual level.

In this chapter, the model inputs are described in detail. Section 4.3.1 provides information about the synthetic population. Section 4.3.2 describes the activity frequency values. Section 4.3.3 explains the modal shift values. Finally, section 4.3.4 depicts the baseline schedules.

### 4.3.1. Synthetic population

The synthetic population is a dataset with agents per zone and is a key input to most ABMs for forecasting the behavior of the households and agents in the modeled area (Bhat & Koppelman, 1999). Each agent is classified according to its demographic attributes. Table 3 provides an example of how a synthetic population list is structured.

There is a big variety of demographic attributes that ABMs can use. Examples are age, gender, driving license, paid work, household size, household number of cars, degree of urbanization, and so on. Using this variety of controls produces a synthetic population that is representative of the actual population along all of these dimensions, and thus allows all of these variables to be used as explanatory variables in the model (Castiglione et al., 2014). Table 4 presents the list of categories of each of the attributes listed in the example of Table 3. Each agent in the synthetic population must have a unique value for each of the attributes.

*Table 3 - Synthetic population list example*

| agent_id | location_id | age_person | gender | education | working_sector |
|---|---|---|---|---|---|
| **1** | 2 | 3 | 1 | 4 | 1 |
| **2** | 5 | 3 | 1 | 3 | 3 |
| **3** | 11 | 3 | 2 | 4 | 5 |
| **4** | 28 | 3 | 2 | 4 | 0 |
| **5** | 14 | 3 | 2 | 3 | 0 |
| **6** | 55 | 4 | 1 | 4 | 4 |
| **7** | 2 | 4 | 1 | 3 | 6 |
| **8** | 11 | 4 | 2 | 3 | 2 |
| **9** | 5 | 4 | 2 | 4 | 1 |
| **10** | 11 | 5 | 1 | 4 | 2 |
| **11** | 2 | 5 | 1 | 1 | 2 |
| **12** | 2 | 5 | 1 | 4 | 0 |

*Table 4 - Demographic attributes of the synthetic population*

| Attribute | Value | Description | Unit |
|---|---|---|---|
| **agent_id** | 0-N | Unique ID of agent | - |
| **location_id** | 0-7740 | Zone where agent lives | Zone number |
| **gender** | - | Gender of person | - |
| | 1 | Male | |
| | 2 | Female | - |
| **age_person** | - | Age group of person | - |
| | 1 | Age < 15 | - |
| | 2 | Age >=15 & Age < 25 | - |
| | 3 | Age >= 25 & Age < 45 | - |
| | 4 | Age >= 45 & Age < 65 | - |
| | 5 | Age >= 65 | - |
| **education** | - | Highest education obtained | - |
| | 1 | Primary | - |
| | 2 | Lower | - |
| | 3 | Secondary | - |
| | 4 | Higher | - |
| | 5 | Other | - |
| **working_sector** | - | Sector which the person works | - |
| | 0 | Not working | - |
| | 1 | Industry and production | - |
| | 2 | Healthcare | - |
| | 3 | Retail | - |
| | 4 | Education | - |
| | 5 | Office | - |
| | 6 | Other | - |

### 4.3.2. Activity frequency values

The activity frequency values are new information assigned to the synthetic population. It tells with which frequency each agent performs each of the activity types in a one-week period. The idea to use frequency tables as inputs for the model came from looking at studies published by KIM (2020) about the frequency that agents do outdoor activities before and during the corona crisis. Table 5 presents an example of how the activity frequency tables are structured. In this example, people answer the number of times they go shopping in a week. The answers are split per age group. From the figure, it can be derived for example that 80% of agents in age group 1 go shopping once a week, while 5% go twice, and only 5% go more than three times in a week.

*Table 5 - Frequency tables input example*

| Activity | Age | 0 days | 1 day | 2 days | 3 days | 4 days | 5 days | 6 days | 7 days | All |
|---|---|---|---|---|---|---|---|---|---|---|
| **Shopping** | 1 | 10% | 80% | 5% | 4% | 1% | 0% | 0% | 0% | 100% |
| | 2 | 0% | 92% | 4% | 4% | 0% | 0% | 0% | 0% | 100% |
| | 3 | 1% | 85% | 6% | 6% | 1% | 1% | 0% | 0% | 100% |
| | 4 | 0% | 84% | 7% | 7% | 2% | 0% | 0% | 0% | 100% |
| | 5 | 0% | 75% | 10% | 11% | 1% | 1% | 2% | 0% | 100% |

In total, there are six activity types in the model: work, business, bring/get, education, shopping and other[2]. For each of these activities, a frequency table is created. Table 6 exemplifies the characteristics required to structure the frequency tables for each activity type.

With regard to the attributes, for the non-work-related activity types data (bring/get, education, shopping and other), agents are classified by age. For the work-related activity types data (work and business), agents are classified by age, gender and work sector.

Another characteristic that distinguishes activity types is the number of times people usually perform them in a denominated period. For the model, the period in consideration is a full week (seven days). It is assumed that the majority of the population performs work, business and education activities only during weekdays, while for other activities (bring/get, shopping, other) there is not a standard pattern. Therefore, the model assumes that an agent can perform work, business and education activities 0 to 5 days a week and for the other activities an agent can perform them 0 to 7 days a week.

*Table 6 - Characteristics of activity frequency tables*

| Activity type | Attributes | Days |
|---|---|---|
| **Work** | Age x gender x sector | 0,1,2,3,4,5 |
| **Business** | Age x gender x sector | 0,1,2,3,4,5 |
| **Bring/get** | Age | 0,1,2,3,4,5,6,7 |
| **Education** | Age | 0,1,2,3,4,5 |
| **Shopping** | Age | 0,1,2,3,4,5,6,7 |
| **Other** | Age | 0,1,2,3,4,5,6,7 |

[2] The activity named Other include activities such as visit someone, touring/walk, do sports, personal care, other leisure activities or a different purpose

### 4.3.3. Modal shift values

The modal shift values are data provided by third parties about the change of mode of transport when performing trips. For example, switching from public transport to bike to go to work. This data is used by the modal shift module to estimate the number of trips that shift from one mode to another and to estimate the number of trips that will not be performed anymore.

This data is structured in a table format, such as the made-up example provided in Table 7. The rows are the percentage of trips that one mode gives to another mode, and the columns are the percentage of trips that one mode takes from another mode. In this made-up example, there is a significant shift from public transport to bike and car (3.2% and 4.10% of the original PT trips, respectively).

*Table 7 - Modal shift values format example*

| From\To | Walk | Bike | E-bike | Car | Car passenger | On demand | PT |
|---|---|---|---|---|---|---|---|
| **Walk** | - | 0,50% | 0,00% | 0,80% | 0,00% | 0,00% | 0,10% |
| **Bike** | 0,50% | - | 0,10% | 0,80% | 0,00% | 0,00% | 0,00% |
| **E-bike** | 0,00% | 0,00% | - | 0,00% | 0,00% | 0,00% | 0,00% |
| **Car** | 1,40% | 0,90% | 0,00% | - | 0,00% | 0,00% | 0,40% |
| **Car passenger** | 0,00% | 0,00% | 0,00% | 0,00% | - | 0,10% | 0,00% |
| **On demand** | 0,00% | 0,00% | 0,00% | 0,00% | 0,00% | - | 0,00% |
| **PT** | 0,30% | 3,20% | 0,00% | 4,10% | 0,40% | 0,10% | - |

### 4.3.4. Baseline schedules

As stated previously, the baseline schedules are the outputs of ABMs that are used as inputs for the model. Figure 4-2 gives an example of how the baseline schedules look like. Every row is an activity performed by an agent, and the columns are trip information regarding that activity. Table 8 presents the attributes of the example of Figure 4-2.

In Figure 4-2, it is shown the daily schedule of agents 1, 7, and 13. Each agent has one tour, that can be identified in the 'activity type' column:

- Agent 1: home-shopping-home (1-6-1)
- Agent 2: home-other-bring/get-home (1-7-4-1)
- Agent 3: home-other-home (1-7-1)

| agent id | activity type | activity location | activity start time | activity duration | trip transport mode | trip origin | trip destination | trip start time | trip duration | trip distance |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 2 | 180 | 598 | -2 | -2 | -2 | 0 | 0 | 0 |
| 1 | 6 | 6 | 780 | 75 | 2 | 2 | 6 | 778 | 2 | <1 |
| 1 | 1 | 2 | 857 | 763 | 2 | 6 | 2 | 855 | 2 | <1 |
| 7 | 1 | 2 | 180 | 755 | -2 | -2 | -2 | 0 | 0 | 0 |
| 7 | 7 | 7024 | 960 | 75 | 5 | 2 | 7024 | 935 | 25 | 32 |
| 7 | 4 | 51 | 1062 | 15 | 4 | 7024 | 51 | 1035 | 27 | 34 |
| 7 | 1 | 2 | 1085 | 535 | 5 | 51 | 2 | 1077 | 7 | 4 |
| 13 | 1 | 2 | 180 | 288 | -2 | -2 | -2 | 0 | 0 | 0 |
| 13 | 7 | 1487 | 480 | 135 | 4 | 2 | 1487 | 468 | 12 | 8 |
| 13 | 1 | 2 | 626 | 994 | 4 | 1487 | 2 | 615 | 11 | 8 |

*Figure 4-2 - Baseline schedules format example*

The upcoming columns provide information about where (which zone) the activity is taking place, what time the activity starts (in minutes), how long it takes (in minutes), the transport mode used, the origin zone, what time the trip starts (in minutes), the trip duration (in minutes) and the trip distance (in kilometers).

*Table 8 - Schedules attributes example*

| Attribute | Value | Description | Unit |
|---|---|---|---|
| **agent_id** | 0-N | Unique ID | - |
| **activity_type** | - | The type of activity a person is going to do at the destination | - |
| | 1 | Home | - |
| | 2 | Work | - |
| | 3 | Business | - |
| | 4 | Bring/get | - |
| | 5 | Education | - |
| | 6 | Shopping | - |
| | 7 | Other | - |
| **activity_location** | 0-7740 | Zone where activity takes place | Zone number |
| **activity_start_time** | 180-1619 | Start of activity in minutes since midnight | minute |
| **activity_duration** | 1-1440 | Length of activity | minute |
| **trip_transport_mode** | - | Main transport mode of the whole trip | - |
| | 1 | Walk | - |
| | 2 | Bike | - |
| | 3 | E-bike | - |
| | 4 | Car driver | - |
| | 5 | Car passenger | - |
| | 6 | Shared on-demand | - |
| | 7 | Public transport | - |
| **trip_origin** | 0-7740 | Zone where traveler departed | Zone number |
| **trip_destination** | 0-7740 | Zone where traveler arrives | Zone number |
| **trip_start_time** | 180-1619 | Start of trip in minutes since midnight | minute |
| **trip_duration** | 0-N | Length of trip | minute |
| **trip_distance** | 0-N | Distance of trip | km |

## 4.4. MODELING STEPS

In this section, the modeling steps of the model are explained in detail. The model is divided into three parts. The first part is the Activity module and it is described in section 4.4.1. The second is the Modal shift module, which is explained in section 4.4.2. The third is the Schedules adjustment module, which is described in section 4.4.3. Together with the explanation of each module, an example is presented to better illustrate how they work.

### 4.4.1. Activity frequency module

This module calculates the number of agents that do out-home activities (for each activity type) in the modeled day. For example, for a certain population, it estimates how many people are going shopping and how many people will not. That is done for all the different activity types.

An important consideration about this module is that it calculates the activity frequency for the scenarios and also for the baseline scenario. Then, the difference between the activity frequency of a scenario and the baseline scenario (scenario divided by baseline scenario) is used to change the baseline schedules and estimate the schedules for the scenario. In other words, the model takes the difference between the activity frequency of one scenario and the activity frequency of the baseline scenario and applies this difference in the already existing baseline schedules to estimate the schedules for that scenario.

In section 4.4.1.1, a framework of the activity frequency module is presented and its modeling sequence is explained in detail. In section 4.4.1.2, an example of how the model works is provided.

##### *4.4.1.1. Description*

In Figure 4-3, the framework of the activity frequency module is depicted. The principle of the module is as follows: for every scenario, first, it distributes the activity frequency values (*f)* for the population (*u)* to estimate how many agents have a certain activity frequency value (*v*). Second, it estimates how many agents are going to do each of the activity types in the modeled day (*e*). Third, it takes the difference between the number of agents doing activities of one scenario compared to the number of agents doing activities in the baseline scenario ($e/e_0$), and this difference is the number of agents that are going to do activities for that scenario (*r*).

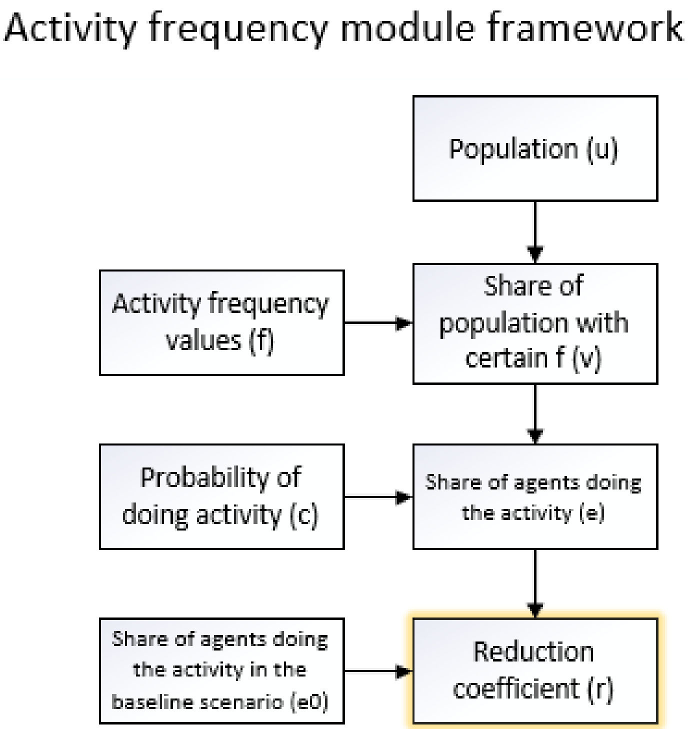


*Figure 4-3 - Activity frequency module framework*

Mathematically, for every scenario *w*, activity type *a*, and agent type *t*, are assumed. Then, *f* is the probability of an agent of having activity frequency *p*, and *F* is the summation of all activity frequency probabilities:

$$F_{wat} = \sum_{p \in P}^{P} f_{watp} = 1 \qquad \forall\, w \in W, a \in A, t \in T \tag{1}$$

From the total population $U$ we estimate the share of agents $u$ with agent type $t$:

$$U = \sum_{t \in T}^{t} u_t \qquad \forall \ t \in T \tag{2}$$

Then, the product of the population $u_t$ and the activity frequency $f_{watp}$ is the share of agents $v$ that have a certain activity frequency $f$:

$$v_{watp} = f_{watp} * u_t \qquad \forall \, w \in W, a \in A, t \in T, p \in P \tag{3}$$

Next, the following condition variables $C_{ap}$ = {$c_{a1}$, $c_{a2}$, $c_{a3}$, ..., $c_{ap}$} are considered, where $a$ is the activity type, $p$ is the activity frequency and $C$ is the probability that the agent does this activity in one day. For activities work, business and education, the agent can travel 0-5 days in one week. For activities bring/get, shopping and other, the agent can travel 0-7 days in one week. For instance, a person that works two days per week in the office has a 40% chance of working in the office in one day (2/5=0.4). In summary: for activities that the maximum number of days is five, the probabilities of doing the activity in one day are [$c_0$, $c_1$, $c_2$, $c_3$, $c_4$, $c_5$] = [0%, 20%, 40%, 60%, 80%, 100%]. If the maximum number of days is seven, then [$c_0$, $c_1$, $c_2$, $c_3$, $c_4$, $c_5$, $c_6$, $c_7$] = [0%, 14.3%, 28.6%, 42.9%, 57.2%, 71.5%, 85.8%, 100%].

Then, the product of the share of agents $v$ and their corresponding probability $c$ is the number of agents $e$ of type $t$ and probability $p$ that does the activity type $a$ in one day:

$$e_{watp} = v_{watp} * c_{ap} \qquad \forall \, w \in W, a \in A, t \in T, p \in P \tag{4}$$

Next, the sum of the number of agents $e$ is the total number of agents E of type $t$ that do the activity in one day:

$$E_{wat} = \sum_{p \in P}^{P} e_{watp} \qquad \forall \, w \in W, a \in A, t \in T \tag{5}$$

Finally, the quotient between the total number of agents $E$ for one scenario and the baseline scenario is the difference $r$ between them:

$$r_{wat} = \frac{E_{wat}}{E_{0at}} \qquad \forall \, w \in W, a \in A, t \in T \tag{6}$$

The difference $r$ is called the 'reduction coefficient', which is the number of agents that will do activities in that scenario, for every different activity type and agent type. The reduction coefficient is used in the next module, together with the modal shift values, to estimate the number of activities that will be done in a scenario taking into account the transport mode used to travel.

##### *4.4.1.2. Example activity frequency module*

In this example, the number of agents doing activity 'shopping' for the fictional scenario 1 is calculated. Table 9 shows the activity frequency values of shopping activity for the baseline scenario and scenario 1. Table 10 presents the population $U$ split by age category. The probabilities $C$ of doing shopping activity in one day in a week are [$c_0$, $c_1$, $c_2$, $c_3$, $c_4$, $c_5$, $c_6$, $c_7$] = [0%, 14.3%, 28.6%, 42.9%, 57.2%, 71.5%, 85.8%, 100%].

*Table 9 – Activity frequency example: activity frequency values “$f_{wat}$”*

| Activity | Scenario | Age | 0 days | 1 day | 2 days | 3 days | 4 days | 5 days | 6 days | 7 days | All |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Shopping** | **Baseline** | **1** | 0.00% | 92.20% | 3.90% | 3.90% | 0.00% | 0.00% | 0.00% | 0.00% | 100% |
| | | **2** | 0.00% | 92.20% | 3.90% | 3.90% | 0.00% | 0.00% | 0.00% | 0.00% | 100% |
| | | **3** | 0.00% | 85.70% | 6.85% | 6.85% | 0.15% | 0.15% | 0.15% | 0.15% | 100% |
| | | **4** | 0.00% | 86.00% | 6.65% | 6.65% | 0.20% | 0.20% | 0.15% | 0.15% | 100% |
| | | **5** | 0.00% | 75.20% | 11.45% | 11.45% | 0.48% | 0.48% | 0.48% | 0.48% | 100% |
| | **1** | **1** | 77.90% | 20.80% | 0.65% | 0.65% | 0.00% | 0.00% | 0.00% | 0.00% | 100% |
| | | **2** | 77.90% | 20.80% | 0.65% | 0.65% | 0.00% | 0.00% | 0.00% | 0.00% | 100% |
| | | **3** | 68.30% | 26.30% | 2.70% | 2.70% | 0.00% | 0.00% | 0.00% | 0.00% | 100% |
| | | **4** | 75.50% | 20.30% | 1.60% | 1.60% | 0.35% | 0.35% | 0.15% | 0.15% | 100% |
| | | **5** | 80.60% | 14.30% | 2.40% | 2.40% | 0.15% | 0.15% | 0.00% | 0.00% | 100% |

*Table 10 - Activity frequency example: population split per age category “$u_t$”*

| Age | $u_t$ | Population |
|---|---|---|
| **1** | 17% | 612419 |
| **2** | 12% | 453897 |
| **3** | 26% | 949871 |
| **4** | 27% | 994489 |
| **5** | 18% | 638823 |
| **Total** | 100% | 3649499 |

The share of agents *v* with certain activity frequency *f* is estimated using equation 3. The results are in Table 11. In this table, it can be observed that in the baseline scenario most agents go shopping only once a week while in scenario 1 most agents do not go shopping at all.

*Table 11 – Activity frequency example: share of agents with certain activity frequency “$v_{wat}$”*

| Activity | Scenario | Age | 0 days | 1 day | 2 days | 3 days | 4 days | 5 days | 6 days | 7 days |
|---|---|---|---|---|---|---|---|---|---|---|
| **Shopping** | **Baseline** | **1** | 0.00% | 15.47% | 0.65% | 0.65% | 0.00% | 0.00% | 0.00% | 0.00% |
| | | **2** | 0.00% | 11.47% | 0.49% | 0.49% | 0.00% | 0.00% | 0.00% | 0.00% |
| | | **3** | 0.00% | 22.31% | 1.78% | 1.78% | 0.04% | 0.04% | 0.04% | 0.04% |
| | | **4** | 0.00% | 23.44% | 1.81% | 1.81% | 0.05% | 0.05% | 0.04% | 0.04% |
| | | **5** | 0.00% | 13.16% | 2.00% | 2.00% | 0.08% | 0.08% | 0.08% | 0.08% |
| | **1** | **1** | 13.07% | 3.49% | 0.11% | 0.11% | 0.00% | 0.00% | 0.00% | 0.00% |
| | | **2** | 9.69% | 2.59% | 0.08% | 0.08% | 0.00% | 0.00% | 0.00% | 0.00% |
| | | **3** | 17.78% | 6.85% | 0.70% | 0.70% | 0.00% | 0.00% | 0.00% | 0.00% |
| | | **4** | 20.57% | 5.53% | 0.44% | 0.44% | 0.10% | 0.10% | 0.04% | 0.04% |
| | | **5** | 14.11% | 2.50% | 0.42% | 0.42% | 0.03% | 0.03% | 0.00% | 0.00% |

The share of agents *e* of activity type *t* with probability *c* that does shopping activity in the modeled day is estimated using equation 4. The total share of agents *E* per type *t* doing shopping activity is estimated using equation 5. The results are in Table 12. Note that in column $E_{wat}$ are the shares of the population that go shopping on the modeled day, and this number is significantly lower in scenario 1 than in the baseline scenario, which means that very few people in scenario 1 will go shopping.

Table 12 – Activity frequency example: share of agents that do activity in the modeled day "$e_{watp}$" and "$E_{wat}$"

| Activity | Scenario | Age | 0 days | 1 day | 2 days | 3 days | 4 days | 5 days | 6 days | 7 days | $E_{wat}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Shopping** | **Baseline** | **1** | 0.00% | 2.21% | 0.19% | 0.28% | 0.00% | 0.00% | 0.00% | 0.00% | 2.68% |
| | | **2** | 0.00% | 1.64% | 0.14% | 0.21% | 0.00% | 0.00% | 0.00% | 0.00% | 1.99% |
| | | **3** | 0.00% | 3.19% | 0.51% | 0.76% | 0.02% | 0.03% | 0.03% | 0.04% | 4.58% |
| | | **4** | 0.00% | 3.35% | 0.52% | 0.78% | 0.03% | 0.04% | 0.04% | 0.04% | 4.79% |
| | | **5** | 0.00% | 1.88% | 0.57% | 0.86% | 0.05% | 0.06% | 0.07% | 0.08% | 3.57% |
| | **1** | **1** | 0.00% | 0.50% | 0.03% | 0.05% | 0.00% | 0.00% | 0.00% | 0.00% | 0.58% |
| | | **2** | 0.00% | 0.37% | 0.02% | 0.03% | 0.00% | 0.00% | 0.00% | 0.00% | 0.43% |
| | | **3** | 0.00% | 0.98% | 0.20% | 0.30% | 0.00% | 0.00% | 0.00% | 0.00% | 1.48% |
| | | **4** | 0.00% | 0.79% | 0.12% | 0.19% | 0.05% | 0.07% | 0.04% | 0.04% | 1.30% |
| | | **5** | 0.00% | 0.36% | 0.12% | 0.18% | 0.02% | 0.02% | 0.00% | 0.00% | 0.69% |

Next, the reduction coefficient *r* for each agent type *t* is calculated using equation 6. The results are presented in Table 13. The information from this table can be read as follows: in the baseline scenario ($E_0$), 2.68% of the population does shopping trips, while in scenario 1 ($E_1$) that number is only 0.58%. Hence, the quotient between 0.58% and 2.68% is 21.53%, which is the share of the population that will do shopping trips in scenario 1 ($r_1$).

Table 13 – Activity frequency example: reduction coefficient "$r_{wat}$"

| Age | $E_0$ | $E_1$ | $r_1$ |
|---|---|---|---|
| **1** | 2.68% | 0.58% | 21.53% |
| **2** | 1.99% | 0.43% | 21.53% |
| **3** | 4.58% | 1.48% | 32.29% |
| **4** | 4.79% | 1.30% | 27.15% |
| **5** | 3.57% | 0.69% | 19.35% |

### 4.4.2. Modal shift module

The modal shift module estimates how many trips will be performed in a scenario taking into account the transport modes used to travel and a modal shift between these modes. In section 4.4.2.1, a framework of the modal shift module is presented and its modeling sequence is explained in detail. In section 4.4.2.2, an example of how the model works is provided.

#### *4.4.2.1. Description*

The framework of the modal shift module is depicted in Figure 4-4. The principle of this module is as follows: First, the initial number of trips per transport mode (*z*) is extracted from the baseline schedules. Second, the number of trips per transport mode that will still be done (*n*) is estimated using the initial number of trips per transport mode (*z*) and the reduction coefficient (*r*). Third, the number of trips shifted between modes (*g*) is calculated using the modal shift values (*s*) of the scenario and taking into account the initial number of trips per transport mode (*z*). Fourth, the new number of trips that will be done per transport mode (*h*) is estimated by adding *g* to *n*. Finally, the difference between the initial number of trips per transport mode (*z*) and the new number of trips that will still be done per transport mode (*h*) is the share, in percentage, of trips to keep in the schedules for the scenario (*k*).

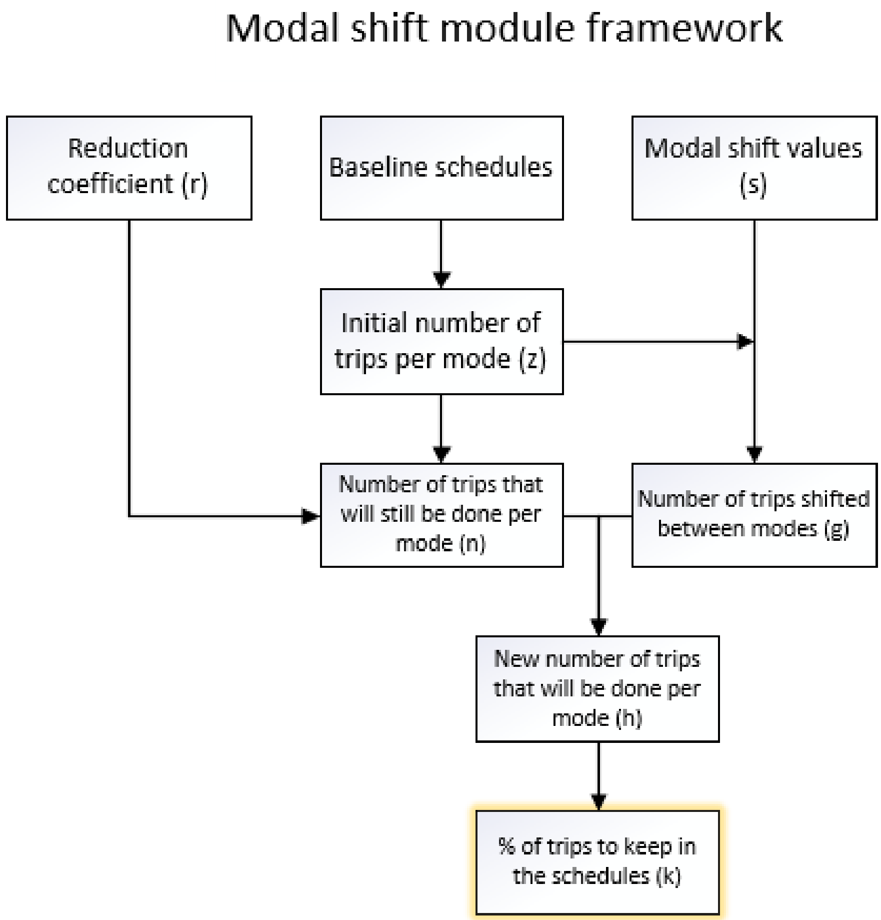


*Figure 4-4 - Modal shift module framework*

Mathematically, for every scenario *w*, activity type *a,* and agent type *t*, are assumed. Then, *z* is the number of trips by each transport mode *v* and *Z* is the summation of the trips of all transport modes:

$$Z_{wat} = \sum_{v \in V}^{V} z_{watv} \qquad \forall\, w \in W, a \in A, t \in T, v \in V \tag{7}$$

Then, the product of the number of trips *z* of each transport mode and the reduction coefficient *r* estimated in the activity frequency module is the number of trips *n* that will be done by each transport mode in the scenario:

$$n_{watv} = z_{watv} * r_{wat} \qquad \forall\, w \in W, a \in A, t \in T, v \in V \tag{8}$$

Next, the number of trips shifted between transport modes (*g*) is estimated. To do so, the modal shift values *s* of each mode are multiplied by the initial number of trips of each mode z, and $\Delta g$ of a transport mode is the difference between the number of trips taken from other modes and the number of trips given other modes. In these equations, *v* is the current transport mode and *q* are the other transport modes alternatives:

$$g_{watv} = \sum_{v \in V}^{V} \Delta g_{watv} \qquad \forall\, w \in W, a \in A, t \in T, v \in V \tag{9}$$

And

$$\Delta g_{watv} = (s_{watqv} * z_{watj}) - (s_{watvq} * z_{watv}) \quad \forall\, w \in W, a \in A, t \in T, v, j \in V \tag{10}$$

Then, the sum of the number of trips *n* that will be done by each transport mode and the result of the number of trips shifted between transport modes *g* is the new number of trips *h* that will be done by each transport mode:

$$h_{watv} = n_{watv} + g_{watv} \tag{11}$$

Finally, the quotient between the new number of trips that will be done *h* and the initial number of trips *z* is the share of trips to keep in the schedules *k* (for each transport mode):

$$k_{watv} = \frac{h_{watv}}{z_{watv}} \tag{12}$$

The share of trips to keep in the schedules, which will be referred to as the "*k* value", is given in percentage and is used in the schedules adjustment module to estimate the schedules for the scenarios.

#### *4.4.2.2. Example modal shift module*

In this example, the *k* value of activity 'shopping' for one agent type is calculated. The reduction coefficient *r* is assumed to be 0.6. For simplicity, the example only takes into account four transport modes: walk, bike, car and PT. Table 14 presents the made-up example of modal shift values *s*. From the table, it can be derived that public transport gives 3%, 5% and 10% of its trips to walk, bike and car, respectively.

*Table 14 – Modal shift example: modal shift values*

| Modal shift values '*s*' | | | | |
|---|---|---|---|---|
| Gives to \ Takes from | Walk | Bike | Car | PT |
| Walk | - | 0.00% | 0.00% | 0.00% |
| Bike | 0.00% | - | 0.00% | 0.00% |
| Car | 0.00% | 0.00% | - | 0.00% |
| PT | 3.00% | 5.00% | 10.00% | - |

Table 15 shows the results of the calculations. Column *z* shows the initial number of trips for each transport mode, which has been extracted from the baseline schedules using equation 7. Column *n* shows the number of trips *n* that will be done by each transport mode, which is calculated using equation 8. Columns g1 and g2 are the numbers of trips taken from other modes and given to other modes, which are calculated using equations 9 and 10, respectively. Column *h* is the new number of trips that will be done by each transport mode, which is calculated using equation 10. Finally, column *k* is the *k* value, which is calculated using equation 12.

The reduction coefficient *r* of the example is 0.6 or 60%. That means that 60% of the trips of all transport modes will be done and 40% of the trips will not be done anymore. For example, from the initial 500 trips done walking, only 300 will be done and 200 will not be done anymore. Then, the number of trips taken from and given to other modes is calculated. The only transport mode that gives trips to other modes is public transport, which gives 144 of its trips to the other modes.

Next, the *k* value is calculated by dividing the new number of trips *h* by the initial number of trips *z* (equation 12). Note that walk, bike and car increased their *k* value from 60% to 65%, 64% and 64%, respectively, while public transport decreased its *k* value from 60% to 42%. That means that when estimating the schedules of this scenario, for example, 65% of the walk trips that are in the baseline schedules will be kept, and 42% of the public transport trips will be kept.

*Table 15 - Modal shift calculation example: estimation of k values of transport modes for shopping activity*

| Mode | Initial number of trips (z) | Initial modal share | Number of trips kept (n) | Number of trips removed | Trips taken (g1) | Trips given (g2) | New number of trips (h) | Percentage of trips to keep in schedules (k) | New modal share | New modal share* |
|---|---|---|---|---|---|---|---|---|---|---|
| **Walk** | 500 | 11,63% | 300 | 200 | 24 | 0 | 324 | **65%** | 12,56% | 7,5% |
| **Bike** | 1000 | 23,26% | 600 | 400 | 40 | 0 | 640 | **64%** | 24,81% | 14,9% |
| **Car** | 2000 | 46,51% | 1200 | 800 | 80 | 0 | 1280 | **64%** | 49,61% | 29,8% |
| **PT** | 800 | 18,60% | 480 | 320 | 0 | 144 | 336 | **42%** | 13,02% | 7,8% |
| **Do not travel** | - | - | - | - | - | - | - | **-** | | 40,0% |

*including 'Do not travel' category

Note also that in the second column of Table 15 is the initial modal share, and in the two last columns are the new modal share and the new modal share considering trips that are not done anymore. In the initial modal share, no trips were assigned to 'do not travel', and in the new modal share it can be seen that 40% of all trips were then assigned to 'do not travel', and the remaining 60% were distributed within the transport mode alternatives. To better visualize what happens in this example, Figure 4-3 depicts the share of trips that were shifted between transport modes and given to 'do not travel'.

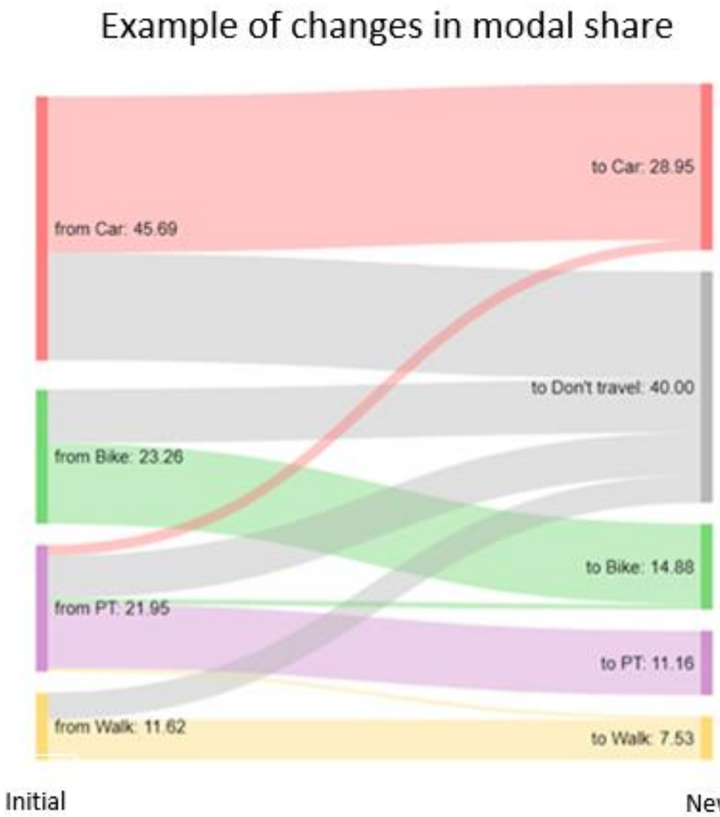


*Figure 4-5- Modal shift example: Initial modal share and new modal share after estimations using the reduction coefficient and the modal shift values*

### 4.4.3. Schedule adjustment module

This module re-estimates the daily schedules of the synthetic population using the *k* values and adjusts tours whenever activities and trips are removed. In section 4.4.3.1, a framework of the schedules adjustment module is presented and its modeling sequence is explained. In section 4.4.3.2, an example of how the model works is provided.

#### *4.4.3.1. Description*

The framework of the activity frequency module is depicted in Figure 4-6. The principle of this module is as follows: First, the baseline schedules are read to identify the initial agents' schedules and trip details. Second, random numbers *x* on the interval [0,1] are uniformly distributed for all agents. Third, for every activity trip in the schedule of an agent, his random number *x* is compared to his corresponding *k* value. If $x < k$, the agent keeps the activity trip in the schedule; if $x > k$, then the agent removes the activity trip from the schedule. An important observation about this module is that, in order to ensure a different set of results every time a scenario is estimated, no random seeds are used to generate the random numbers.

Once the decision to remove or keep activity trips is done for all the trips in the schedules, then the model adjusts the remaining trips and tours so that they still look consistent. To do so, the model identifies where the activity trip has been removed and, whenever necessary, updates details such as trip origin, trip start time, trip duration, activity start time, activity duration, and transport mode. The process of adjusting the remaining schedules is explained in detail in the example of the next section.

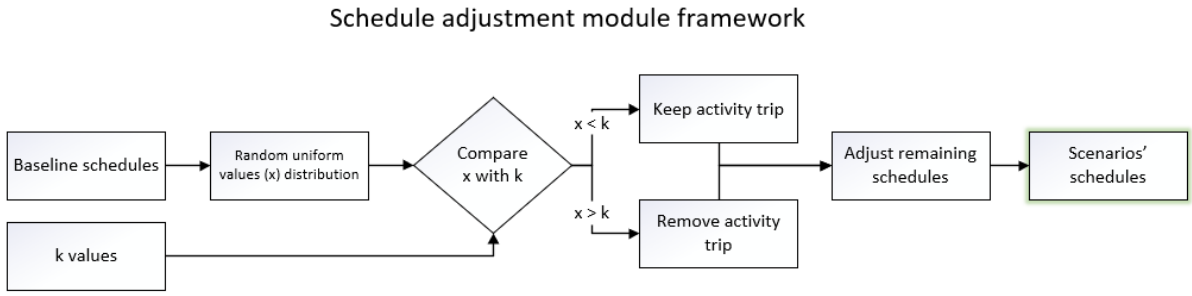


*Figure 4-6 - Schedule adjustment module framework*

#### *4.4.3.2. Example schedule adjustment module*

The following example shows the modeling sequence of the schedule adjustment module to estimate how the schedule of an agent is estimated from the baseline schedules.

Table 16 is the initial schedule for one workday of an agent labeled 43. The unit of time is minutes and the unit of distance is kilometers. This agent does seven trips and a total of three tours: 1-4-7-6-1 (tour 1), 1-7-1 (tour 2) and 1-6-1 (tour 3). As explained before, tours are chains of trips that start and end at home. Agent 43 starts his day at home (activity type = 1) at his house (first activity location = 2). The ABM used to estimate the baseline schedules generates a home activity as a starting point for every agent, which starts at minute 180, and since this is not a trip, it assigns a default value of -2 for trip transport mode, trip origin, and trip destination.

Next, it is assumed that the model estimated that agent 43 will not do activity 'Other' (activity 7) in his workday. That means that indexes 2 and 5 of Table 16 are deleted (colored in red) and the schedule of this agent now has only five trips and two tours: 1-4-6-1 (tour 1) and 1-6-1 (tour 2). Note that the second tour (1-7-1) is completely removed because index 5 has activity 7 (which is deleted) and therefore index 6 is also deleted because the agent does not need to travel at all.

Table 16 – Schedules adjustment example: initial schedule of agent 43

| index | agent id | activity type | activity location | activity start time | activity duration | trip transport mode | trip origin | trip destination | trip start time | trip duration | trip distance |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 43 | 1 | 2 | 180 | 290 | -2 | -2 | -2 | 0 | 0 | 0 |
| **1** | 43 | 4 | 612 | 480 | 15 | 4 | 2 | 612 | 470 | 10 | 6 |
| **2** | 43 | 7 | 191 | 502 | 15 | 4 | 612 | 191 | 495 | 7 | 4 |
| **3** | 43 | 6 | 1242 | 577 | 105 | 1 | 191 | 1242 | 517 | 60 | 5 |
| **4** | 43 | 1 | 2 | 687 | 17 | 4 | 1242 | 2 | 682 | 5 | 2 |
| **5** | 43 | 7 | 580 | 720 | 45 | 2 | 2 | 580 | 704 | 16 | 4 |
| **6** | 43 | 1 | 2 | 781 | 407 | 2 | 580 | 2 | 765 | 16 | 4 |
| **7** | 43 | 6 | 1389 | 1200 | 15 | 4 | 2 | 1389 | 1188 | 12 | 9 |
| **8** | 43 | 1 | 2 | 1226 | 394 | 4 | 1389 | 2 | 1215 | 11 | 9 |

With the removal of these trips from the schedule, it is then necessary to make some adjustments so the schedules remain consistent. In this example, when index 2 is removed, the activity location of index 1 becomes the trip origin of index 3. Therefore, the trip route needs to be re-estimated, and that changes the trip start time, the trip duration, the trip distance and the activity start time of index 3. Hence, it can be concluded that once one or more trips are removed from a tour, the rest of the tour needs to be adjusted. To do so, some premises are established:

i. When the first trip of a tour is removed, the agent waits at home until it is time to travel to the new first trip of the tour (Figure 4-7).

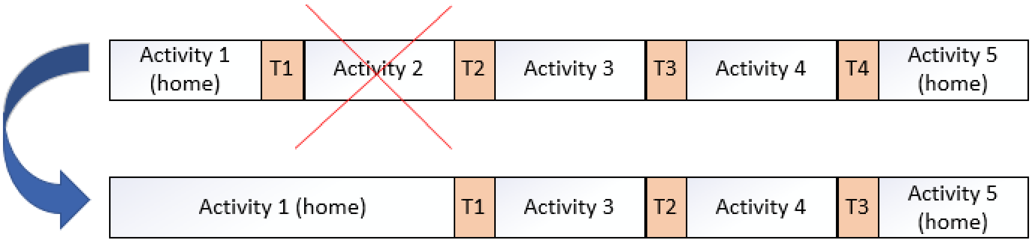


Figure 4-7 - Schedule adjustment module: first premise

ii. When one or more trips are removed from a tour, all the subsequent activities of this tour are done earlier so that the agent arrives at home earlier (Figure 4-8).

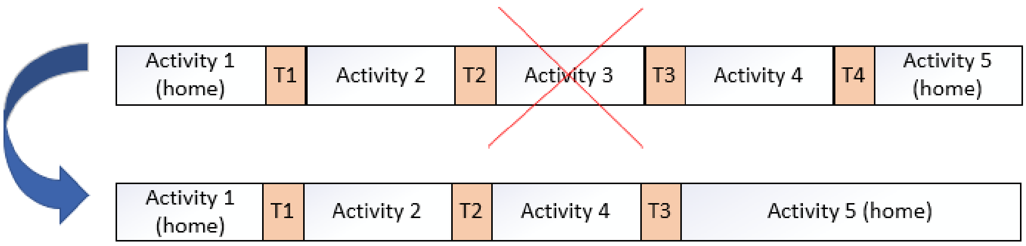


Figure 4-8 - Schedule adjustment module: second premise

iii. The activity duration never changes, except for home activity.

The rules to update an index vary according to the activity type. If activity type = 1 (home), a certain command sequence is applied. If activity type ≠ 1, then another command sequence is applied.

Table 17 shows how the schedule of agent 43 becomes after adjusting the remaining trips of the schedule. The values from this table can be compared to the values of Table 16 to check the difference between before and after the adjustment. The colored cells are the attributes that have been adjusted. Considering that the grey rows are already deleted, they are kept in the table just to illustrate how the schedule is adjusted.

In the example, activity 7 of the 1st tour is deleted, so it changes from 1-4-7-6-1 to 1-4-6-1. Taking into account premise ii, the agent does activity 6 earlier and arrives at home earlier as well. Then, the 2nd tour is totally removed (1-7-1), so the agent does not travel, and instead, he waits at home (premise i) until he starts the 3rd tour (1-6-1).

*Table 17 – Schedules adjustment example: adjusted schedules of agent 43*

| index | agent id | activity type | activity location | activity start time | activity duration | trip transport mode | trip origin | trip destination | trip start time | trip duration | trip distance |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 43 | 1 | 2 | 180 | 290 | -2 | -2 | -2 | 0 | 0 | 0 |
| 1 | 43 | 4 | 612 | 480 | 15 | 4 | 2 | 612 | 470 | 10 | 6 |
| 2 | 43 | 7 | 191 | 502 | 15 | 4 | 612 | 191 | 495 | 7 | 4 |
| 3 | 43 | 6 | 1242 | 577 | 105 | 1 | 191 | 1242 | 517 | 60 | 5 |
| 4 | 43 | 1 | 2 | 687 | 501 | 4 | 1242 | 2 | 682 | 5 | 2 |
| 5 | 43 | 7 | 580 | 720 | 45 | 2 | 2 | 580 | 704 | 16 | 4 |
| 6 | 43 | 1 | 2 | 781 | 407 | 2 | 580 | 2 | 765 | 16 | 4 |
| 7 | 43 | 6 | 1389 | 1200 | 15 | 4 | 2 | 1389 | 1188 | 12 | 9 |
| 8 | 43 | 1 | 2 | 1226 | 394 | 4 | 1389 | 2 | 1215 | 11 | 9 |

To better understand the example, index 3 is referred to as "i" and indexes 1 and 4 are referred to as "i-1" and "i+1", respectively. To update index 3, the command sequence for activity type ≠ 1 is performed:

a. Update trip_origin$_i$ → replace by activity_location$_{i-1}$ (green cell)
b. Update trip_start_time$_i$ → activity_start_time$_{i-1}$ + activity_duration$_{i-1}$ (pink cell)
c. Update trip_duration$_i$ → LOS between trip_origin$_i$ and trip_destination$_i$ (blue cell)
d. Update activity_start_time$_i$ → trip_start_time$_i$ + trip_duration$_i$ (orange cell)

Then, the next index is 4 and the activity type = 1, which is the end of the tour. Index 4 is referred as "i" and indexes 3 and 5 are referred as "i-1" and "i+1", respectively. To update this index, the command sequence for activity type = 1 is performed:

e. Update trip_start_time$_i$ → activity_duration$_{i-1}$ + trip_duration$_{i-1}$ (yellow cell)
f. Update activity_start_time$_i$ → trip_start_time$_i$ + trip_duration$_i$ (cyan cell)
g. Update activity_duration$_i$ → trip_start_time$_{i+1}$– activity_start_time$_i$ (red cell)

Home activity is always the last activity of a tour or the last activity of a schedule. Therefore, two other rules are used to update home activity:

h. When all the tours of an agent are removed, he stays at home for the entire day. Hence, the activity duration of home activity is updated to 1440 minutes.
i. The activity duration of the last activity of the schedule of an agent is equal to 1440 minutes subtracted by the activity start time.

These are the command sequences to update the schedules in the model. The product of these adjustments is the schedules for the scenarios, which is the final output of the model.

## 4.5. Limitations and considerations

In this section, some limitations and considerations about the model are highlighted. As explained in chapter 3, this model has been built to study the impacts of COVID-19 as an initial purpose. Therefore, the methods and data formats designed for the model were structured taking into account the availability of data and resources by the time this study was planned.

i. The model is not a full ABM, but a model that uses the output from ABMs as inputs to estimate new outputs. Therefore, the schedules estimated by the model are still similar to the baseline schedules but with several modifications and adjustments.
ii. Describing in a simplified way, one of the functions of the model is to estimate if agents still travel to do activities or if they do not travel and stay at home. Hence, the model cannot add new trips to the schedules, only remove them. That means that scenarios will always have fewer trips than the baseline scenario.
iii. Because the model uses a microsimulation approach at the person-day level, it is subject to some degree of simulation variation. However, when performing many runs for the same scenario, the aggregated performance measures within these runs should be consistent. Therefore, when running the results of scenarios, a run statistical formula must be used to define the appropriate minimum number of runs to ensure consistency.
iv. To calibrate the model, the estimates of travel demand and related choices output by the model should be compared to observed real-world data. The calibration of the demand model components is primarily based on household travel survey data, which can provide necessary information describing observed activity patterns, and choices of destination, mode, and time. Other sources of calibration can be count databases or transit agency reporting. The calibration of the model also must include sensitivity testing to ensure that the model responds plausibly to changes in model inputs and that these changes are reasonably consistent with real-world outcomes (Castiglione et al., 2014).
v. To validate the model, keys metrics are identified, and comparisons between model estimates and observed data that have not been used in the model estimation are made.

# 5. Case study

The case study developed for this study has as objective the estimation of changes in activity-travel behavior of travelers in the MRDH, the Netherlands, during different stages of the COVID-19 pandemic and the assessment of the effects of such changes on mobility. This is done to validate the framework's performance by comparing its outcomes with data counts and outcomes of other studies and sources.

In this chapter, the case study is presented. Section 5.1 introduces the area of study. Section 5.2 defines the COVID-19 stages that are analyzed. Section 5.3 describes the data inputs of the model.

## 5.1. Case study: Rotterdam-The Hague metropolitan area

The area of study is the Rotterdam-The Hague metropolitan area (MRDH), the Netherlands, which encompasses the cities of Rotterdam and The Hague as well as 21 other municipalities. These are the yellow and orange areas shown in Figure 5-1. The area has a population of approximately 2.7 million. There are around 1.3 million jobs and 13.5% of the Dutch population work there (Metropoolregio Rotterdam-Den Haag, 2021a).


*Figure 5-1 - The Rotterdam-The Hague metropolitan area (MRDH)*

The motivation to use this region as a case study is because TNO, which is one of the companies collaborating with this study, has several ongoing projects in this region. One of them is the Urban Tools Next project (UTN) (de Romph et al., 2019). In this project, it is investigated the extent to which ABMs can be used to gain insight into the effects of various developments and interventions around mobility in the MRDH. To do so, an ABM prototype was made for the region. The ABM software used in this study is FEATHERS (Bellemans et al., 2010), which is an acronym for Forecasting Evolutionary Activity-Travel of Household and their Environmental Repercussions. FEATHERS is a full implementation of an ABM and has been used to estimate the schedules for the MRDH population. Those schedules were estimated for a period before the outbreak of the COVID-19 pandemic when travel decisions were not affected by it. Therefore, it was decided to use the schedules predicted by FEATHERS as the baseline schedules for this case study.

## 5.2. Defining COVID-19 stages

Four stages of the corona crisis are defined to run the model, as well as the baseline stage. These stages are designed and intended to showcase the differences in activity-travel behavior in different moments of the pandemic in the MRDH. Therefore, the stages' inputs vary in the activity frequency that agents have for different activity types and also in the modal shift values according to the period in analysis. Real data inputs have been used to estimate the different stages, and the data sources, as well as the inputs, are presented and described in the next section. In total, five stages are considered and they are presented in Table 18. These are the baseline or stage 0 (September 2019), stage 1 (March 2020), stage 2 (July 2020), stage 3 (October 2020) and stage 4 (January 2021). For reasons of clarity, the phases are strictly separated, where in reality there is clearly a more gradual evolving situation.

The motivation to select these stages is because they represent different moments of the impacts of COVID-19 and the measures applied against it. Figure 5-2 shows the number of hospital admissions over time in the Netherlands during the pandemic (Rijksoverheid, 2021). In March 2020, the first wave of COVID-19 started in the Netherlands, with the number of hospital admissions reaching more than 400 admissions per day. That is when the intelligent lockdown (Kuiper et al., 2020) was implemented (Stage 1). Then, around July 2020 the number of admissions decreased and measures against the corona virus were relaxed (Muhlberg, 2020) (Stage 2). However, a second wave started in October 2020 and a partial lockdown came into effect (Government of the Netherlands, 2020) (Stage 3). In the upcoming months, the high number of hospital admissions became stable, and by January 2021 a strict lockdown (Government of the Netherlands, 2021b) was implemented together with the curfew (Stage 4).

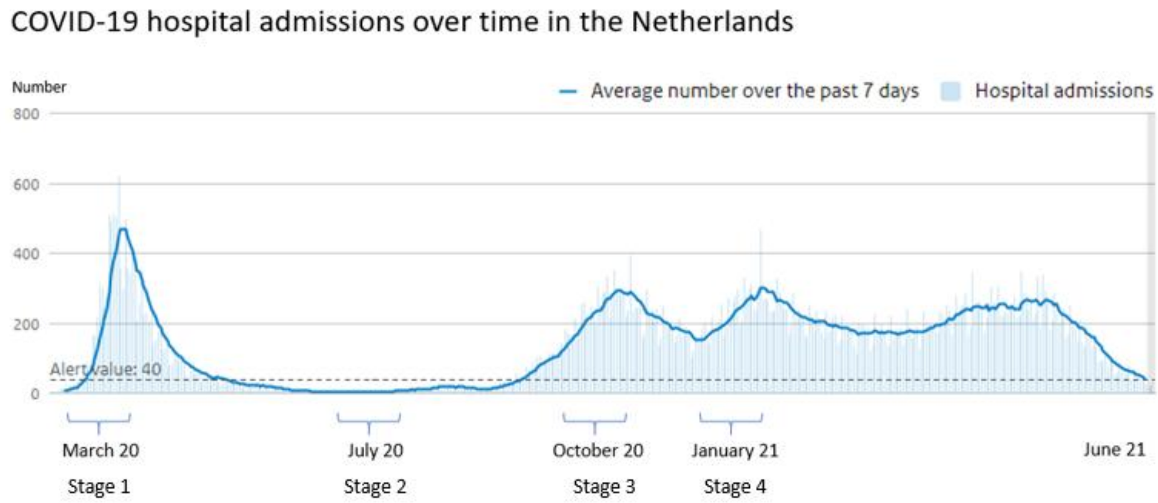


*Figure 5-2 - Timeline of the number of hospital admissions due to COVID-19 in the Netherlands (Source: Rijksoverheid, 2021)*

Another way to distinguish COVID-19 stages is by differing the strength of measures applied during the pandemic. The Oxford Corona virus Government Response Tracker (OxCGRT) created the COVID-19 Stringency Index (Ritchie et al., 2021), which tracks the impact of the pandemic across different countries and subject areas. In Table 18, the strength of Dutch policy responses to the pandemic on workplace closure, school closure, and stay-at-home restrictions are presented in the last three columns, respectively, according to the COVID-19 Stringency Index. There are four levels of policy measures strength for workplace and school closures. These are: (1) no measures, (2) recommended to close, (3) required for some to close, (4) required for all but key workers to close. For stay-at-home restrictions, there are also four levels, namely: (1) no measures, (2) recommended to stay-at-home, (3) required (except essentials) to stay-at-home and (4) required (few exceptions) to stay-at-home.

*Table 18 – Stages of COVID-19 analyzed in the case study*

| Stage | Period | Description | Workplace closure measures* | School closure measures* | Stay-at-home restrictions* |
|---|---|---|---|---|---|
| **Baseline** | Sep-19 | Normal behavior | No measures | No measures | No measures |
| **1** | Mar-20 | Intelligent lockdown | Required for some | Required (all levels) | Required (except essentials) |
| **2** | Jul-20 | Summer Relaxations | Required for some | Recommended | Recommended |
| **3** | Oct-20 | Semi Lockdown | Required for some | Recommended | Recommended |
| **4** | Jan-21 | Strict lockdown | Required for all but key workers | Required (all levels) | Required (except essentials) |

*Source: COVID-19 Stringency Index in the Netherlands (Ritchie et al., 2021)

## 5.3. DATA

In this section, the data used to estimate the different COVID-19 stages is presented and described in detail. Section 5.3.1 describes the data sources and gives an overview of which data is used for each module. Section 5.3.2 describes the synthetic population of the study area. Section 5.3.3 describes the baseline schedules. Section 5.3.4 presents the activity frequency values. Section 5.3.5 presents the modal shift values. Finally, section 5.3.6 discusses the constraints imposed by the data.

### 5.3.1. Data sources

In total, the model has four data inputs. These are the activity frequency values, the modal shift values, the synthesized population and the baseline schedules. These inputs come from five different data sources as shown in Table 19. In this section, each of these data sources is presented and an explanation about how the data is derived is given.

*Table 19 - Input data sources of the case study*

| Data source | | Data type | Input for which module | Input usage |
|---|---|---|---|---|
| **1** | KIM | Activity frequency data in the form of frequency tables | Activity module | Estimate non-work-related activity frequency values |
| **2** | TNO W&HT | WFH frequency microdata | Activity module | Estimate work-related frequency values |
| **3** | DAT.Mobility | Modal shift values | Modal shift module | Estimate the modal shift between modes |
| **4** | TNO SUMS | Synthetic population list | Activity module | Estimate the number of agents performing activities in the simulations |
| **5** | Hasselt University | Baseline schedules | Schedules adjustment module | Estimate new schedules |

The first data source is KIM (Netherlands Institute for Transport Policy Analysis), which provided longitudinal data of surveys they conduct on mobility behavior in the Netherlands during the pandemic (de Haas, Hamersma, et al., 2020a, 2020c, 2020b). Their microdata is only publicly accessible after two years of their collection. However, they kindly provided some frequency tables (macro data) with interesting data about the weekly frequency people do outdoor activities (groceries, shopping, catering, sports, visit friends and others) and the location where people attend education. The data was broken down by age group. In total, there are longitudinal data collected for a period before COVID (September 2019) and three COVID periods: March 2020, July 2020 and January 2021. This data is input for the activity module to estimate the frequency of non-work-related activities.

The second data source is TNO's Work Health Technology department (TNO W&HT), which provided longitudinal data from their study named National Survey on Working Conditions COVID-19 (NEA-COVID). In their study, they investigate the quality of work and employment in the Netherlands. It contains information about workers' work conditions, job type, the number of hours worked in the office and also from home, and their industry sector. Their datasets are private but since TNO also sponsors this study, they allowed its use. They provided raw microdata that has been processed during this study. The data process is explained in section 5.3.4. In total, there are longitudinal data collected for three periods: September 2019 (pre-COVID), July 2020, and October/November 2020. This data is input for the activity module to estimate the frequency of work-related activities.

The third data source is DAT.Mobility, which provided a workbook with data from the Nederlands Verplaatsingspanel (NVP). NVP is a large-scale source of information about travel behavior, motives and background characteristics of the Dutch (DAT.Mobility, 2021). Their workbook contains processed aggregates on observed travel behavior from March 2020 to the present. Several indicators have been elaborated, such as number of trips, travel times, distance traveled, modal shifts and peak hours. For each indicator, data are available for the modes of car, bike, walking and public transport. For this case study, only the modal shift data has been used. This data is input for the modal shift module to estimate the modal shift between modes.

The fourth data source is TNO's Sustainable Urban Mobility and Safety (SUMS), which provided the synthetic population for the study area (de Romph et al., 2019). This data is input for the activity frequency module to estimate the number of agents that perform activities in the simulations.

The fifth and final data source is the University of Hasselt, Belgium, which provided the baseline schedules generated by their ABM FEATHERS (Bellemans et al., 2010). These baseline schedules were generated for the synthetic population provided by TNO for a period before the COVID-19 pandemic. This data is input for the schedules adjustment model to estimate schedules for each stage.

In Table 20 an overview of data sources used to estimate the different COVID-19 stages of the study case is presented. The 'work activity data' column shows the data sources of the activity frequency values of activities work and business. The 'non-work activities data' column shows the data sources of the activity frequency values of activities bring/get, shopping, education and others. For stage 3, there were no measurements of 'non-work activity data', so the average between the percentages of stages 2 and 4 for all activity types was considered. The 'modal shift data' column shows the periods of the modal shift data used from the NVP data of DAT.Mobility.

Note that for the 'work activity data' of stages 1 and 4 and, the data source is described as 'perception'. For this stages, TNO didn't collect data. Therefore, it was decided to estimate the percentages for these stages based on how essential workers of different sectors are (McNicholas & Poydock, 2020) and the strength of work-related policy measures for the correspondent periods (Ritchie et al., 2021).

By essential workers, it is meant that the employees of a certain sector are required to work on-site. According to the study of McNicholas & Poydock (2020), the majority of essential workers during the COVID-10 pandemic are employed in healthcare, food & agriculture, and industrial & production sectors, while the minority of essential workers are in the office sector and in (most of) the retail sector. Therefore, for sectors considered essential, the percentage of home workers has been estimated lower compared to the sectors considered non-essential. The values estimated for these two stages are described in detail in section 5.3.4.

*Table 20 - Overview of the data sources of the case study*

| Stage | Period | Description | Work activity data | Non-work activities data | Modal shift data |
|---|---|---|---|---|---|
| **Baseline** | Sep-20 | Normal behavior | TNO Wave 0 | KiM 0 | Weeks 10-11, 2020 |
| **1** | Mar-20 | Intelligent lockdown | Perception | KiM 1 | Weeks 13-14, 2020 |
| **2** | Jul-20 | Summer Relaxations | TNO Wave 1 | KiM 2 | Weeks 29-30, 2020 |
| **3** | Oct-20 | Semi Lockdown | TNO Wave 2 | Average KiM 2 & KIM 4 | Weeks 42-43, 2020 |
| **4** | Jan-21 | Strict lockdown | Perception | KiM 4 | Weeks 03-04, 2021 |

### 5.3.2.Synthetic population

The synthetic population of the case study has been developed by TNO for the MRDH (de Romph et al., 2019). The study area has a population of approximately 3.65 million. This number is higher than the population of the MRDH because the population of nearby external areas is also included since they also make trips to the model area.

A synthetic population can have many demographic attributes, and that depends on the study purposes and also on the data availability. For this case study, the synthetic population is classified using four different attributes: gender, education, age and work sector. That is because the activity frequency values input data had only these four attributes. If there were more, they could have been used. Table 21 presents the categories of each of the four demographic attributes. Please note that there are two other attributes, 'agent_id' and 'location_id', that identify each agent in the population and the zone where this agent lives.

The graphs of Figure 5-3 show how the population is distributed per each demographic attribute. Attributes age, gender and education are classified taking into account the 3.65 million inhabitants of the study area. The attribute work sector takes into account only the workers of the study area, which are approximately 1.24 million.

*Table 21 – Demographic attributes of the synthetic population of the case study*

| Attribute | Value | Description | Unit |
|---|---|---|---|
| **agent_id** | 0-N | Unique ID of agent | - |
| **location_id** | 0-7740 | Zone where agent lives | Zone number |
| **gender** | - | Gender of person | - |
| | 1 | Male | |
| | 2 | Female | - |
| **age_person** | - | Age group of person | - |
| | 1 | Age < 15 | - |
| | 2 | Age >=15 & Age < 25 | - |
| | 3 | Age >= 25 & Age < 45 | - |
| | 4 | Age >= 45 & Age < 65 | - |
| | 5 | Age >= 65 | - |
| **education** | - | Highest education obtained | - |
| | 1 | Primary | - |
| | 2 | Lower | - |
| | 3 | Secondary | - |
| | 4 | Higher | - |
| | 5 | Other | - |
| **working_sector** | - | Sector which the person works | - |
| | 0 | Not working | - |
| | 1 | Industry and production | - |
| | 2 | Healthcare | - |
| | 3 | Retail | - |
| | 4 | Education | - |
| | 5 | Office | - |
| | 6 | Other | - |

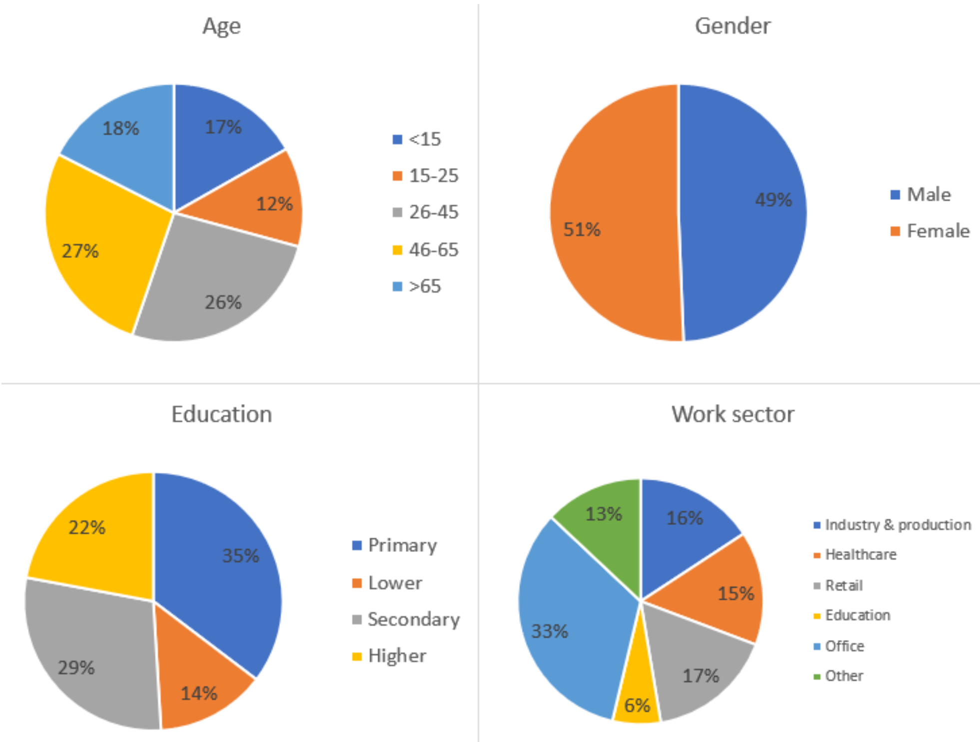


*Figure 5-3 - Synthetic population distribution per different attributes*

From all the demographic attributes of the case study, the work sector is the only attribute that was not previously included in the synthetic population of FEATHERS. For this study, this attribute has been estimated and included in the synthetic population due to its importance in modeling commuting behavior. In the remainder of this section, the addition of the work sector attribute to the synthetic population is explained.

The work sector is added to the population using data from the Central Agency of Statistics of the Netherlands (CBS). Their data contain information of employee jobs for the Dutch population, such as the type of job and work sector (CBS, 2020). From their datasets, data about the work sector of individuals in the MRDH are extracted and distributed to the synthetic population. Due to permission constraints, the distribution of work sectors for the synthetic population is done at a regional level, which means that all the zones of the study area have the same work sector distributions. However, it would be better to have these distributions at the zonal level to have more accurate results.

In total, there are 70 work sectors in CBS datasets. However, it is decided for this study to group these sectors into 6 smaller groups to limit the number of possible agent type combinations. The six sectors considered in the case study are: (1) industry and production, (2) healthcare, (3) retail, (4) education, (5) office, (6) other. The 'other' sector includes sectors such as transportation, sports and recreation, and other service activities.

These sectors are distributed to the synthetic population according to the number of workers of each zone. Figure 5-3 indicates the share of different work sectors in the MRDH. For example, if a zone has 100 inhabitants that are workers, then sixteen of these workers will be from the industry & production sector, fifteen will be workers from the healthcare sector, and so on.

### 5.3.3. Baseline schedules

The baseline schedules used as input for the study case have been developed by TNO and the University of Hasselt by the use of the ABM FEATHERS (Bellemans & Kochan, 2016). The network used to build the baseline schedules is the modal that is used by MRDH, the V-MRDH 2.0 (MRDH, 2021b). The ABM FEATHERS has been used for a synthetic population in the V-MRDH regions 1 to 5. These are the non-green areas shown on the right of Figure 5-4, also referred to as the model area or the internal area. This application contains almost all trips made from internal to internal, but only a part of the trips from internal to external areas, external to internal areas and external-external traffic. The farther away the zones are from the MRDH, the larger the fraction of external-related trips. For this study, all the schedules within regions 1 to 5 are considered.

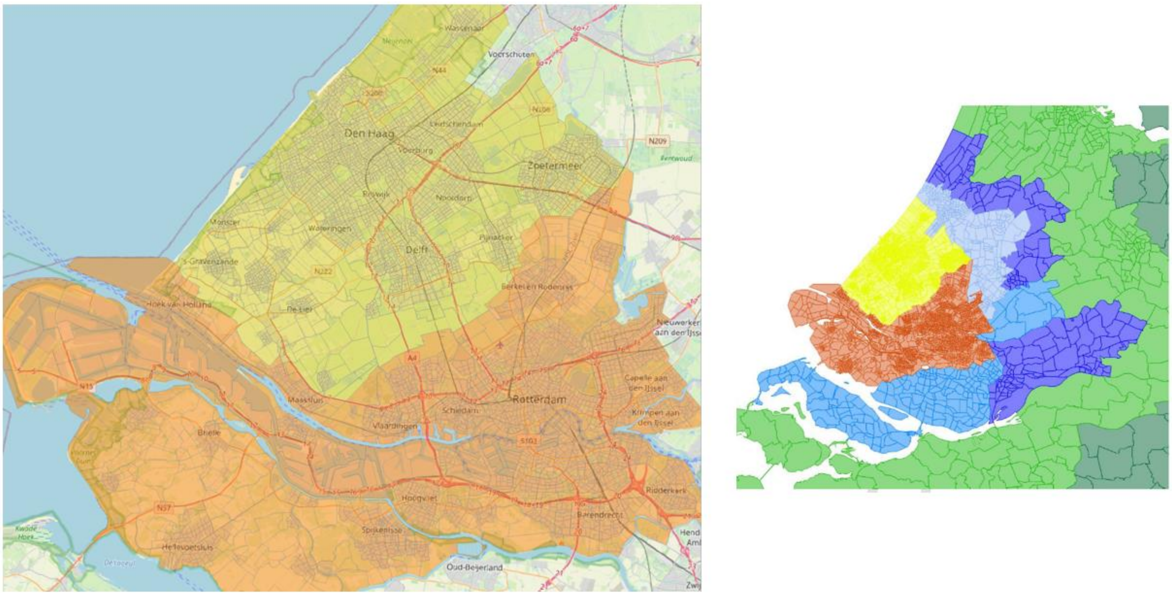


*Figure 5-4 – MRDH study area (left); V-MRDH (right): schedules for areas 1 to 5: yellow, orange, light blue, dark blue and purple*

Table 22 presents the attributes included in the (baseline) schedules of the case study. In total, the study area has 7740 zones. There are 7 different activity types and 7 different transport mode alternatives. The unit of time is minutes. The unit of distance is kilometers.

*Table 22 - Schedules attributes of the case study*

| Attribute | Value | Description | Unit |
|---|---|---|---|
| **agent_id** | 0-N | Unique ID to identify agents | - |
| **activity_type** | - | The type of activity a person is going to do at the destination | - |
| | 1 | Home | - |
| | 2 | Work | - |
| | 3 | Business | - |
| | 4 | Bring/get | - |
| | 5 | Education | - |
| | 6 | Shopping | - |
| | 7 | Other | - |
| **activity_location** | 0-7740 | Zone where activity takes place | Zone number |
| **activity_start_time** | 180-1619 | Start of activity in minutes since midnight | minute |
| **activity_duration** | 1-1440 | Length of activity | minute |
| **trip_transport_mode** | - | Main transport mode of the whole trip | - |
| | 1 | Walk | - |
| | 2 | Bike | - |
| | 3 | E-bike | - |
| | 4 | Car driver | - |
| | 5 | Car passenger | - |
| | 6 | Shared on-demand | - |
| | 7 | Public transport | - |
| **trip_origin** | 0-7740 | Zone where traveler departed | Zone number |
| **trip_destination** | 0-7740 | Zone where traveler arrives | Zone number |
| **trip_start_time** | 180-1619 | Start of trip in minutes since midnight | minute |
| **trip_duration** | 0-N | Length of trip | minute |
| **trip_distance** | 0-N | Distance of trip | km |

### 5.3.4. Activity frequency values

The activity frequency values used for this case study comes from data provided by KIM (de Haas, Hamersma, et al., 2020c, 2020a, 2020b) and TNO W&HT (Hooftman et al., 2021; Hooftman, Bouwens, et al., 2020; Hooftman, Hengel, et al., 2020). The data provided by KIM was already provided in the desired structure, while the data provided by TNO W&HT needed to be processed. Thus, for some stages, there was no data available from these two data sources so they were estimated using a different approach.

Section 5.3.4.1 describes the activity frequency value tables used in the case study. Section 5.3.4.2 discusses the steps to process the NEA-COVID data. Section 5.3.4.3 explains the approach taken to estimate data for stages that there was no NEA-COVID data available.

#### *5.3.4.1. Activity frequency tables*

The activity frequency values are inputs in the format of tables. For this case study, there are six activity types available (see Table 22) and for each activity type, there is an activity frequency table. For activity types 'work' and 'business', three attributes are used to categorize agents: age, gender and work sector. Age has 5 categories, gender has 2, and work sector has 7 (including agents that do not work), which means that there are 70 different combinations of agent types. For activity types 'education', 'shopping', 'bring/get' and 'other', only the age attribute is used, so there are 5 different combinations of agent types.

The activity frequency value tables of all the stages considered in this case study are presented in Appendix A.

An important aspect of this case study is that the tables for activity 'education' are not in the format of 0-5 days as explained in chapter 4, section 4.3.2. Instead, agents have three frequency options: 'full online', 'partial online', and 'full on campus'. That is because the data provided by KIM only considered these options in their survey. 'Full online' means that the student does not travel to study, 'partial online' means that the student has a 50% chance of traveling to study per day, and 'full on campus' means that the student has a 100% chance of traveling to study per day.

#### *5.3.4.2. NEA-COVID data processing*

As explained before, NEA-COVID data comes from the study conducted by TNO W&TH (Hooftman et al., 2021; Hooftman, Bouwens, et al., 2020; Hooftman, Hengel, et al., 2020) about the quality of work and employment in the Netherlands during the COVID-19 pandemic. It contains information about workers' work conditions, job type, the number of hours worked in the office and also from home, and their industry sector.

The steps to process the data from TNO W&TH are as follows: first, the attributes that were useful for the project were identified. For this study, it is of interest to use attributes that can help to explain the frequency in which workers work from home, but taking into account the behavior of different groups of people, such as their age and work sector. Therefore, from the dataset, the following attributes were selected: agent ID, stage, gender, age, education, industry sector, number of hours worked per week in their job contract ('Worked_hours'), number of hours worked from home per week ('WFH_hours'), job change (if they changed job during the pandemic), and working conditions (not working, working only at the office, working only at home, and working both at the office and at home). The other attributes were filtered out, as well as rows that had invalid or empty cells.

The 'working conditions' attribute indicates whether agents are currently working or from where they work (from home or from the office). That already splits the population into workers and non-workers. From the 'Worked_hours' and 'WFH_hours' attributes, it is possible to estimate how many hours people work per week and also the share of hours that they work at the office and at home. The range of Worked_hours and WFH_hours values is broad and sometimes uncommon (e.g. 7, 9, 21, 65, 70 hours a week). According to Hooftman et al. (2020), sometimes people might not have understood the question well and filled something like the number of hours they feel they work instead of their contract hours. Therefore, for simplicity, it was decided to group Worked_hours and WFH_hours attributes into categories as presented in Table 23. For this categorization, we assume that a person can work a maximum of five days a week, and one day of work is less or equal to eight work hours. Hence, the variables Worked_hours and WFH_hours are transformed into the variables Worked_days and WFH_days, respectively.

*Table 23 – Categorization of number of days worked*

| Hours worked per week | Days of work per week (max = 5) |
|---|---|
| **0** | 0 |
| **<8** | 1 |
| **9-16** | 2 |
| **17-24** | 3 |
| **25-32** | 4 |
| **>32** | 5 |

Then, from the difference between the Worked_days and WFH_days, the number of days an agent commute to work every week can be estimated. That is the attribute Work_trip_days. The processed data at this stage is presented in Figure 5-5. It has the background variables of agents, as well as the period it has been collected.

| | ID | Period | Gender | Age | Education | Paid_work | Sector | Work_condition | Worked_hours | WFH_hours | Worked_days | WFH_days | Work_trip_days |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 2919030 | 0 | 2 | 4 | 1 | 3 | 1 | 1 | 32 | 0 | 4 | 0 | 4 days |
| **1** | 2919030 | 1 | 2 | 4 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 days |
| **2** | 2919052 | 0 | 1 | 3 | 2 | 3 | 1 | 1 | 40 | 0 | 5 | 0 | 5 days |
| **3** | 2919052 | 1 | 1 | 3 | 2 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 days |
| **4** | 2919052 | 2 | 1 | 3 | 2 | 3 | 1 | 3 | 40 | 10 | 5 | 2 | 3 days |
| **5** | 2919056 | 0 | 1 | 4 | 1 | 3 | 1 | 1 | 40 | 0 | 5 | 0 | 5 days |

*Figure 5-5 - NEA-COVID processed data example*

When all agents of the dataset have their Work_trip_day attribute, then the activity frequency tables are generated. The data processed from NEA-COVID is available for the baseline stage and stages 2 and 3.

#### *5.3.4.3. Data estimation for stages 1 and 4*

As explained in section 5.3.1, there were no inputs of work activity data available for stages 1 and 4, and they were estimated based on how essential workers of different sectors are (McNicholas & Poydock, 2020) and the strength of work-related policy measures for the correspondent periods (Ritchie et al., 2021). Sectors considered non-essential (retail, office, education) have fewer on-site workers while sectors considered essential (industry & production, healthcare) have more.

In Table 24 the estimated share of on-site workers for each working sector during stages 1 and 4 is presented. In the Netherlands, the recommendation during stage 1 was to work from home as much as possible while in stage 4 the requirement was for all but key workers to work from home.

As explained in section 5.2, there are four levels of workplace closure restrictions. Stage 1 was in the second level of restrictions, while stage 4 was in the fourth. Therefore, for non-essential sectors in stage 1, it is decided to assign 25% of workers to work on-site, and a bit less (10%) to the office sector since that is the sector that more often works from home (CBS, 2020). For essential jobs, the healthcare sector is assigned 100% since they were highly required during the pandemic, and 50% is assigned to the industry & production sector since this sector is broad and not all of it can be considered essential. For stage 4, it is decided to reduce even more the numbers for non-essential jobs and the industry & production sector, since only key workers were allowed to work on-site. The healthcare sector is the only sector to keep the same percentage as in stage 1.

*Table 24 – Share of on-site workers estimated for stages 1 and 4 of the case study*

| Sector | Stage 1 (intelligent lockdown) | Stage 4 (strict lockdown) |
|---|---|---|
| **Industry & production** | 50% | 10% |
| **Healthcare** | 100% | 100% |
| **Retail** | 25% | 10% |
| **Education** | 25% | 2% |
| **Office** | 10% | 2% |
| **Other** | 25% | 10% |
| **Workplace closure during COVID-19** (Ritchie et al., 2021) | Required for some | Required for all but key workers |

### 5.3.5. Modal shift values

The modal shift values used for this case study come from data provided by DAT.Mobility (2021). They calculate the amount of time that a population sample spends traveling using different transport modes on a weekly basis. Then, the time difference between the same modes in week X and week Y is calculated. This yields transport modes with a surplus of travel time, and transport modes with a deficit of travel time. For example, if an agent travels 20 minutes by car in week X, and 10 minutes in week Y, then 10 minutes go from car to car. Then, the remaining 10 minutes (surplus) is distributed evenly among the modes with a deficit. This is done for all the transport mode categories.

For this case study, the time difference to define the modal shift is calculated considering a week before the pandemic (Week 10, 2020) and weeks during the pandemic. Table 25 presents the weeks chosen to use the modal shift data provided by DAT.Mobility.

*Table 25 - Weeks chosen to use the modal shift data provided by DAT.Mobility*

| Stage | Period | Description | Modal shift data |
|---|---|---|---|
| **Baseline** | Sep-20 | Normal behavior | Week 10, 2020 |
| **1** | Mar-20 | Intelligent lockdown | Weeks 13-14, 2020 |
| **2** | Jul-20 | Summer Relaxations | Weeks 29-30, 2020 |
| **3** | Oct-20 | Semi Lockdown | Weeks 42-43, 2020 |
| **4** | Jan-21 | Strict lockdown | Weeks 03-04, 2021 |

Table 26 presents the modal shift values considered for the different stages. The rows are the percentage of trips that transport mode gives to other modes and the columns are the percentage of trips that they take from other modes.

To use this data for this case study, two important aspects need to be considered. The first aspect is that this data is aggregated and there is no distinction in the modal shift values between different activity or agent types. Therefore, the same values are used for all activities and agents. The second aspect is that these datasets did not include transport modes e-bike, car passenger and on-demand services. Hence, only walk, bike, car and public transport were considered for the modal shift.

*Table 26 - Modal shift values of the different stages (data source: DAT.Mobility)*

| Stage 1 (intelligent lockdown) | | | | |
|---|---|---|---|---|
| **To\From** | Walk | Bike | Car | PT |
| Walk | - | 0,20% | 0,40% | 0,00% |
| Bike | 0,50% | - | 0,70% | 0,00% |
| Car | 1,20% | 1,00% | - | 0,10% |
| PT | 0,30% | 0,10% | 0,40% | - |

| Stage 3 (semi lockdown) | | | | |
|---|---|---|---|---|
| **To\From** | Walk | Bike | Car | PT |
| Walk | - | 0,50% | 0,60% | 0,10% |
| Bike | 0,50% | - | 0,90% | 0,10% |
| Car | 1,80% | 1,80% | - | 0,10% |
| PT | 0,40% | 0,20% | 0,70% | - |

| Stage 2 (summer relaxations) | | | | |
|---|---|---|---|---|
| **To\From** | Walk | Bike | Car | PT |
| Walk | - | 0,30% | 1,00% | 0,00% |
| Bike | 0,60% | - | 1,00% | 0,10% |
| Car | 1,60% | 1,50% | - | 0,20% |
| PT | 0,30% | 0,10% | 0,80% | - |

| Stage 4 (strict lockdown) | | | | |
|---|---|---|---|---|
| **To\From** | Walk | Bike | Car | PT |
| Walk | - | 0,20% | 0,80% | 0,10% |
| Bike | 0,50% | - | 1,10% | 0,10% |
| Car | 2,00% | 0,90% | - | 0,10% |
| PT | 0,30% | 0,10% | 0,60% | - |

### 5.3.6. Data constraints

The data available for this case study imposes some constraints to the model and some limitations to the level of detail of the results. In this section, those constraints and limitations are presented and explained.

i. As explained in section 5.3.2, the work sector attribute has been added to the synthetic population of this study because it was not previously included. It has been distributed at a regional level. However, it would be better to distribute it at the zonal level to capture more mode detailed insights about distinguished zones.
ii. There was no initial information about who in the synthesized population was working from home in the pre-pandemic period. Therefore, for stage 0 only agents that have work trips in the baseline schedules are considered workers. Then, when running the other stages, agents that do not have work trips are considered home workers.
iii. The activity frequency values provided by KIM about non-work-related activities only use the demographic attribute 'age' to classify agents. With more combinations of attributes, the model would be able to consider way more different types of persons and provide a more detailed estimation.
iv. The data provided by TNO H&WT about work-related activities uses demographic attributes age, gender, education and work sector to classify agents. For the proposed model, however, only age, gender and work sector attributes were considered because the number of different combinations of agents was too big and some classes of agents did not have a sufficient number of observations ($n > 30$).
v. The modal shift values provided by DAT.Mobility only considers transport modes walk, bike, car and public transport. However, in the case study of this research, there are three other transport modes (e-bike, car passenger and on-demand services). Therefore, for the modal shift estimations, these three modes do not shift trips with other modes.

# 6. RESULTS

Based on the principles defined in the previous chapters, the modeling framework is used to predict the schedules of the MRDH population for the different COVID-19 stages described in chapter 5. Each stage offers a wide set of results and outcomes that provide a picture of the displacement patterns down to the individual level. Insights into which impact applies to which class of persons are therefore possible. It is precise because of the very wide range of results that a full quantitative reporting of all figures is outside the focus of this study. The most relevant tables are presented in this chapter.

When doing the exploratory analysis, it is important to keep in mind that no unambiguous explanation can be drawn up for various aspects. After all, the current circumstances concerning falling back from demand to travel are unseen in various areas, and there is no framework or numerical substantiation for the changed behavior. For example, it is clear that greatly increased homeworking leads to fewer trips, but no historical law can be found that explains exactly how large this proportion is. It can only fall back on current observations. In this respect, these analyzes do not intend to precisely quantify and predict the proportion of working from home or activity frequency in itself, but rather the impact of a predetermined level of them on activity-travel patterns. For this reason, the stages are based on survey data and assumptions of certain levels. The exploratory analyzes are essentially what-if exercises that make predictions in terms of journeys and mobility density, given certain assumptions about aspects that play a role in the COVID-19 pandemic.

As a reminder of chapter 4, section 4.5, because the model uses a microsimulation approach at the person-day level, it is subject to some degree of simulation variation. However, it is important to check if the aggregated results do not vary significantly. In order to do that, the model runs each stage five times and calculates the standard deviation for each stage. The calculated standard deviation for stages 1, 2, 3 and 4 are 0.0, $2.5 \times 10^{-3}$, 0.0, and 0.01, respectively. These standard deviation values are low and confirm that five runs are an appropriate number to have consistency in the results. The next step then was to take the average of the outcomes of the five runs and those values are used for analysis in this chapter.

The results chapter is divided into two sections. Section 6.1 provides insights into the implications of COVID-19 on activity-travel behavior. For the different COVID-19 stages, differences are analyzed in the number of tours, modal share, number of trips per activity type, the complexity of tours, and the number of home stayers. Section 6.2 provides insights into the implications of COVID-19 on work and commuting behavior. It is analyzed the number of work trips, modal share, traveled distance per mode, number of onsite workers (and therefore the number of homeworkers), and also a spatial analysis about the number of onsite workers per zone in the area. Finally, section 6.3 provides an overview of the results.

## 6.1. IMPLICATIONS OF COVID-19 ON ACTIVITY-TRAVEL BEHAVIOR

As discussed in the literature review, activity-travel behavior changed significantly because of COVID-19. In this section, several activity-travel and mobility indicators are presented and the main findings are discussed.

### 6.1.1. Number of tours

Table 27 presents the results of the number of tours, also split by age group; and the changes of modal share for the different stages. The last four columns provide a percent difference comparison of stages and the baseline stage (S0).

The way policy measures are implemented affects directly the activity behavior of travelers. For stages 1 (intelligent lockdown) and 4 (strict lockdown), more strict policy measures regarding social distance were implemented (Schlosser et al., 2020), and as a consequence, fewer trips and tours were observed. During the intelligent lockdown, a decrease of 67% in the total number of tours is observed while during the strict lockdown it decreased around 69%. For stage 2 (summer relaxations), there is a decrease of 36% compared to the pre-pandemic, but it is still around two times higher than during the intelligent lockdown. For stage 3 (semi lockdown), the total number of tours dropped 48%, which is 20% less than the summer relaxations, but around 40% more than the strict lockdown.

*Table 27 – Results of the total number of tours and modal share*

| | S0 | S1 | S2 | S3 | S4 | *% S1* | *% S2* | *% S3* | *% S4* |
|---|---|---|---|---|---|---|---|---|---|
| **Total tours** | 4,919,061 | 1,635,742 | 3,144,483 | 2,571,188 | 1,529,054 | -66.7 | -36.1 | -47.7 | -68.9 |
| **Tours age 1 (<15)** | 945,214 | 363,263 | 563,712 | 426,224 | 280,800 | -62 | -40 | -55 | -70 |
| **Tours age 2 (15-25)** | 592,140 | 178,251 | 286,605 | 237,077 | 146,250 | -70 | -52 | -60 | -75 |
| **Tours age 3 (26-45)** | 1,346,111 | 486,595 | 966,001 | 806,635 | 453,104 | -64 | -28 | -40 | -66 |
| **Tours age 4 (46-65)** | 1,334,787 | 452,202 | 918,332 | 781,630 | 419,816 | -66 | -31 | -41 | -69 |
| **Tours age 5 (>65)** | 700,809 | 155,431 | 409,834 | 319,622 | 229,084 | -78 | -42 | -54 | -67 |
| **Modal share walk** | 17.71% | 18.32% | 18.77% | 18.21% | 20.73% | 3.5 | 6.0 | 2.8 | 17.1 |
| **Modal share bike** | 22.01% | 23.21% | 21.46% | 21.53% | 20.73% | 5.4 | -2.5 | -2.2 | -5.8 |
| **Modal share e-bike** | 2.96% | 2.96% | 2.98% | 3.02% | 3.01% | 0.0 | 0.8 | 2.0 | 1.7 |
| **Modal share car** | 37.80% | 35.96% | 37.89% | 38.14% | 35.75% | -4.9 | 0.2 | 0.9 | -5.4 |
| **Modal share passenger** | 10.23% | 10.21% | 10.24% | 9.95% | 11.41% | -0.2 | 0.1 | -2.8 | 11.5 |
| **Modal share on demand** | 0.10% | 0.10% | 0.09% | 0.09% | 0.10% | -1.1 | -7.8 | -11.0 | 1.0 |
| **Modal share PT** | 9.19% | 9.24% | 8.56% | 9.07% | 8.27% | 0.5 | -6.8 | -1.2 | -10.0 |

Even though the results show people of all age groups to be less active outdoors, it is also interesting to analyze these indicators for different age groups because the reasons for that may vary. During the intelligent lockdown (S1), which was the first lockdown implemented, no one knew how to behave against the virus spread, so no considerable differentiation between age groups can be observed. A decrease between 62% and 68% is observed in the number of tours for all ages of S1. The highest decrease in the number of tours is observed for people in age groups 2 (15-25) and 5 (<65), with decreases of 70% and 78%, respectively. The reasons for having more elder people traveling less might be due to the recommendations of the government about the risk groups for the corona virus (RIVM, 2021), where they state that elder people and people with comorbidities were more vulnerable to the virus. During the summer relaxations (S2), some other patterns can be observed. While a decrease of around 28-31% of tours is observed for people in age groups 3 (25-45) and 4 (45-65), an interesting decrease of 52% is seen for people in age group 2. This can be explained by the fact that this group used to be more active in terms of participating in activities such as sports and going out before the corona virus. In addition, they are more likely to be affected in terms of work (more flexible and temporary contracts) and education (de Haas et al., 2020). In the strict lockdown (S4), the number of tours for all ages decreased similarly, ranging between 66% and 75%. That was the moment where all sectors were closed and the curfew was implemented (Government of the Netherlands, 2021b).

### 6.1.2. Modal share

The modal share also provides interesting results within stages. Although the total volume of trips has been greatly reduced in all stages, plotting all trips in relative modal share does not decrease its importance. The modal shift values applied in the model improve the estimations of modal shares for the different stages. Table 27 shows the results.

As discussed in the literature review, during the corona crisis a positive movement towards active modes would be a natural behavior to avoid social contact (Oirbans, 2021). For all stages, an increase between 3% to 6% is observed for walking trips, except for the strict lockdown S4 where it increases around 17%. Surprisingly, the share of bike decreased in stages 2, 3 and 4. A reason for that might be a modal shift between active modes since the modal share of walking trips increased significantly. On the other hand, the share of e-bike slightly increased for the same stages. According to the study of MuConsult (2021), the share the e-bike during 2020 has gained travel share particularly due to shopping and leisure activities.

Concerning public transport, as expected, the share of public transport decreased in stages 2, 3 and 4. However, it peculiarly increased 0.5% in stage 1. For cars, the share decreased around 5% in stages 1 and 4 and slightly increased in stages 2 and 3.

The decrease of bike share in three stages and the increase of PT share in stage 1 were not expected. The reasons for these outcomes in modal shift can be technically (partially) explained. In our model, the removal of trips is done in two steps. In the first step, the number of trips to be removed is evenly distributed for all the transport modes. As a result, modes with higher shares will have more trips removed than modes with lower shares. Second, the modal shift values are shifted between modes, and the number of trips shifted is based on the total number of trips of each mode before the reduction. Therefore, once the number of trips is evenly reduced for all transport modes, the modal share becomes more sensitive if a high number of trips is shifted between modes. Hence, the removal of trips together with the shift between modes can directly influence the final modal share, and for some cases, the final modal share can present unusual results. In the PT case of stage 1, the cause for the increase in its share might be because there was a substantial decrease in the total number of trips by car, which is the mode with the highest modal share. Thus, for this particular stage, car gives almost 3.3% of its trips to other modes. Therefore, that particular reduction affects directly the modal share, including the share of modes that are expected to reduce. In conclusion, the modal share does not mean that a particular mode has more trips being performed; what it actually means is that for some modes, the number of trips reduction is higher than for other modes.

### 6.1.3. Number of trips per activity type

Regarding the motives why people perform trips, Table 28 presents the particular outcomes of each stage. The last four columns provide a percent difference comparison of the stages and the baseline stage (S0).

The total number of trips for the stages decreased linearly to the number of tours presented in Table 27. Fewer trips were observed for the strict lockdown S4 (only 29.1%), followed closely by the intelligent lockdown S1 (30.7%). The summer relaxation S2 period had the most number of trips of all stages (61.6%), but it is still 38.4% less than the pre-pandemic stage.

With regard to the activity types, for some stages, the number of work-related trips decreased more than of non-work-related trips, and for other stages the opposite happened. In S1 and S4, work-related trips decreased more than non-work-related trips. In S2, the other way around. A reason for that is the strength of related policies measures during these periods. According to Ritchie et al. (2021), work-related policy measures were stronger in the periods of stages 1 and 4 compared to non-work-related policy measures. During stage 2, however, both work-related and non-work-related policies were at the same moderate level.

*Table 28 – Results of the total number of trips per activity type*

| | S0 | S1 | S2 | S3 | S4 | % S1 | % S2 | % S3 | % S4 |
|---|---|---|---|---|---|---|---|---|---|
| **Total trips** | 10,991,221 | 3,379,440 | 6,766,033 | 5,440,005 | 3,171,583 | -69.3 | -38.4 | -50.5 | -71.1 |
| **Trips home** | 4,919,061 | 1,635,742 | 3,144,483 | 2,571,188 | 1,529,054 | -67 | -36 | -48 | -69 |
| **Trips work** | 1,317,889 | 439,978 | 780,462 | 743,768 | 268,148 | -67 | -41 | -44 | -80 |
| **Trips business** | 95,676 | 29,731 | 56,522 | 53,391 | 16,359 | -69 | -41 | -44 | -83 |
| **Trips bring/get** | 514,864 | 142,965 | 385,048 | 256,297 | 127,574 | -72 | -25 | -50 | -75 |
| **Trips education** | 892,288 | 334,060 | 316,394 | 207,675 | 99,338 | -63 | -65 | -77 | -89 |
| **Trips shopping** | 1,230,405 | 311,288 | 855,301 | 570,591 | 286,020 | -75 | -30 | -54 | -77 |
| **Trips other** | 2,021,038 | 485,675 | 1,227,824 | 1,037,095 | 845,090 | -76 | -35 | -49 | -58 |

During the intelligent lockdown (S1), there is a certain equilibrium in the decrease of trips among all the activity types. The decreases ranged between 63% and 76%. In the summer relaxations (S2), however, those numbers are contrasting. The highest drop in the number of trips is seen for work-related (41%) and education trips (65%), while for shopping and other activities the drop remained low (30% and 35%, respectively). A reason for that is that leisure-related measures have been relaxed during the summer (Muhlberg, 2020) while the recommendation of work-related policies was to work from home as much as possible (Chelsea & Mulder, 2021). Thus, in stage 2 the education sector was on vacation.

During the semi-lockdown (S3), as the number of people admitted at hospitals started to increase (Figure 5-2), new policies were implemented to stop the virus' spread. During this stage, the number of work trips did not change much compared to the summer relaxations (only 3%), but the number of education trips reduced almost to three-quarters of the pre-pandemic conditions. This continuous reduction can be explained by the fact that institutions have adapted their methodologies to hold education classes online as much as possible with the beginning of the new semester (Boztas, 2020). The number of shopping trips also decreased significantly compared to S2 (from 30% to 54%) and even more in the strict lockdown S4 (77%). The cause for those drops could be the stricter policy measures for shopping and the increase of acceptability of the population for online shopping (Silicon Canals, 2020).

The number of trips for all activities types has been noticeably reduced during the strict lockdown phase (S4). New measures against COVID-19 were implemented, like the curfew (Government of the Netherlands, 2021b), and people were strongly advised to leave their houses only for essential motives. The only activity type that the decrease is less than 80% is the 'other' category (i.e. walking, doing sports). That is because the lockdown implemented by the government only allowed people to leave their houses for walking, doing individual sports or other essential motives (Government of the Netherlands, 2021a).

### 6.1.4. Number of home-stayers

Due to fear of infection and strict measures against COVID-19, many people stopped leaving their homes during the pandemic. In Table 29 it is presented the number of home-stayers for the different stages. (Fully) Home-stayers are people that did not leave their houses. The last five columns are the percentage of home-stayers compared to the total population that falls in the same (age) group.

In a macroscopic overview, the number of home-stayers varies considerably for the different stages. From the 3.65 million agents of the study area, around 368 thousand (10%) were home-stayers during the pre-pandemic (S0). That number rose to 2.23 million (61%) during the intelligent lockdown S1.

During the summer relaxations S2, that number dropped to 1.28 million (35%) and in the semi lockdown, it rose to 1.58 million (43%). During the strict lockdown, 2.33 million (63%) of the population did not have any trips during the day. These numbers can be explained. During the strict lockdown where everything was closed, one of the only alternatives for people (and allowed by the policies implemented) was to go for a walk or do individual sports (NL Times, 2021). Therefore, even though in stage 4 only 63% of the population did not have any tours, the other 37% might have had few trips or tours, like for example going only for a short walk during the entire day.

*Table 29 – Results of the number of fully-home stayers; also split by age group*

| | | | | | | | % of the population | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| *Population* | **Home-stayers** | S0 | S1 | S2 | S3 | S4 | *S0* | *S1* | *S2* | *S3* | *S4* |
| 3,649,499 | **Total home-stayers** | 368,057 | 2,232,918 | 1,280,282 | 1,589,906 | 2,333,662 | 10 | 61 | 35 | 44 | 64 |
| 612,419 | **Age 1 (<15)** | 34,307 | 308,210 | 200,943 | 276,838 | 373,132 | 6 | 50 | 33 | 45 | 61 |
| 453,897 | **Age 2 (15-25)** | 34,785 | 292,979 | 217,063 | 250,836 | 322,055 | 8 | 65 | 48 | 55 | 71 |
| 949,871 | **Age 3 (26-45)** | 74,504 | 538,195 | 261,973 | 329,357 | 569,896 | 8 | 57 | 28 | 35 | 60 |
| 994,489 | **Age 4 (46-65)** | 92,394 | 598,757 | 298,307 | 368,586 | 634,474 | 9 | 60 | 30 | 37 | 64 |
| 638,823 | **Age 5 (>65)** | 132,067 | 494,777 | 301,996 | 364,289 | 434,105 | 21 | 77 | 47 | 57 | 68 |

### 6.1.5. Complexity of tours

Table 30 presents indicators about the types of tours present in the schedules. The percentage of single tours (i.e. tours with only one activity) is predominant in stage 0, with around 81% of the total share. During the pandemic, the predominance of single tours increased significantly in all stages, reaching 94% of the share of all tour types in stage 1. The most preferred tour among the population is home-other-home tour, which is around 25,3% of the tours in stage 1 and almost 50% of the tours in stage 4. As discussed before, the reason for an increase in the number of 'other' activities is due to the lockdown implemented by the government, in which people were allowed to leave their houses only for essential activities like walking, doing individual sports or other essential motives (Government of the Netherlands, 2021a).

The appearance of different tour types varied significantly for the different stages. In stage 0, there were more than 2500 tour types, which means that many tours were multi-activity tours (i.e. tours with more than one activity). However, the number of different tour types dropped almost 50% in the summer relaxations S2 and around 82% during the intelligent lockdown S1 and the strict lockdown S4, which means that people preferred less complex tours during the pandemic.

*Table 30 – Results of tour-related performance indicators*

| | **S0** | **S1** | **S2** | **S3** | **S4** | ***% S1*** | ***% S2*** | ***% S3*** | ***% S4*** |
|---|---|---|---|---|---|---|---|---|---|
| **Total number of tours*** | 4,919,061 | 1,635,742 | 3,144,483 | 2,571,188 | 1,529,054 | -66.7 | -36.1 | -47.7 | -68.9 |
| **% of single tours** | 81% | 94% | 87% | 90% | 93% | 16 | 7 | 11 | 14 |
| **Home-Other-Home tours** | 25,3% | 25,6% | 28,7% | 31,7% | 47,7% | 1 | 13 | 25 | 88 |
| **Average tours per agent** | 1,45 | 1,06 | 1,21 | 1,14 | 1,06 | -27 | -17 | -21 | -27 |
| **Number of different tour types** | 2648 | 489 | 1269 | 861 | 405 | -82 | -52 | -67 | -85 |

*Excluding stay at home tours

## 6.2. IMPLICATIONS OF COVID-19 ON WORK AND COMMUTING BEHAVIOR

As discussed in the literature review, the commuting behavior of different groups of people changed significantly because of COVID-19. In this section, several commuting indicators are presented and the main findings are discussed.

### 6.2.1. Number of work trips

Table 31 presents the results of the total number of work trips, changes in modal share and total distance traveled per transport mode. The last four columns provide a percent difference of stages and the baseline stage (S0).

The decrease in the total number of work trips observed in the stages is distinct. The decrease in the strict lockdown S4 is the highest (80%) whereas in summer relaxations S2 and semi lockdown S3 the number of work trips decreased two times less than in S4. Clearly, the work-related policy measures during S4 were more restrictive than the measures imposed during S2 and S3, which means that more people started to work from home (Hooftman, Bouwens, et al., 2020).

*Table 31 – Results of commuting behavior: number of work trips; modal share; distance traveled per mode*

| | S0 | S1 | S2 | S3 | S4 | % S1 | % S2 | % S3 | % S4 |
|---|---|---|---|---|---|---|---|---|---|
| **Total work trips** | 1,317,889 | 439,978 | 780,462 | 743,768 | 268,148 | -67 | -41 | -44 | -80 |
| **Modal share walk** | 4.9% | 6.9% | 6.4% | 6.6% | 9.9% | 40.8 | 30.6 | 34.7 | 102.0 |
| **Modal share bike** | 17.9% | 18.9% | 18.7% | 19.1% | 20.4% | 5.6 | 4.5 | 6.7 | 14.0 |
| **Modal share e-bike** | 3.6% | 3.7% | 3.6% | 3.6% | 3.8% | 2.8 | 0.0 | 0.0 | 5.6 |
| **Modal share car** | 52.9% | 49.5% | 51.1% | 50.6% | 45.6% | -6.4 | -3.4 | -4.3 | -13.8 |
| **Modal share passenger** | 2.6% | 2.8% | 2.6% | 2.6% | 3.1% | 7.7 | 0.0 | 0.0 | 19.2 |
| **Modal share on demand** | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0 | 0.0 | 0.0 | 0.0 |
| **Modal share PT** | 18.1% | 18.2% | 17.6% | 17.5% | 17.2% | 0.6 | -2.8 | -3.3 | -5.0 |
| **Distance traveled (KM) Total** | 22,915,991 | 7,531,628 | 13,322,785 | 12,686,805 | 4,435,438 | -67 | -42 | -45 | -81 |
| **KM walk** | 161,066 | 77,627 | 127,584 | 124,258 | 68,212 | -52 | -21 | -23 | -58 |
| **KM bike** | 967,765 | 343,221 | 599,137 | 586,276 | 211,710 | -65 | -38 | -39 | -78 |
| **KM e-bike** | 273,749 | 96,044 | 163,273 | 154,696 | 58,967 | -65 | -40 | -43 | -78 |
| **KM car** | 14,927,186 | 4,760,178 | 8,605,575 | 8,175,093 | 2,679,981 | -68 | -42 | -45 | -82 |
| **KM passenger** | 742,929 | 267,710 | 443,703 | 422,975 | 180,046 | -64 | -40 | -43 | -76 |
| **KM on demand** | 1,517 | 626 | 923 | 835 | 343 | -59 | -39 | -45 | -77 |
| **KM PT** | 5,841,779 | 1,986,221 | 3,382,591 | 3,222,671 | 1,236,179 | -66 | -42 | -45 | -79 |

### 6.2.2. Modal share for commuting

The modal share presented in Table 31 shows that for all stages, workers preferred active commuting to PT or car trips. In stages 1, 2 and 3, the modal shares of walk and bike increased around 30% and 5% respectively, and in stage 4 they increased three times more than that. Meanwhile, drops have been observed mainly in the car and PT shares. These results follow similar conclusions as the measures collected by Taale et al. (2021) about the transport modes used for commuting during the pandemic.

### 6.2.3. Total traveled distance for commuting

Analysis of traveled distance on the MRDH network provides a picture of the traffic on the roads. The total traveled distance in stage 0 is around 23 thousand kilometers. That number dropped to 7.5

thousand during the intelligent lockdown S1 and dropped to less than 4.5 thousand during the strict lockdown S4.

Relatively speaking, the use of public transport and car show the largest decrease. For car, the decrease in the total traveled distance is higher than any other mode in all stages. In the strict lockdown S4, that drop reached 82%. According to the model results, on average, the number of kilometers for car commuting decreased 59% compared to 2019. A reason for that decrease in car use, according to MuConsult (2021), is because the number of days that workers in the Netherlands travel to work by car in 2020 decreased by 15% compared to 2019.

For public transport, the decreases are also high in all stages, especially in S4 where a decrease of 79% is observed. Interestingly, the drops for walking are much lighter compared to those. In S2 and S3, the walking drops are relatively small (around 20-23%) while for all the other modes the drops are about 40%.

#### 6.2.4. Number of on-site and home workers

The measures against COVID-19 resulted in a decrease in people working on site. Table 32 presents the number of onsite workers for the different stages. This number is given as onsite workers because, as explained in section chapter 5, section 5.3.6, there was no data about which people in the synthetic population were home workers. Therefore, it was assumed that in the baseline stage, all the agents that had work trips were onsite workers and that the agents that did not commute anymore were then considered home workers.

According to the model results, in the baseline stage, around 1.24 million people are onsite workers. That is around 30% of the MRDH population. During the intelligent lockdown S1, 66% of them were working from home (or did not work at all). During the summer relaxations S2 and the semi lockdown S3, around 40-42% were working from home. In the strict lockdown S4, almost 80%. From the model results, it can be derived that, on average, more than 60% of onsite workers worked from home during the pandemic. Interestingly, this result is in line with the Dutch National Traveler Survey 2020 reported by MuConsult (2021) for the Ministry of Infrastructure and Water Management of the Netherlands about trends in mobility, which states that comparing April 2020 and October 2020 (stages 1 and 3 of the case study), commuters have started to travel more and work less from home (42% in stage 3 and 69% in stage 1).

*Table 32 – Results of the number of onsite workers; also split per working sector*

| | S0 | S1 | S2 | S3 | S4 | % S1 | % S2 | % S3 | % S4 |
|---|---|---|---|---|---|---|---|---|---|
| **Total onsite workers** | 1,246,074 | 424,034 | 752,697 | 717,212 | 256,426 | -66% | -40% | -42% | -79% |
| **Onsite workers Industry** | 194,691 | 99,379 | 133,934 | 122,813 | 20,300 | -49% | -31% | -37% | -90% |
| **Onsite workers Healthcare** | 188,503 | 186,629 | 159,825 | 158,451 | 186,218 | -1% | -15% | -16% | -1% |
| **Onsite workers Retail** | 207,774 | 53,769 | 137,883 | 124,839 | 21,588 | -74% | -34% | -40% | -90% |
| **Onsite workers Education** | 79,141 | 20,525 | 59,248 | 75,124 | 1,796 | -74% | -25% | -5% | -98% |
| **Onsite workers Office** | 414,430 | 21,729 | 170,713 | 142,845 | 9,589 | -95% | -59% | -66% | -98% |
| **Onsite workers Other** | 161,535 | 42,003 | 91,093 | 93,139 | 16,936 | -74% | -44% | -42% | -90% |

The number of on-site workers can also be presented spatially. Figure 6-1 depicts the number of onsite workers for the different zones in the study area. The zones in dark purple are zones that have more workers. The cities of Rotterdam, Delft and The Hague are mainly dark purple, while the surrounding zones have less number of workers. In the figure, it can be seen that in stages 2 and 3, the number of onsite workers is very similar and not that different compared to the baseline stage. In stages 1 and 4, however, apart from the city of Rotterdam, all the other zones presented a significant decrease in the number of onsite workers.

With respect to the different work sectors that people work in, some interesting findings can be seen. In many moments of the COVID-19 pandemic, the recommendations of work-related policies were to let employees work from home as much as possible, with exception of essential jobs (Ritchie et al., 2021). Therefore, besides the healthcare and the industry & production sector, all the other sectors decreased significantly the number of onsite workers for all the stages. The biggest contrast can be observed in the strict lockdown S4, where only 1% of the healthcare sector works from home while 98% of office workers were working from home. Actually, the number of office workers working from home is the highest for all stages, ranging in between 59% and 98%. These results follow the same outcomes presented in the study of CBS (2020), where it is pointed out that telecommuting was most prevalent among employees with ICT (information and communications technology) occupations.

The results of onsite workers in the education sector presented some unexpected outcomes. While in stages 1 and 4 the number of home workers is high (74% and 98%, respectively), the number of homeworkers in stage 3 is only 5%. The results in stage 3 do not seem to reflect the reality since online classes have been prioritized since the beginning of the pandemic, and even though schools were open until mid-December, the number of on-site workers of the education sector should not be that high (95%). Nonetheless, these numbers do not mean that there were many education trips for the period, as can be seen in Table 28.

For the retail sector and other[3] sectors, the drops were similar in most stages. In the intelligent lockdown S1, almost 75% of onsite workers worked from home. That number rose to 90% in the strict lockdown S4. For these sectors, working from home is relatively hard because a large fraction of jobs is ‘contact professions’, so whether they have worked onsite or did not work at all. That is also what the study of the European Commission (2021) indicates, in which it is stated that between the end of 2019 and the end of 2020, the sectors in which job losses were seen most clearly are travel, food and hotel service, culture, sport and recreation, and the temporary employment sectors.

[3] The ‘other’ sector includes sectors such as Transportation, Sports and Recreation and other service activities

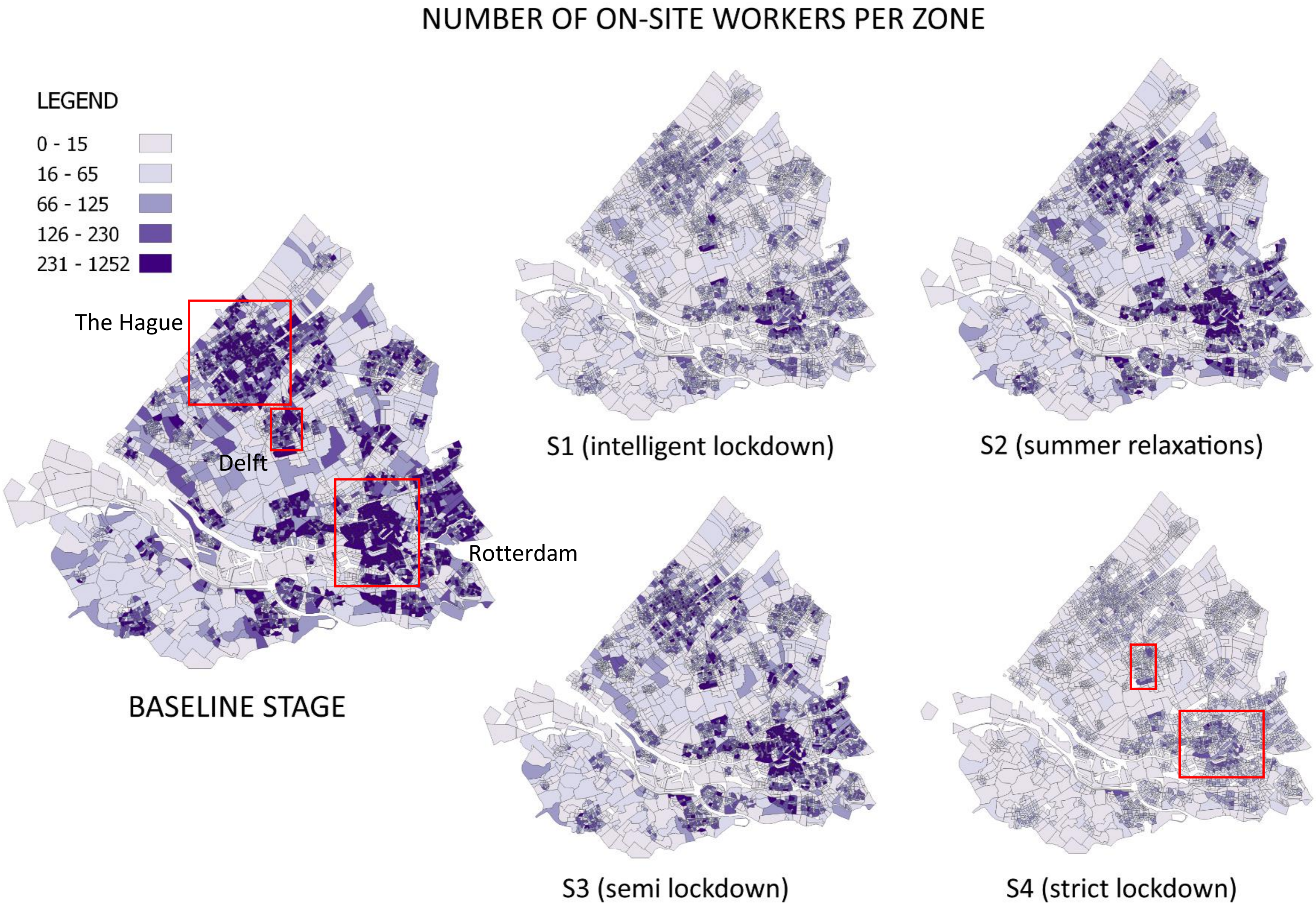


*Figure 6-1 - The number of onsite workers by TAZ in the baseline stage (left) and in the COVID-19 stages (right)*

### 6.2.5. Level of on-site work crowdedness

The level of on-site work crowdedness per zone in the MRDH region has also been estimated for each stage. By level of on-site work crowdedness is meant how busy is a zone considering the total number of jobs available in that zone and the number of workers that commute to that zone. For example, if a zone has 50 jobs and 40 people commuted to that zone, the level of work crowdedness of that zone is 80%.

The left picture in Figure 6-2 depicts the number of jobs of each zone in the MRDH region. This data was provided together with the synthesized population. Note that apart from The Hague, Delft and Rotterdam, the region of the port of Rotterdam also has a high number of jobs.

The right picture in Figure 6-2 presents the level of on-site work crowdedness considering the work trips of the baseline schedules. From this picture, it can be seen that the busiest areas are mainly city areas. Note that the port of Rotterdam region has low levels of on-site work crowdedness, which could mean that the number of trips to the port is underestimated.

Figure 6-3 shows the relative change of the level of on-site work crowdedness of each COVID-19 stage compared to the baseline stage. From these pictures, it is clear that the relative changes vary between each stage. However, it is not clear if the relative changes are significant between zones in the same stage.

There are two reasons to explain these homogeneous patterns. The first reason is that the number of work trips and their origins and destinations is estimated based on travel surveys, and sometimes the samples of these travel surveys do not fully capture all displacement patterns. From Figure 6-2, it can be observed that even though the port of Rotterdam has a high number of jobs, the level of on-site work crowdedness in the baseline stage is very low. That means that the training data used to estimate the baseline schedules probably did not capture a significant number of working trips going to some zones with an elevated number of jobs, such as the port of Rotterdam.

The second reason is that the work sector of agents was not used to estimate the work trips in the baseline schedules. As explained in chapter 5, section 5.3, the work sector attribute was included in this study after the estimation of the baseline schedules. However, to better estimate the location of work trips, first, the work sector of the agents should be estimated, and then the work location of the agents should be estimated based on their work sector and the job characteristics of the zones.

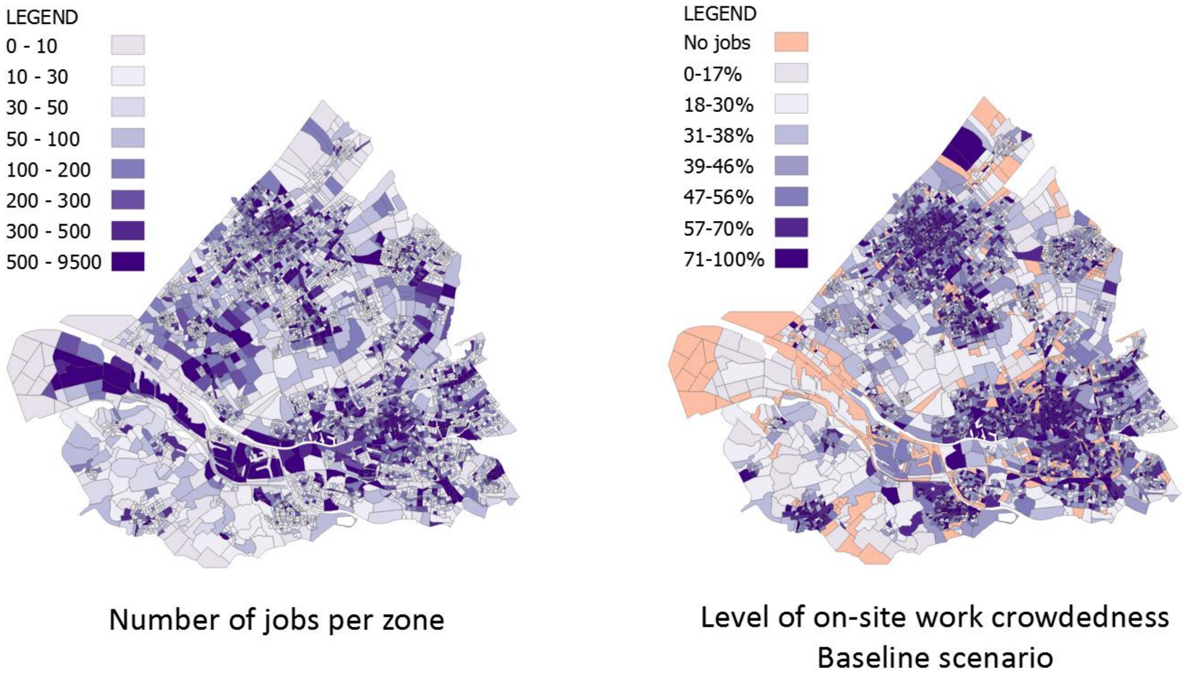


*Figure 6-2 - Number of jobs per zone in the MRDH (left) and level of on-site work crowdedness of baseline stage (right)*


*Figure 6-3 - Relative change of level of on-site work crowdedness of each stage compared to the baseline stage*

## 6.3. Insights on results

In this section, the main insights about the analyzes of results of sections 6.1 and 6.2 are highlighted.

**Number of tours**: During the pandemic, on average, there were 68% fewer tours compared to before the pandemic. During the intelligent lockdown S1 (March 2020) elders are the most affected (78% fewer tours) while during the strict lockdown S4 (January 2021) youngers are the most affected (75% fewer tours).

**Modal share**: A positive movement towards active modes has been observed during the pandemic. Compared to before the pandemic, on average, the shares of walking trips and e-bike increased 7.3% and 1.1%, respectively, while the share of the bike decreased 1.27%. For public transport and car, an average decrease of 4.3% and 2.3% have been observed.

**Number of trips per activity type:** The drops in the number of trips per activity type do not follow similar trends during different stages and depend on the strength of different policy measures. For stages 1 and 4, the highest decreases in the number of trips are observed for work and educational trips while in stages 2 and 3 it is for shopping trips. That can be explained by the fact that leisure-related measures were relaxed during the summer while the recommendations to work from home as much as possible were still strong.

**Number of home-stayers**: On average, more than half of the MRDH population is a fully home-stayer during COVID-19. Before the pandemic, only 10% of people were fully home-stayers. During stage 4, the most strict regarding stay-at-home restrictions, that number rose to 61%. That number is not higher because many people left their houses for short walks during the day.

**Complexity of tours:** Single-activity tours are still predominant. Before the pandemic, 80% of all tours were single tours, and during the pandemic, that number rose to almost 94%. Home-Other-Home is the most frequent tour and walking/touring and individual sports are the most preferred activities.

**Number of work trips:** During the pandemic, on average, there were 58% fewer work trips compared to before. In stage 4, the decrease is 80%, which is two times higher than during stage 2 (summer relaxations).

**Modal share for commuting:** Active commuting is more attractive than public transport and car trips. It increased more than 30% for all stages, and the average increase is more than 50%. Only car and public transport modal shares decreased for commuting trips (decrease averages of 9% and 2.6%, respectively).

**Total traveled distance for commuting**: During the pandemic, on average, the total commuting traveled distance decreased around 58%. The highest decreases are in the car and public transport trips (both around 59%) while for walking it is only 38%.

**Number of on-site and home workers:** On average, more than 60% of onsite workers worked from home during the pandemic. For essential sectors the healthcare sector, the number of on-site workers is still high (ranging between 74% and 99%) while for non-essential sectors such as the office sector the number of on-site workers is low (ranging between 2% and 34%).

**Level of on-site work crowdedness:** There is a clear difference in the level of on-site work crowdedness between stages, but it is not possible to provide insights within zones in each stage because most zones presented similar patterns.

# 7. Conclusions and recommendations

## 7.1. Conclusions

This research aimed to use the activity-based modeling approach to assess the effects of changes in activity-travel behavior on mobility caused by the COVID-19 pandemic. In this section, the questions posed in the introduction are revisited, and an answer is formulated. The primary question is:

*What are the effects of the changes in activity-travel behavior during events such as COVID-19 on mobility in the Rotterdam-The Hague Metropolitan Area, the Netherlands, and how can these effects be estimated, predicted, and analyzed through activity-based modeling?*

The answer to the primary research question is formulated by answering the secondary research questions one by one and then summarizing.

a) *What activity-travel behavior changes may be expected due to the COVID-19 pandemic?*

In the literature review presented in chapter 2 section 2.1, it has been concluded that effects of COVID-19 on activity-travel behavior are likely for a variety of reasons, including breaking habitual behavior, changing attitudes, and increasing the commute distance through relocation or job changes, to the emergence of a new balance in costs and benefits of travel versus online activities. The three major impacts of COVID-19 on activity-travel behavior are (1) a shift from onsite to online activities, (2) re-spacing and re-timing of travel patterns, (3) a modal shift towards the car and active modes.

b) *How can activity-based models be used (and improved) to better explain changes in activity-travel behavior in events such as COVID-19?*

In the literature review presented in chapter 2, section 2.2, an overview of the activity-based modeling approach is given. ABMs are analysis tools that provide a systematic framework for representing how travel demand changes in response to different input assumptions. ABMs work at a disaggregate person-level, which allows representing greater variation across the population and consequently better represent how investments, policies, or other changes will affect people's travel behavior. However, to model the changes in activity-travel behavior due to the COVID-19 pandemic, some adjustments are needed.

As stated in chapter 2, section 2.1, and answered in research question *a*, the COVID-19 pandemic serves as a trigger to accelerate the shift from onsite to online activities, for example teleworking and online shopping. And due to the fear of infection, those online activities turned out to be in-home activities. However, as discussed in chapter 2, section 2.2, most ABMs do not incorporate in-home activity planning in the modeling. Therefore, to improve ABMs and make them better tools to explain changes in activity-travel behavior in events such as COVID-19, it is important to: (1) build models that incorporate in-home activity planning and (2) to collect and use more detailed data about planning and scheduling of in-home activities and out-home activity frequency. The modeling framework developed in this study can be considered as a good step in the improvement of activity-based modeling.

c) *What effects can be expected on mobility during the different stages of the pandemic and what factors influence these effects?*

In chapter 5, four stages of COVID-19 in the MRDH of the Netherlands have been identified. Then, the proposed model was used to estimate mobility patterns for each stage. Next, in chapter 6, those stages were analyzed and insights about their outcomes discussed.

From the literature of chapter 2 and the discussions of chapter 6, it has been concluded that the main factors that influence changes in activity-travel behavior and consequently differences in mobility patterns are: (1) the fear of infection caused by the virus and (2) the strength of policy measures concerning workplace closure, school closure, and stay-at-home restrictions. These factors have been used to motivate the outcomes derived from the model estimations.

From the model outcomes, several insights about the effects of COVID-19 on mobility have been derived. These insights are discussed in detail in chapter 6. The main insights derived from the model outcomes for the MRDH case study are:

- During the pandemic, on average, there are 68% fewer tours compared to before the pandemic. The most affected age groups are elders (>65) and youngers (25-45).
- Home-Other-Home is the most frequent tour in the schedules, and walking/touring is the most preferred activity, especially during the lockdowns.
- A positive movement towards active modes is observed for all stages. On average, the share of walking increased 7.35% compared to before the pandemic.
- During the pandemic, more than half of the MRDH population is a fully home-stayer, which is six times more than before the pandemic.
- During the pandemic, on average, there are 58% fewer work trips compared to before the pandemic. In the strict lockdown (stage 4), there are 80% fewer work trips.
- The total commuting traveled distance decreased around 58%.
- Active commuting is more attractive than public transport or car. On average, its share increased more than 50% compared to before the pandemic.
- More than 60% of onsite workers worked from home. For essential sectors such as the healthcare sector, the number of on-site workers is the highest for all stages (between 74% and 99%) while for non-essential sectors such as the office sector the number of on-site workers is the lowest (between 2% and 35%).

d) *What is the added value of the modeling framework developed in this study to investigate the effects of changes in activity-travel behavior on mobility?*

The modeling framework provides an innovative approach to study the impacts of changes in activity-travel behavior caused by emergency situations such as the corona crisis in a disaggregated manner. It combines the outputs of ABMs and a mix of aggregated and disaggregated data of changes in in-home and out-home activity frequencies and re-estimates the daily schedule of individuals taking into account factors that were not considered before.

The case study developed for the model focused on analyzing different stages of COVID-19. With that, it was possible to check if the model estimations are in line with data counts and results of other studies. The conclusion is that the vast majority of the model outcomes are similar to what other studies estimate. However, some of the outcomes (e.g. total distance traveled, public transport modal share) showed contrast. This was expected because it is the first time that this modeling framework is being used, and it still requires some calibration. The calibration of the demand model components could be done using household travel survey data but also count databases or transit agency reportings.

One of the biggest advantages of the modeling framework is the extension of the synthetic population by the introduction of the work sector attribute. The baseline schedules generated by the ABM FEATHERS did not use the work sector in their estimations before. With this attribute included, it was possible to link the modeling with policy interventions related to specific six different working sectors. The work sector attribute helped to estimate, for instance, which agents work on-site and which work from home.

From a theoretical point of view, the modulation of the modeling framework seems to be ideal, but the type of data needed is hard to obtain. Because of that, some of the input data used in the study case (e.g. modal shift values) is aggregated data, and this sometimes distorted the disaggregated outcomes. However, this imposed limited restrictions when simulating different stages.

Finally, another important consideration is that existing ABMs are more robust and have more sophisticated methodologies than the proposed modeling framework. If an ABM was available for this research, then probably the first approach would be to incorporate in-home activity planning in the existing ABM and use COVID-19 related data to estimate the new schedules.

Circling back to the primary research question, this question can be answered taking into account the answers to the secondary research questions. First, the main factors that cause changes in activity-travel behavior have been identified (fear of infection, policy measures regarding close of workplace, school, and stay-at-home restrictions). Second, the activity-travel behavior expected changes have been identified (shift from onsite to online activities, re-spacing and re-timing of travel patterns and modal shift towards active modes). Third, a literature review on activity-based modeling identified the improvements necessary in ABMs to model activity-travel behavior in situations such as the COVID-19 pandemic. The product of this review is the creation of an activity-based modeling framework that has been used in this study to analyze the effects of changes in activity-travel behavior on mobility in a case study for the MRDH in the Netherlands. Finally, with the outcomes of the simulations, insights about the effects on mobility have been identified and compared to real data counts and outcomes of other studies. From the discussion of results in chapter 6, the model estimations proved to be in line with the majority of estimations of other sources. However, due to some data and modeling limitations, it is clear that there is space for improving the model, the data inputs and therefore the accuracy of the results. These improvements are discussed in the further sections of this chapter.

## 7.2. RECOMMENDATIONS FOR MODEL IMPROVEMENTS

This research identified possible improvements to the modeling framework and the quality of the data inputs.

Concerning the modeling framework, two main improvements are recommended. The first improvement is to enable increment the number of trips per schedule. As it is now, the model is limited to only remove trips from the baseline schedules. This limits the investigation of exit and future scenarios, for which it is important to re-estimate the schedules of individuals' including the addition of new trips. To incorporate this feature, one should investigate how to create a linkage between the generation of schedules of the ABM with the adjustment of schedules of the modeling framework.

The second improvement is to link the modeling framework to a network to provide feedback between the travel demand estimation and the network assignment. Due to time constraints, the linkage of the proposed modeling framework to the MRDH network (the V-MRDH 2.0) did not happen. Therefore, this study was limited to demonstrate the power of the model mainly to estimate travel demand and not on network assignment. That linkage will enable to re-estimate individuals' routes based on feedback with network constraints.

Concerning the data inputs, three main improvements are recommended. The first improvement is to consider more demographic variables when estimating individuals' decisions. As discussed in chapter 4, section 4.3, the type of data used in the model can limit the level of detail of the outcomes. Some of the activity frequency data used in the case study only considered the 'age' attribute to classify agents. That is a problem that can occur due to the scarcity of data. The second improvement is to collect and use more data about in-home and activity frequency. The third improvement is to collect more disaggregated data about modal shifts, but considering the type of agent and the motive for traveling.

The modal shift values used in the case study are aggregated, which means that the same values have been used to estimate modal shifts for all the different agents and activity types. The problem with using aggregated data, in this case, is that the initial modal share for different agent and activity types can vary significantly within each other. For example, when the modal share of a certain mode is very small and giving trips to other modes would result in a negative modal share. Therefore, it is more suitable to have modal shift values categorized by agent and activity type so that the estimations can be more accurate.

Another improvement to the model (and to ABMs in general) is the usage of multiple-day travel datasets. As discussed in chapter 2, section 2.3, applying one-day observation data in travel demand modeling provides an inadequate basis for understanding complex travel behavior to predict the impact of travel demand management strategies Tajaddini et al. (2020). Therefore, it is important to incorporate features that can investigate the capacity of a typical week in capturing rhythms in activity-travel behavior.

## 7.3. RECOMMENDATIONS FOR POLICY MAKERS

The modeling framework developed in this study is useful for policymakers for several reasons. As compared to the traditional ABMs, the effects of COVID-19 on activity-travel behavior and related measures can be studied in more detail. Decisions on whether or not to implement measures can be based on the model as presented, as the model generates effects as expected and is sufficiently consistent with the literature. Furthermore, by linking the modeling framework to a transport network, it should be possible to explore other traffic implications such as levels of congestion, travel time savings, or to assess implications on accessibility. Moreover, it should be possible to transfer the model to other regions due to its generic structure. However, it is necessary to have data with the same or greater level of detail than those presented in the case study.

Overall, maintaining a close and constant relationship with transportation modeling experts is critical for offering the most accurate and relevant treatments in terms of the use of various modes of transportation. Because the virus is constantly evolving, reactions must be developed and modified in real-time.

## 7.4. RECOMMENDATIONS FOR FUTURE RESEARCH

This section presents the study's recommendations and suggestions for future research. There are many ways in which to extend this research to better understand and predict changes in activity-travel behavior and their effects on mobility.

The first recommendation is to assign the results of the case study to the V-MRDH 2.0 network to generate more mobility indicators such as traffic flows and levels of congestion and provide more insights into the effects of COVID-19 on mobility in the MRDH.

The second recommendation is that, considering that the model has shown a satisfactory performance for the case study and its outcomes were similar to what has been observed by other studies, it now should be used to define and calculate what-if and future scenarios concerning the COVID-19 pandemic. For instance, the model can be used to predict mobility changes when a particular sector is fully opened/closed. To do that, one should run the model considering different sets of input assumptions such as the activity frequency and the modal shift values. Those inputs can be estimated using different sets of policy measures, for instance, using the COVID-19 stringency indexes which are estimated by Ritchie et al. (2021).

The third recommendation is to perform identical research for other regions within the Netherlands and compare the results with the results of the MRDH. Thus, the framework could be used to explore potential implications of COVID-19 on a wider scale, for example, the whole Netherlands.

The last recommendation is to use more disaggregated data about out-home and in-home activity frequency. Thus, this data should be collected as multiple-day travel datasets to capture the activity-travel behavior of agents in more than one day (e.g. weekly periods) to make better and more consistent estimations of the activity pattern of agents.

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# APPENDIX A: ACTIVITY FREQUENCY TABLES OF THE CASE STUDY

This appendix contains the activity frequency tables used in the MRDH case study. Table 33 presents the activity frequency values for the work activity. For this activity, three attributes are used to classify agents (A = age, G = gender, and S = work sector). Table 34 presents the activity frequency values for the business activity. The same three attributes are used to classify agents. Finally, Table 35 presents the activity frequency values for shopping and bring/get, other and education activities. For those activity types, only attribute age (A) is used to classify agents. All the values are presented in percentage.

*Table 33 - Work activity frequency values (in %). Columns: A = age; G = gender; S = sector*

| WORK ACTIVITY | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | STAGE 0 (PRE-PANDEMIC) | | | | | | STAGE 1 (INTELLIGENT LOCKDOWN) | | | | | | STAGE 2 (SUMMER RELAXATIONS) | | | | | | STAGE 3 (SEMI LOCKDOWN) | | | | | | STAGE 4 (STRICT LOCKDOWN) | | | | | |
| **A** | **G** | **S** | **0 d** | **1 d** | **2 d** | **3 d** | **4 d** | **5 d** | **0 d** | **1 d** | **2 d** | **3 d** | **4 d** | **5 d** | **0 d** | **1 d** | **2 d** | **3 d** | **4 d** | **5 d** | **0 d** | **1 d** | **2 d** | **3 d** | **4 d** | **5 d** | **0 d** | **1 d** | **2 d** | **3 d** | **4 d** | **5 d** |
| **2** | **1** | **1** | 0,0 | 17,8 | 15,6 | 6,7 | 8,9 | 51,1 | 50,0 | 8,9 | 7,8 | 3,3 | 4,4 | 25,6 | 47,2 | 0,0 | 13,9 | 5,6 | 2,8 | 30,6 | 58,6 | 6,9 | 10,3 | 3,4 | 0,0 | 20,7 | 90,0 | 1,8 | 1,6 | 0,7 | 0,9 | 5,1 |
| **2** | **1** | **2** | 0,0 | 29,4 | 23,5 | 5,9 | 17,6 | 23,5 | 0,0 | 29,4 | 23,5 | 5,9 | 17,6 | 23,5 | 28,6 | 14,3 | 21,4 | 14,3 | 0,0 | 21,4 | 25,0 | 0,0 | 8,3 | 0,0 | 16,7 | 50,0 | 0,0 | 29,4 | 23,5 | 5,9 | 17,6 | 23,5 |
| **2** | **1** | **3** | 0,9 | 25,5 | 46,7 | 8,0 | 8,5 | 10,4 | 75,2 | 6,4 | 11,7 | 2,0 | 2,1 | 2,6 | 54,1 | 10,9 | 19,7 | 3,8 | 4,9 | 6,6 | 63,6 | 7,0 | 10,5 | 2,8 | 4,9 | 11,2 | 90,1 | 2,5 | 4,7 | 0,8 | 0,8 | 1,0 |
| **2** | **1** | **4** | 6,3 | 25,0 | 6,3 | 18,8 | 37,5 | 6,3 | 76,6 | 6,3 | 1,6 | 4,7 | 9,4 | 1,6 | 58,3 | 8,3 | 0,0 | 16,7 | 0,0 | 16,7 | 77,8 | 0,0 | 0,0 | 0,0 | 11,1 | 11,1 | 98,1 | 0,5 | 0,1 | 0,4 | 0,8 | 0,1 |
| **2** | **1** | **5** | 3,7 | 14,8 | 24,7 | 3,7 | 18,5 | 34,6 | 95,2 | 0,7 | 1,2 | 0,2 | 0,9 | 1,7 | 63,3 | 16,7 | 1,7 | 0,0 | 1,7 | 16,7 | 67,3 | 13,5 | 1,9 | 1,9 | 0,0 | 15,4 | 98,1 | 0,3 | 0,5 | 0,1 | 0,4 | 0,7 |
| **2** | **1** | **6** | 0,0 | 4,5 | 22,7 | 18,2 | 18,2 | 36,4 | 75,0 | 1,1 | 5,7 | 4,5 | 4,5 | 9,1 | 60,0 | 5,0 | 10,0 | 10,0 | 5,0 | 10,0 | 63,2 | 5,3 | 0,0 | 5,3 | 0,0 | 26,3 | 90,0 | 0,5 | 2,3 | 1,8 | 1,8 | 3,6 |
| **2** | **2** | **1** | 0,0 | 7,7 | 23,1 | 7,7 | 23,1 | 38,5 | 50,0 | 3,8 | 11,5 | 3,8 | 11,5 | 19,2 | 30,0 | 0,0 | 25,0 | 5,0 | 10,0 | 30,0 | 50,0 | 6,3 | 12,5 | 0,0 | 12,5 | 18,8 | 90,0 | 0,8 | 2,3 | 0,8 | 2,3 | 3,8 |
| **2** | **2** | **2** | 2,9 | 8,6 | 16,2 | 21,0 | 33,3 | 18,1 | 2,9 | 8,6 | 16,2 | 21,0 | 33,3 | 18,1 | 24,4 | 9,3 | 12,8 | 14,0 | 26,7 | 12,8 | 28,2 | 2,6 | 5,1 | 14,1 | 33,3 | 16,7 | 2,9 | 8,6 | 16,2 | 21,0 | 33,3 | 18,1 |
| **2** | **2** | **3** | 0,4 | 25,0 | 48,2 | 11,2 | 5,4 | 9,8 | 75,1 | 6,3 | 12,0 | 2,8 | 1,4 | 2,4 | 65,1 | 4,7 | 15,1 | 6,5 | 2,6 | 6,0 | 71,0 | 4,1 | 10,0 | 6,3 | 3,6 | 5,0 | 90,0 | 2,5 | 4,8 | 1,1 | 0,5 | 1,0 |
| **2** | **2** | **4** | 0,0 | 11,5 | 17,3 | 17,3 | 34,6 | 19,2 | 75,0 | 2,9 | 4,3 | 4,3 | 8,7 | 4,8 | 35,6 | 2,2 | 8,9 | 8,9 | 24,4 | 20,0 | 25,6 | 2,6 | 7,7 | 7,7 | 17,9 | 38,5 | 98,0 | 0,2 | 0,3 | 0,3 | 0,7 | 0,4 |
| **2** | **2** | **5** | 0,9 | 18,1 | 29,3 | 8,6 | 23,3 | 19,8 | 95,0 | 0,9 | 1,5 | 0,4 | 1,2 | 1,0 | 62,0 | 7,6 | 16,3 | 5,4 | 2,2 | 6,5 | 75,6 | 2,3 | 4,7 | 7,0 | 1,2 | 9,3 | 98,0 | 0,4 | 0,6 | 0,2 | 0,5 | 0,4 |
| **2** | **2** | **6** | 0,0 | 21,4 | 17,9 | 21,4 | 17,9 | 21,4 | 75,0 | 5,4 | 4,5 | 5,4 | 4,5 | 5,4 | 62,5 | 12,5 | 12,5 | 0,0 | 0,0 | 12,5 | 62,5 | 4,2 | 8,3 | 8,3 | 4,2 | 12,5 | 90,0 | 2,1 | 1,8 | 2,1 | 1,8 | 2,1 |
| **3** | **1** | **1** | 1,1 | 3,6 | 3,0 | 6,1 | 33,9 | 52,3 | 50,6 | 1,8 | 1,5 | 3,0 | 16,9 | 26,2 | 26,8 | 9,1 | 7,2 | 3,8 | 4,5 | 48,7 | 30,7 | 9,0 | 6,7 | 4,9 | 3,0 | 45,7 | 90,1 | 0,4 | 0,3 | 0,6 | 3,4 | 5,2 |
| **3** | **1** | **2** | 2,5 | 3,3 | 0,8 | 18,3 | 38,3 | 36,7 | 2,5 | 3,3 | 0,8 | 18,3 | 38,3 | 36,7 | 11,6 | 7,0 | 9,3 | 9,3 | 26,7 | 36,0 | 17,2 | 6,9 | 5,7 | 12,6 | 20,7 | 36,8 | 2,5 | 3,3 | 0,8 | 18,3 | 38,3 | 36,7 |
| **3** | **1** | **3** | 1,0 | 2,6 | 6,1 | 9,6 | 32,8 | 47,9 | 75,2 | 0,6 | 1,5 | 2,4 | 8,2 | 12,0 | 26,3 | 3,5 | 9,0 | 3,9 | 9,8 | 47,5 | 32,2 | 4,7 | 7,1 | 5,2 | 7,6 | 43,1 | 90,1 | 0,3 | 0,6 | 1,0 | 3,3 | 4,8 |
| **3** | **1** | **4** | 1,4 | 3,2 | 14,1 | 26,5 | 38,2 | 16,6 | 75,4 | 0,8 | 3,5 | 6,6 | 9,5 | 4,2 | 30,0 | 9,9 | 12,1 | 11,2 | 14,8 | 22,0 | 14,6 | 5,2 | 6,8 | 7,8 | 19,3 | 46,4 | 98,0 | 0,1 | 0,3 | 0,5 | 0,8 | 0,3 |
| **3** | **1** | **5** | 2,4 | 4,1 | 4,2 | 14,5 | 45,1 | 29,7 | 95,1 | 0,2 | 0,2 | 0,7 | 2,3 | 1,5 | 51,4 | 11,0 | 8,9 | 3,7 | 3,4 | 21,6 | 61,8 | 8,6 | 5,6 | 2,6 | 3,7 | 17,7 | 98,0 | 0,1 | 0,1 | 0,3 | 0,9 | 0,6 |
| **3** | **1** | **6** | 2,2 | 3,0 | 5,2 | 7,5 | 33,6 | 48,5 | 75,6 | 0,7 | 1,3 | 1,9 | 8,4 | 12,1 | 25,7 | 11,9 | 6,9 | 5,9 | 12,9 | 36,6 | 36,6 | 3,2 | 5,4 | 3,2 | 11,8 | 39,8 | 90,2 | 0,3 | 0,5 | 0,7 | 3,4 | 4,9 |
| **3** | **2** | **1** | 0,7 | 2,8 | 6,3 | 32,6 | 34,7 | 22,9 | 50,3 | 1,4 | 3,1 | 16,3 | 17,4 | 11,5 | 42,0 | 12,5 | 11,6 | 12,5 | 9,8 | 11,6 | 36,5 | 20,2 | 11,5 | 9,6 | 7,7 | 14,4 | 90,1 | 0,3 | 0,6 | 3,3 | 3,5 | 2,3 |
| **3** | **2** | **2** | 0,8 | 4,9 | 12,1 | 39,3 | 32,1 | 10,8 | 0,8 | 4,9 | 12,1 | 39,3 | 32,1 | 10,8 | 14,4 | 7,5 | 10,7 | 25,7 | 29,2 | 12,5 | 14,1 | 5,4 | 12,2 | 26,3 | 29,8 | 12,2 | 0,8 | 4,9 | 12,1 | 39,3 | 32,1 | 10,8 |
| **3** | **2** | **3** | 1,9 | 3,0 | 9,3 | 30,5 | 30,9 | 24,5 | 75,5 | 0,7 | 2,3 | 7,6 | 7,7 | 6,1 | 26,7 | 7,8 | 6,3 | 22,3 | 19,9 | 17,0 | 34,9 | 7,2 | 7,2 | 20,0 | 18,5 | 12,3 | 90,2 | 0,3 | 0,9 | 3,0 | 3,1 | 2,5 |
| **3** | **2** | **4** | 2,2 | 7,4 | 24,1 | 34,6 | 23,4 | 8,3 | 75,5 | 1,9 | 6,0 | 8,7 | 5,9 | 2,1 | 24,2 | 11,0 | 10,3 | 22,1 | 18,1 | 14,3 | 14,0 | 5,1 | 8,5 | 26,0 | 26,9 | 19,5 | 98,0 | 0,1 | 0,5 | 0,7 | 0,5 | 0,2 |
| **3** | **2** | **5** | 1,7 | 3,8 | 9,4 | 29,6 | 39,4 | 16,1 | 95,1 | 0,2 | 0,5 | 1,5 | 2,0 | 0,8 | 51,5 | 15,4 | 9,5 | 5,1 | 8,1 | 10,5 | 64,1 | 10,7 | 7,7 | 4,9 | 6,6 | 6,0 | 98,0 | 0,1 | 0,2 | 0,6 | 0,8 | 0,3 |
| **3** | **2** | **6** | 4,3 | 5,0 | 10,1 | 29,5 | 32,4 | 18,7 | 76,1 | 1,3 | 2,5 | 7,4 | 8,1 | 4,7 | 50,0 | 9,8 | 10,8 | 5,9 | 15,7 | 7,8 | 50,5 | 9,2 | 10,1 | 8,3 | 14,7 | 7,3 | 90,4 | 0,5 | 1,0 | 2,9 | 3,2 | 1,9 |
| **4** | **1** | **1** | 0,5 | 1,9 | 3,0 | 5,0 | 33,9 | 55,8 | 50,2 | 0,9 | 1,5 | 2,5 | 17,0 | 27,9 | 22,5 | 5,5 | 6,9 | 4,6 | 6,9 | 53,5 | 26,5 | 6,2 | 6,7 | 3,9 | 8,2 | 48,6 | 90,0 | 0,2 | 0,3 | 0,5 | 3,4 | 5,6 |
| **4** | **1** | **2** | 2,5 | 5,0 | 11,6 | 16,1 | 42,7 | 22,1 | 2,5 | 5,0 | 11,6 | 16,1 | 42,7 | 22,1 | 18,0 | 6,6 | 15,0 | 9,0 | 22,8 | 28,7 | 18,5 | 6,8 | 10,3 | 13,7 | 21,9 | 28,8 | 2,5 | 5,0 | 11,6 | 16,1 | 42,7 | 22,1 |
| **4** | **1** | **3** | 0,7 | 3,3 | 5,0 | 11,8 | 29,1 | 50,0 | 75,2 | 0,8 | 1,2 | 3,0 | 7,3 | 12,5 | 25,7 | 5,4 | 7,8 | 4,2 | 6,3 | 50,7 | 35,2 | 7,0 | 5,1 | 3,5 | 6,7 | 42,5 | 90,1 | 0,3 | 0,5 | 1,2 | 2,9 | 5,0 |
| **4** | **1** | **4** | 2,5 | 6,0 | 13,9 | 32,8 | 30,2 | 14,6 | 75,6 | 1,5 | 3,5 | 8,2 | 7,5 | 3,7 | 34,4 | 13,1 | 9,6 | 8,9 | 13,3 | 20,6 | 18,9 | 7,2 | 8,6 | 11,0 | 17,7 | 36,6 | 98,0 | 0,1 | 0,3 | 0,7 | 0,6 | 0,3 |
| **4** | **1** | **5** | 4,2 | 3,2 | 6,4 | 20,5 | 40,3 | 25,3 | 95,2 | 0,2 | 0,3 | 1,0 | 2,0 | 1,3 | 52,6 | 11,3 | 7,9 | 3,9 | 5,1 | 19,2 | 56,6 | 10,8 | 7,1 | 3,5 | 4,1 | 17,9 | 98,1 | 0,1 | 0,1 | 0,4 | 0,8 | 0,5 |
| **4** | **1** | **6** | 0,9 | 4,9 | 7,1 | 14,7 | 31,9 | 40,5 | 75,2 | 1,2 | 1,8 | 3,7 | 8,0 | 10,1 | 31,9 | 5,4 | 7,8 | 7,8 | 7,0 | 40,1 | 28,1 | 5,6 | 7,2 | 5,2 | 12,0 | 41,8 | 90,1 | 0,5 | 0,7 | 1,5 | 3,2 | 4,0 |
| **4** | **2** | **1** | 1,1 | 4,5 | 10,7 | 30,5 | 31,1 | 22,0 | 50,6 | 2,3 | 5,4 | 15,3 | 15,5 | 11,0 | 36,0 | 4,7 | 16,0 | 17,3 | 8,7 | 17,3 | 37,2 | 9,3 | 14,0 | 14,7 | 12,4 | 12,4 | 90,1 | 0,5 | 1,1 | 3,1 | 3,1 | 2,2 |
| **4** | **2** | **2** | 1,3 | 5,2 | 21,5 | 40,9 | 25,6 | 5,5 | 1,3 | 5,2 | 21,5 | 40,9 | 25,6 | 5,5 | 15,2 | 7,2 | 16,8 | 31,1 | 23,9 | 5,9 | 18,1 | 6,6 | 14,4 | 30,8 | 23,9 | 6,1 | 1,3 | 5,2 | 21,5 | 40,9 | 25,6 | 5,5 |
| **4** | **2** | **3** | 2,9 | 5,0 | 12,5 | 28,0 | 38,2 | 13,4 | 75,7 | 1,2 | 3,1 | 7,0 | 9,5 | 3,4 | 23,0 | 5,5 | 13,1 | 19,3 | 23,4 | 15,7 | 27,6 | 5,5 | 7,9 | 21,7 | 24,8 | 12,6 | 90,3 | 0,5 | 1,3 | 2,8 | 3,8 | 1,3 |
| **4** | **2** | **4** | 3,1 | 7,8 | 24,1 | 35,2 | 22,9 | 6,9 | 75,8 | 1,9 | 6,0 | 8,8 | 5,7 | 1,7 | 26,8 | 10,0 | 11,8 | 17,8 | 20,2 | 13,3 | 15,7 | 6,2 | 10,4 | 22,6 | 26,8 | 18,4 | 98,1 | 0,2 | 0,5 | 0,7 | 0,5 | 0,1 |
| **4** | **2** | **5** | 3,7 | 4,7 | 16,2 | 31,5 | 32,0 | 11,9 | 95,2 | 0,2 | 0,8 | 1,6 | 1,6 | 0,6 | 55,4 | 10,9 | 10,8 | 8,4 | 7,5 | 7,0 | 60,0 | 12,2 | 8,0 | 6,9 | 7,8 | 5,1 | 98,1 | 0,1 | 0,3 | 0,6 | 0,6 | 0,2 |
| **4** | **2** | **6** | 3,8 | 4,4 | 24,7 | 35,7 | 18,7 | 12,6 | 76,0 | 1,1 | 6,2 | 8,9 | 4,7 | 3,2 | 43,4 | 7,7 | 16,1 | 15,4 | 7,7 | 9,8 | 37,1 | 11,3 | 18,5 | 13,9 | 8,6 | 10,6 | 90,4 | 0,4 | 2,5 | 3,6 | 1,9 | 1,3 |
| **5** | **1** | **1** | 4,9 | 9,8 | 14,6 | 12,2 | 19,5 | 39,0 | 52,4 | 4,9 | 7,3 | 6,1 | 9,8 | 19,5 | 42,4 | 15,2 | 6,1 | 9,1 | 6,1 | 21,2 | 80,6 | 0,0 | 3,2 | 9,7 | 3,2 | 3,2 | 90,5 | 1,0 | 1,5 | 1,2 | 2,0 | 3,9 |
| **5** | **1** | **2** | 7,1 | 7,1 | 0,0 | 28,6 | 14,3 | 42,9 | 7,1 | 7,1 | 0,0 | 28,6 | 14,3 | 42,9 | 75,0 | 0,0 | 8,3 | 8,3 | 0,0 | 8,3 | 83,3 | 0,0 | 0,0 | 8,3 | 0,0 | 8,3 | 7,1 | 7,1 | 0,0 | 28,6 | 14,3 | 42,9 |
| **5** | **1** | **3** | 0,0 | 12,2 | 31,7 | 14,6 | 14,6 | 26,8 | 75,0 | 3,0 | 7,9 | 3,7 | 3,7 | 6,7 | 77,1 | 8,6 | 0,0 | 2,9 | 0,0 | 11,4 | 64,9 | 5,4 | 2,7 | 10,8 | 5,4 | 10,8 | 90,0 | 1,2 | 3,2 | 1,5 | 1,5 | 2,7 |
| **5** | **1** | **4** | 0,0 | 18,4 | 22,4 | 20,4 | 20,4 | 18,4 | 75,0 | 4,6 | 5,6 | 5,1 | 5,1 | 4,6 | 72,1 | 9,3 | 4,7 | 4,7 | 0,0 | 9,3 | 79,1 | 4,7 | 7,0 | 7,0 | 2,3 | 0,0 | 98,0 | 0,4 | 0,4 | 0,4 | 0,4 | 0,4 |
| **5** | **1** | **5** | 2,9 | 5,7 | 31,4 | 14,3 | 20,0 | 25,7 | 95,1 | 0,3 | 1,6 | 0,7 | 1,0 | 1,3 | 70,0 | 8,3 | 11,7 | 3,3 | 3,3 | 3,3 | 82,8 | 3,1 | 6,3 | 0,0 | 3,1 | 4,7 | 98,1 | 0,1 | 0,6 | 0,3 | 0,4 | 0,5 |
| **5** | **1** | **6** | 0,0 | 11,8 | 41,2 | 17,6 | 17,6 | 11,8 | 75,0 | 2,9 | 10,3 | 4,4 | 4,4 | 2,9 | 50,0 | 3,6 | 21,4 | 10,7 | 10,7 | 3,6 | 72,7 | 6,1 | 6,1 | 12,1 | 3,0 | 0,0 | 90,0 | 1,2 | 4,1 | 1,8 | 1,8 | 1,2 |
| **5** | **2** | **1** | 12,5 | 0,0 | 0,0 | 25,0 | 37,5 | 25,0 | 56,3 | 0,0 | 0,0 | 12,5 | 18,8 | 12,5 | 60,0 | 20,0 | 0,0 | 20,0 | 0,0 | 0,0 | 100,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 91,3 | 0,0 | 0,0 | 2,5 | 3,8 | 2,5 |
| **5** | **2** | **2** | 7,7 | 3,8 | 38,5 | 30,8 | 19,2 | 0,0 | 7,7 | 3,8 | 38,5 | 30,8 | 19,2 | 0,0 | 65,4 | 3,8 | 11,5 | 11,5 | 7,7 | 0,0 | 90,9 | 0,0 | 9,1 | 0,0 | 0,0 | 0,0 | 7,7 | 3,8 | 38,5 | 30,8 | 19,2 | 0,0 |
| **5** | **2** | **3** | 0,0 | 0,0 | 33,3 | 50,0 | 0,0 | 16,7 | 75,0 | 0,0 | 8,3 | 12,5 | 0,0 | 4,2 | 25,0 | 0,0 | 25,0 | 25,0 | 25,0 | 0,0 | 50,0 | 0,0 | 16,7 | 16,7 | 16,7 | 0,0 | 90,0 | 0,0 | 3,3 | 5,0 | 0,0 | 1,7 |
| **5** | **2** | **4** | 3,2 | 9,7 | 32,3 | 22,6 | 12,9 | 19,4 | 75,8 | 2,4 | 8,1 | 5,6 | 3,2 | 4,8 | 62,5 | 6,3 | 3,1 | 9,4 | 9,4 | 9,4 | 73,3 | 3,3 | 3,3 | 10,0 | 10,0 | 0,0 | 98,1 | 0,2 | 0,6 | 0,5 | 0,3 | 0,4 |
| **5** | **2** | **5** | 4,5 | 9,1 | 9,1 | 27,3 | 27,3 | 22,7 | 95,2 | 0,5 | 0,5 | 1,4 | 1,4 | 1,1 | 58,8 | 5,9 | 5,9 | 11,8 | 11,8 | 5,9 | 76,2 | 4,8 | 4,8 | 4,8 | 9,5 | 0,0 | 98,1 | 0,2 | 0,2 | 0,5 | 0,5 | 0,5 |
| **5** | **2** | **6** | 0,0 | 0,0 | 22,2 | 11,1 | 33,3 | 33,3 | 75,0 | 0,0 | 5,6 | 2,8 | 8,3 | 8,3 | 71,4 | 14,3 | 0,0 | 0,0 | 0,0 | 14,3 | 85,7 | 0,0 | 14,3 | 0,0 | 0,0 | 0,0 | 90,0 | 0,0 | 2,2 | 1,1 | 3,3 | 3,3 |

*Table 34 - Business activity frequency values (in %). Columns: A = age; G = gender; S = sector*

| BUSINESS ACTIVITY | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | STAGE 0 (PRE-PANDEMIC) | | | | | | STAGE 1 (INTELLIGENT LOCKDOWN) | | | | | | STAGE 2 (SUMMER RELAXATIONS) | | | | | | STAGE 3 (SEMI LOCKDOWN) | | | | | | STAGE 4 (STRICT LOCKDOWN) | | | | | |
| **A** | **G** | **S** | **0 d** | **1 d** | **2 d** | **3 d** | **4 d** | **5 d** | **0 d** | **1 d** | **2 d** | **3 d** | **4 d** | **5 d** | **0 d** | **1 d** | **2 d** | **3 d** | **4 d** | **5 d** | **0 d** | **1 d** | **2 d** | **3 d** | **4 d** | **5 d** | **0 d** | **1 d** | **2 d** | **3 d** | **4 d** | **5 d** |
| **2** | **1** | **1** | 50,0 | 8,9 | 7,8 | 3,3 | 4,4 | 25,6 | 75,0 | 4,4 | 3,9 | 1,7 | 2,2 | 12,8 | 73,6 | 0,0 | 6,9 | 2,8 | 1,4 | 15,3 | 79,3 | 3,4 | 5,2 | 1,7 | 0,0 | 10,3 | 95,0 | 0,9 | 0,8 | 0,3 | 0,4 | 2,6 |
| **2** | **1** | **2** | 50,0 | 14,7 | 11,8 | 2,9 | 8,8 | 11,8 | 50,0 | 14,7 | 11,8 | 2,9 | 8,8 | 11,8 | 64,3 | 7,1 | 10,7 | 7,1 | 0,0 | 10,7 | 62,5 | 0,0 | 4,2 | 0,0 | 8,3 | 25,0 | 50,0 | 14,7 | 11,8 | 2,9 | 8,8 | 11,8 |
| **2** | **1** | **3** | 50,5 | 12,7 | 23,3 | 4,0 | 4,2 | 5,2 | 87,6 | 3,2 | 5,8 | 1,0 | 1,1 | 1,3 | 77,0 | 5,5 | 9,8 | 1,9 | 2,5 | 3,3 | 81,8 | 3,5 | 5,2 | 1,4 | 2,4 | 5,6 | 95,0 | 1,3 | 2,3 | 0,4 | 0,4 | 0,5 |
| **2** | **1** | **4** | 53,1 | 12,5 | 3,1 | 9,4 | 18,8 | 3,1 | 88,3 | 3,1 | 0,8 | 2,3 | 4,7 | 0,8 | 79,2 | 4,2 | 0,0 | 8,3 | 0,0 | 8,3 | 88,9 | 0,0 | 0,0 | 0,0 | 5,6 | 5,6 | 99,1 | 0,3 | 0,1 | 0,2 | 0,4 | 0,1 |
| **2** | **1** | **5** | 51,9 | 7,4 | 12,3 | 1,9 | 9,3 | 17,3 | 97,6 | 0,4 | 0,6 | 0,1 | 0,5 | 0,9 | 81,7 | 8,3 | 0,8 | 0,0 | 0,8 | 8,3 | 83,7 | 6,7 | 1,0 | 1,0 | 0,0 | 7,7 | 99,0 | 0,1 | 0,2 | 0,0 | 0,2 | 0,3 |
| **2** | **1** | **6** | 50,0 | 2,3 | 11,4 | 9,1 | 9,1 | 18,2 | 87,5 | 0,6 | 2,8 | 2,3 | 2,3 | 4,5 | 80,0 | 2,5 | 5,0 | 5,0 | 2,5 | 5,0 | 81,6 | 2,6 | 0,0 | 2,6 | 0,0 | 13,2 | 95,0 | 0,2 | 1,1 | 0,9 | 0,9 | 1,8 |
| **2** | **2** | **1** | 50,0 | 3,8 | 11,5 | 3,8 | 11,5 | 19,2 | 75,0 | 1,9 | 5,8 | 1,9 | 5,8 | 9,6 | 65,0 | 0,0 | 12,5 | 2,5 | 5,0 | 15,0 | 75,0 | 3,1 | 6,3 | 0,0 | 6,3 | 9,4 | 95,0 | 0,4 | 1,2 | 0,4 | 1,2 | 1,9 |
| **2** | **2** | **2** | 51,4 | 4,3 | 8,1 | 10,5 | 16,7 | 9,0 | 51,4 | 4,3 | 8,1 | 10,5 | 16,7 | 9,0 | 62,2 | 4,7 | 6,4 | 7,0 | 13,4 | 6,4 | 64,1 | 1,3 | 2,6 | 7,1 | 16,7 | 8,3 | 51,4 | 4,3 | 8,1 | 10,5 | 16,7 | 9,0 |
| **2** | **2** | **3** | 50,2 | 12,5 | 24,1 | 5,6 | 2,7 | 4,9 | 87,5 | 3,1 | 6,0 | 1,4 | 0,7 | 1,2 | 82,5 | 2,4 | 7,5 | 3,2 | 1,3 | 3,0 | 85,5 | 2,0 | 5,0 | 3,2 | 1,8 | 2,5 | 95,0 | 1,3 | 2,4 | 0,6 | 0,3 | 0,5 |
| **2** | **2** | **4** | 50,0 | 5,8 | 8,7 | 8,7 | 17,3 | 9,6 | 87,5 | 1,4 | 2,2 | 2,2 | 4,3 | 2,4 | 67,8 | 1,1 | 4,4 | 4,4 | 12,2 | 10,0 | 62,8 | 1,3 | 3,8 | 3,8 | 9,0 | 19,2 | 99,0 | 0,1 | 0,2 | 0,2 | 0,3 | 0,2 |
| **2** | **2** | **5** | 50,4 | 9,1 | 14,7 | 4,3 | 11,6 | 9,9 | 97,5 | 0,5 | 0,7 | 0,2 | 0,6 | 0,5 | 81,0 | 3,8 | 8,2 | 2,7 | 1,1 | 3,3 | 87,8 | 1,2 | 2,3 | 3,5 | 0,6 | 4,7 | 99,0 | 0,2 | 0,3 | 0,1 | 0,2 | 0,2 |
| **2** | **2** | **6** | 50,0 | 10,7 | 8,9 | 10,7 | 8,9 | 10,7 | 87,5 | 2,7 | 2,2 | 2,7 | 2,2 | 2,7 | 81,3 | 6,3 | 6,3 | 0,0 | 0,0 | 6,3 | 81,3 | 2,1 | 4,2 | 4,2 | 2,1 | 6,3 | 95,0 | 1,1 | 0,9 | 1,1 | 0,9 | 1,1 |
| **3** | **1** | **1** | 50,6 | 1,8 | 1,5 | 3,0 | 16,9 | 26,2 | 75,3 | 0,9 | 0,8 | 1,5 | 8,5 | 13,1 | 63,4 | 4,5 | 3,6 | 1,9 | 2,3 | 24,3 | 65,4 | 4,5 | 3,4 | 2,4 | 1,5 | 22,8 | 95,1 | 0,2 | 0,2 | 0,3 | 1,7 | 2,6 |
| **3** | **1** | **2** | 51,3 | 1,7 | 0,4 | 9,2 | 19,2 | 18,3 | 51,3 | 1,7 | 0,4 | 9,2 | 19,2 | 18,3 | 55,8 | 3,5 | 4,7 | 4,7 | 13,4 | 18,0 | 58,6 | 3,4 | 2,9 | 6,3 | 10,3 | 18,4 | 51,3 | 1,7 | 0,4 | 9,2 | 19,2 | 18,3 |
| **3** | **1** | **3** | 50,5 | 1,3 | 3,1 | 4,8 | 16,4 | 24,0 | 87,6 | 0,3 | 0,8 | 1,2 | 4,1 | 6,0 | 63,1 | 1,8 | 4,5 | 2,0 | 4,9 | 23,7 | 66,1 | 2,4 | 3,6 | 2,6 | 3,8 | 21,6 | 95,0 | 0,1 | 0,3 | 0,5 | 1,6 | 2,4 |
| **3** | **1** | **4** | 50,7 | 1,6 | 7,1 | 13,3 | 19,1 | 8,3 | 87,7 | 0,4 | 1,8 | 3,3 | 4,8 | 2,1 | 65,0 | 4,9 | 6,1 | 5,6 | 7,4 | 11,0 | 57,3 | 2,6 | 3,4 | 3,9 | 9,6 | 23,2 | 99,0 | 0,0 | 0,1 | 0,3 | 0,4 | 0,2 |
| **3** | **1** | **5** | 51,2 | 2,0 | 2,1 | 7,2 | 22,6 | 14,9 | 97,6 | 0,1 | 0,1 | 0,4 | 1,1 | 0,7 | 75,7 | 5,5 | 4,5 | 1,9 | 1,7 | 10,8 | 80,9 | 4,3 | 2,8 | 1,3 | 1,9 | 8,9 | 99,0 | 0,0 | 0,0 | 0,1 | 0,5 | 0,3 |
| **3** | **1** | **6** | 51,1 | 1,5 | 2,6 | 3,7 | 16,8 | 24,3 | 87,8 | 0,4 | 0,7 | 0,9 | 4,2 | 6,1 | 62,9 | 5,9 | 3,5 | 3,0 | 6,4 | 18,3 | 68,3 | 1,6 | 2,7 | 1,6 | 5,9 | 19,9 | 95,1 | 0,1 | 0,3 | 0,4 | 1,7 | 2,4 |
| **3** | **2** | **1** | 50,3 | 1,4 | 3,1 | 16,3 | 17,4 | 11,5 | 75,2 | 0,7 | 1,6 | 8,2 | 8,7 | 5,7 | 71,0 | 6,3 | 5,8 | 6,3 | 4,9 | 5,8 | 68,3 | 10,1 | 5,8 | 4,8 | 3,8 | 7,2 | 95,0 | 0,1 | 0,3 | 1,6 | 1,7 | 1,1 |
| **3** | **2** | **2** | 50,4 | 2,4 | 6,0 | 19,7 | 16,1 | 5,4 | 50,4 | 2,4 | 6,0 | 19,7 | 16,1 | 5,4 | 57,2 | 3,8 | 5,3 | 12,8 | 14,6 | 6,2 | 57,1 | 2,7 | 6,1 | 13,2 | 14,9 | 6,1 | 50,4 | 2,4 | 6,0 | 19,7 | 16,1 | 5,4 |
| **3** | **2** | **3** | 50,9 | 1,5 | 4,6 | 15,2 | 15,4 | 12,3 | 87,7 | 0,4 | 1,2 | 3,8 | 3,9 | 3,1 | 63,3 | 3,9 | 3,2 | 11,2 | 10,0 | 8,5 | 67,4 | 3,6 | 3,6 | 10,0 | 9,2 | 6,2 | 95,1 | 0,1 | 0,5 | 1,5 | 1,5 | 1,2 |
| **3** | **2** | **4** | 51,1 | 3,7 | 12,0 | 17,3 | 11,7 | 4,1 | 87,8 | 0,9 | 3,0 | 4,3 | 2,9 | 1,0 | 62,1 | 5,5 | 5,2 | 11,0 | 9,0 | 7,1 | 57,0 | 2,5 | 4,3 | 13,0 | 13,5 | 9,7 | 99,0 | 0,1 | 0,2 | 0,3 | 0,2 | 0,1 |
| **3** | **2** | **5** | 50,8 | 1,9 | 4,7 | 14,8 | 19,7 | 8,1 | 97,5 | 0,1 | 0,2 | 0,7 | 1,0 | 0,4 | 75,8 | 7,7 | 4,7 | 2,5 | 4,0 | 5,3 | 82,1 | 5,3 | 3,8 | 2,5 | 3,3 | 3,0 | 99,0 | 0,0 | 0,1 | 0,3 | 0,4 | 0,2 |
| **3** | **2** | **6** | 52,2 | 2,5 | 5,0 | 14,7 | 16,2 | 9,4 | 88,0 | 0,6 | 1,3 | 3,7 | 4,0 | 2,3 | 75,0 | 4,9 | 5,4 | 2,9 | 7,8 | 3,9 | 75,2 | 4,6 | 5,0 | 4,1 | 7,3 | 3,7 | 95,2 | 0,3 | 0,5 | 1,5 | 1,6 | 0,9 |
| **4** | **1** | **1** | 50,2 | 0,9 | 1,5 | 2,5 | 17,0 | 27,9 | 75,1 | 0,5 | 0,7 | 1,2 | 8,5 | 13,9 | 61,2 | 2,8 | 3,5 | 2,3 | 3,5 | 26,7 | 63,2 | 3,1 | 3,4 | 1,9 | 4,1 | 24,3 | 95,0 | 0,1 | 0,1 | 0,2 | 1,7 | 2,8 |
| **4** | **1** | **2** | 51,3 | 2,5 | 5,8 | 8,0 | 21,4 | 11,1 | 51,3 | 2,5 | 5,8 | 8,0 | 21,4 | 11,1 | 59,0 | 3,3 | 7,5 | 4,5 | 11,4 | 14,4 | 59,2 | 3,4 | 5,1 | 6,8 | 11,0 | 14,4 | 51,3 | 2,5 | 5,8 | 8,0 | 21,4 | 11,1 |
| **4** | **1** | **3** | 50,4 | 1,7 | 2,5 | 5,9 | 14,6 | 25,0 | 87,6 | 0,4 | 0,6 | 1,5 | 3,6 | 6,3 | 62,8 | 2,7 | 3,9 | 2,1 | 3,1 | 25,4 | 67,6 | 3,5 | 2,5 | 1,7 | 3,3 | 21,3 | 95,0 | 0,2 | 0,2 | 0,6 | 1,5 | 2,5 |
| **4** | **1** | **4** | 51,2 | 3,0 | 7,0 | 16,4 | 15,1 | 7,3 | 87,8 | 0,7 | 1,7 | 4,1 | 3,8 | 1,8 | 67,2 | 6,5 | 4,8 | 4,5 | 6,7 | 10,3 | 59,4 | 3,6 | 4,3 | 5,5 | 8,9 | 18,3 | 99,0 | 0,1 | 0,1 | 0,3 | 0,3 | 0,1 |
| **4** | **1** | **5** | 52,1 | 1,6 | 3,2 | 10,3 | 20,1 | 12,7 | 97,6 | 0,1 | 0,2 | 0,5 | 1,0 | 0,6 | 76,3 | 5,7 | 3,9 | 2,0 | 2,5 | 9,6 | 78,3 | 5,4 | 3,6 | 1,8 | 2,0 | 8,9 | 99,0 | 0,0 | 0,1 | 0,2 | 0,4 | 0,3 |
| **4** | **1** | **6** | 50,5 | 2,5 | 3,5 | 7,4 | 16,0 | 20,2 | 87,6 | 0,6 | 0,9 | 1,8 | 4,0 | 5,1 | 66,0 | 2,7 | 3,9 | 3,9 | 3,5 | 20,0 | 64,1 | 2,8 | 3,6 | 2,6 | 6,0 | 20,9 | 95,0 | 0,2 | 0,4 | 0,7 | 1,6 | 2,0 |
| **4** | **2** | **1** | 50,6 | 2,3 | 5,4 | 15,3 | 15,5 | 11,0 | 75,3 | 1,1 | 2,7 | 7,6 | 7,8 | 5,5 | 68,0 | 2,3 | 8,0 | 8,7 | 4,3 | 8,7 | 68,6 | 4,7 | 7,0 | 7,4 | 6,2 | 6,2 | 95,1 | 0,2 | 0,5 | 1,5 | 1,6 | 1,1 |
| **4** | **2** | **2** | 50,7 | 2,6 | 10,8 | 20,4 | 12,8 | 2,7 | 50,7 | 2,6 | 10,8 | 20,4 | 12,8 | 2,7 | 57,6 | 3,6 | 8,4 | 15,6 | 12,0 | 2,9 | 59,1 | 3,3 | 7,2 | 15,4 | 11,9 | 3,1 | 50,7 | 2,6 | 10,8 | 20,4 | 12,8 | 2,7 |
| **4** | **2** | **3** | 51,5 | 2,5 | 6,3 | 14,0 | 19,1 | 6,7 | 87,9 | 0,6 | 1,6 | 3,5 | 4,8 | 1,7 | 61,5 | 2,7 | 6,6 | 9,7 | 11,7 | 7,8 | 63,8 | 2,8 | 3,9 | 10,8 | 12,4 | 6,3 | 95,1 | 0,2 | 0,6 | 1,4 | 1,9 | 0,7 |
| **4** | **2** | **4** | 51,6 | 3,9 | 12,1 | 17,6 | 11,4 | 3,5 | 87,9 | 1,0 | 3,0 | 4,4 | 2,9 | 0,9 | 63,4 | 5,0 | 5,9 | 8,9 | 10,1 | 6,6 | 57,9 | 3,1 | 5,2 | 11,3 | 13,4 | 9,2 | 99,0 | 0,1 | 0,2 | 0,4 | 0,2 | 0,1 |
| **4** | **2** | **5** | 51,8 | 2,3 | 8,1 | 15,8 | 16,0 | 6,0 | 97,6 | 0,1 | 0,4 | 0,8 | 0,8 | 0,3 | 77,7 | 5,5 | 5,4 | 4,2 | 3,8 | 3,5 | 80,0 | 6,1 | 4,0 | 3,5 | 3,9 | 2,6 | 99,0 | 0,0 | 0,2 | 0,3 | 0,3 | 0,1 |
| **4** | **2** | **6** | 51,9 | 2,2 | 12,4 | 17,9 | 9,3 | 6,3 | 88,0 | 0,5 | 3,1 | 4,5 | 2,3 | 1,6 | 71,7 | 3,8 | 8,0 | 7,7 | 3,8 | 4,9 | 68,5 | 5,6 | 9,3 | 7,0 | 4,3 | 5,3 | 95,2 | 0,2 | 1,2 | 1,8 | 0,9 | 0,6 |
| **5** | **1** | **1** | 52,4 | 4,9 | 7,3 | 6,1 | 9,8 | 19,5 | 76,2 | 2,4 | 3,7 | 3,0 | 4,9 | 9,8 | 71,2 | 7,6 | 3,0 | 4,5 | 3,0 | 10,6 | 90,3 | 0,0 | 1,6 | 4,8 | 1,6 | 1,6 | 95,2 | 0,5 | 0,7 | 0,6 | 1,0 | 2,0 |
| **5** | **1** | **2** | 53,6 | 3,6 | 0,0 | 14,3 | 7,1 | 21,4 | 53,6 | 3,6 | 0,0 | 14,3 | 7,1 | 21,4 | 87,5 | 0,0 | 4,2 | 4,2 | 0,0 | 4,2 | 91,7 | 0,0 | 0,0 | 4,2 | 0,0 | 4,2 | 53,6 | 3,6 | 0,0 | 14,3 | 7,1 | 21,4 |
| **5** | **1** | **3** | 50,0 | 6,1 | 15,9 | 7,3 | 7,3 | 13,4 | 87,5 | 1,5 | 4,0 | 1,8 | 1,8 | 3,4 | 88,6 | 4,3 | 0,0 | 1,4 | 0,0 | 5,7 | 82,4 | 2,7 | 1,4 | 5,4 | 2,7 | 5,4 | 95,0 | 0,6 | 1,6 | 0,7 | 0,7 | 1,3 |
| **5** | **1** | **4** | 50,0 | 9,2 | 11,2 | 10,2 | 10,2 | 9,2 | 87,5 | 2,3 | 2,8 | 2,6 | 2,6 | 2,3 | 86,0 | 4,7 | 2,3 | 2,3 | 0,0 | 4,7 | 89,5 | 2,3 | 3,5 | 3,5 | 1,2 | 0,0 | 99,0 | 0,2 | 0,2 | 0,2 | 0,2 | 0,2 |
| **5** | **1** | **5** | 51,4 | 2,9 | 15,7 | 7,1 | 10,0 | 12,9 | 97,6 | 0,1 | 0,8 | 0,4 | 0,5 | 0,6 | 85,0 | 4,2 | 5,8 | 1,7 | 1,7 | 1,7 | 91,4 | 1,6 | 3,1 | 0,0 | 1,6 | 2,3 | 99,0 | 0,1 | 0,3 | 0,1 | 0,2 | 0,3 |
| **5** | **1** | **6** | 50,0 | 5,9 | 20,6 | 8,8 | 8,8 | 5,9 | 87,5 | 1,5 | 5,1 | 2,2 | 2,2 | 1,5 | 75,0 | 1,8 | 10,7 | 5,4 | 5,4 | 1,8 | 86,4 | 3,0 | 3,0 | 6,1 | 1,5 | 0,0 | 95,0 | 0,6 | 2,1 | 0,9 | 0,9 | 0,6 |
| **5** | **2** | **1** | 56,3 | 0,0 | 0,0 | 12,5 | 18,8 | 12,5 | 78,1 | 0,0 | 0,0 | 6,3 | 9,4 | 6,3 | 80,0 | 10,0 | 0,0 | 10,0 | 0,0 | 0,0 | 100,0 | 0,0 | 0,0 | 0,0 | 0,0 | 0,0 | 95,6 | 0,0 | 0,0 | 1,3 | 1,9 | 1,3 |
| **5** | **2** | **2** | 53,8 | 1,9 | 19,2 | 15,4 | 9,6 | 0,0 | 53,8 | 1,9 | 19,2 | 15,4 | 9,6 | 0,0 | 82,7 | 1,9 | 5,8 | 5,8 | 3,8 | 0,0 | 95,5 | 0,0 | 4,5 | 0,0 | 0,0 | 0,0 | 53,8 | 1,9 | 19,2 | 15,4 | 9,6 | 0,0 |
| **5** | **2** | **3** | 50,0 | 0,0 | 16,7 | 25,0 | 0,0 | 8,3 | 87,5 | 0,0 | 4,2 | 6,3 | 0,0 | 2,1 | 62,5 | 0,0 | 12,5 | 12,5 | 12,5 | 0,0 | 75,0 | 0,0 | 8,3 | 8,3 | 8,3 | 0,0 | 95,0 | 0,0 | 1,7 | 2,5 | 0,0 | 0,8 |
| **5** | **2** | **4** | 51,6 | 4,8 | 16,1 | 11,3 | 6,5 | 9,7 | 87,9 | 1,2 | 4,0 | 2,8 | 1,6 | 2,4 | 81,3 | 3,1 | 1,6 | 4,7 | 4,7 | 4,7 | 86,7 | 1,7 | 1,7 | 5,0 | 5,0 | 0,0 | 99,0 | 0,1 | 0,3 | 0,2 | 0,1 | 0,2 |
| **5** | **2** | **5** | 52,3 | 4,5 | 4,5 | 13,6 | 13,6 | 11,4 | 97,6 | 0,2 | 0,2 | 0,7 | 0,7 | 0,6 | 79,4 | 2,9 | 2,9 | 5,9 | 5,9 | 2,9 | 88,1 | 2,4 | 2,4 | 2,4 | 4,8 | 0,0 | 99,0 | 0,1 | 0,1 | 0,3 | 0,3 | 0,2 |
| **5** | **2** | **6** | 50,0 | 0,0 | 11,1 | 5,6 | 16,7 | 16,7 | 87,5 | 0,0 | 2,8 | 1,4 | 4,2 | 4,2 | 85,7 | 7,1 | 0,0 | 0,0 | 0,0 | 7,1 | 92,9 | 0,0 | 7,1 | 0,0 | 0,0 | 0,0 | 95,0 | 0,0 | 1,1 | 0,6 | 1,7 | 1,7 |

*Table 35 - Activity frequency values of scenarios (in %): Shopping & bring/get (Left); Other (Center); Education (right)*

**SHOPPING & BRING/GET ACTIVITIES**

| STAGE 0 (PRE-PANDEMIC) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Age | 0 d | 1 d | 2 d | 3 d | 4 d | 5 d | 6 d | 7 d |
| 1 | 0,00 | 92,20 | 3,90 | 3,90 | 0,00 | 0,00 | 0,00 | 0,00 |
| 2 | 0,00 | 92,20 | 3,90 | 3,90 | 0,00 | 0,00 | 0,00 | 0,00 |
| 3 | 0,00 | 85,70 | 6,85 | 6,85 | 0,15 | 0,15 | 0,15 | 0,15 |
| 4 | 0,00 | 86,00 | 6,65 | 6,65 | 0,20 | 0,20 | 0,15 | 0,15 |
| 5 | 0,00 | 75,20 | 11,45 | 11,45 | 0,48 | 0,48 | 0,48 | 0,48 |

| STAGE 1 (INTELLIGENT LOCKDOWN) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Age | 0 d | 1 d | 2 d | 3 d | 4 d | 5 d | 6 d | 7 d |
| 1 | 77,90 | 20,80 | 0,65 | 0,65 | 0,00 | 0,00 | 0,00 | 0,00 |
| 2 | 77,90 | 20,80 | 0,65 | 0,65 | 0,00 | 0,00 | 0,00 | 0,00 |
| 3 | 68,30 | 26,30 | 2,70 | 2,70 | 0,00 | 0,00 | 0,00 | 0,00 |
| 4 | 75,50 | 20,30 | 1,60 | 1,60 | 0,35 | 0,35 | 0,15 | 0,15 |
| 5 | 80,60 | 14,30 | 2,40 | 2,40 | 0,15 | 0,15 | 0,00 | 0,00 |

| STAGE 2 (SUMMER RELAXATIONS) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Age | 0 d | 1 d | 2 d | 3 d | 4 d | 5 d | 6 d | 7 d |
| 1 | 29,30 | 60,80 | 4,75 | 4,75 | 0,20 | 0,20 | 0,00 | 0,00 |
| 2 | 29,30 | 60,80 | 4,75 | 4,75 | 0,20 | 0,20 | 0,00 | 0,00 |
| 3 | 24,60 | 63,60 | 5,15 | 5,15 | 0,55 | 0,55 | 0,20 | 0,20 |
| 4 | 29,80 | 61,50 | 3,65 | 3,65 | 0,50 | 0,50 | 0,20 | 0,20 |
| 5 | 44,40 | 42,50 | 5,70 | 5,70 | 0,55 | 0,55 | 0,30 | 0,30 |

| STAGE 3 (SEMI LOCKDOWN) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Age | 0 d | 1 d | 2 d | 3 d | 4 d | 5 d | 6 d | 7 d |
| 1 | 51,40 | 42,30 | 3,05 | 3,05 | 0,10 | 0,10 | 0,00 | 0,00 |
| 2 | 51,40 | 42,30 | 3,05 | 3,05 | 0,10 | 0,10 | 0,00 | 0,00 |
| 3 | 49,30 | 43,25 | 3,25 | 3,25 | 0,38 | 0,38 | 0,10 | 0,10 |
| 4 | 54,10 | 40,20 | 2,38 | 2,38 | 0,38 | 0,38 | 0,10 | 0,10 |
| 5 | 60,50 | 31,35 | 3,55 | 3,55 | 0,38 | 0,38 | 0,18 | 0,18 |

| STAGE 4 (STRICT LOCKDOWN) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Age | 0 d | 1 d | 2 d | 3 d | 4 d | 5 d | 6 d | 7 d |
| 1 | 73,50 | 23,80 | 1,35 | 1,35 | 0,00 | 0,00 | 0,00 | 0,00 |
| 2 | 73,50 | 23,80 | 1,35 | 1,35 | 0,00 | 0,00 | 0,00 | 0,00 |
| 3 | 74,00 | 22,90 | 1,35 | 1,35 | 0,20 | 0,20 | 0,00 | 0,00 |
| 4 | 78,40 | 18,90 | 1,10 | 1,10 | 0,25 | 0,25 | 0,00 | 0,00 |
| 5 | 76,60 | 20,20 | 1,40 | 1,40 | 0,20 | 0,20 | 0,05 | 0,05 |

**OTHER ACTIVITY**

| STAGE 0 (PRE-PANDEMIC) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Age | 0 d | 1 d | 2 d | 3 d | 4 d | 5 d | 6 d | 7 d |
| 1 | 0,00 | 60,21 | 18,33 | 18,33 | 0,79 | 0,79 | 0,79 | 0,79 |
| 2 | 0,00 | 60,21 | 18,33 | 18,33 | 0,79 | 0,79 | 0,79 | 0,79 |
| 3 | 0,00 | 68,99 | 14,28 | 14,28 | 0,62 | 0,62 | 0,62 | 0,62 |
| 4 | 0,00 | 73,55 | 12,15 | 12,15 | 0,54 | 0,54 | 0,54 | 0,54 |
| 5 | 0,00 | 72,03 | 12,69 | 12,69 | 0,65 | 0,65 | 0,65 | 0,65 |

| STAGE 1 (INTELLIGENT LOCKDOWN) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Age | 0 d | 1 d | 2 d | 3 d | 4 d | 5 d | 6 d | 7 d |
| 1 | 75,06 | 12,63 | 5,59 | 5,59 | 0,54 | 0,54 | 0,03 | 0,03 |
| 2 | 75,06 | 12,63 | 5,59 | 5,59 | 0,54 | 0,54 | 0,03 | 0,03 |
| 3 | 76,62 | 12,70 | 4,50 | 4,50 | 0,63 | 0,63 | 0,21 | 0,21 |
| 4 | 81,26 | 11,31 | 3,03 | 3,03 | 0,36 | 0,36 | 0,34 | 0,34 |
| 5 | 87,25 | 7,64 | 1,96 | 1,96 | 0,26 | 0,26 | 0,35 | 0,35 |

| STAGE 2 (SUMMER RELAXATIONS) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Age | 0 d | 1 d | 2 d | 3 d | 4 d | 5 d | 6 d | 7 d |
| 1 | 38,04 | 37,91 | 11,05 | 11,05 | 0,84 | 0,84 | 0,14 | 0,14 |
| 2 | 38,04 | 37,91 | 11,05 | 11,05 | 0,84 | 0,84 | 0,14 | 0,14 |
| 3 | 34,86 | 40,79 | 11,12 | 11,12 | 0,77 | 0,77 | 0,29 | 0,29 |
| 4 | 42,60 | 40,48 | 7,65 | 7,65 | 0,42 | 0,42 | 0,40 | 0,40 |
| 5 | 50,37 | 32,86 | 7,59 | 7,59 | 0,49 | 0,49 | 0,32 | 0,32 |

| STAGE 3 (SEMI LOCKDOWN) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Age | 0 d | 1 d | 2 d | 3 d | 4 d | 5 d | 6 d | 7 d |
| 1 | 49,35 | 29,90 | 9,35 | 9,35 | 0,76 | 0,76 | 0,27 | 0,27 |
| 2 | 49,35 | 29,90 | 9,35 | 9,35 | 0,76 | 0,76 | 0,27 | 0,27 |
| 3 | 45,69 | 32,64 | 9,75 | 9,75 | 0,76 | 0,76 | 0,33 | 0,33 |
| 4 | 54,71 | 30,87 | 6,33 | 6,33 | 0,51 | 0,51 | 0,37 | 0,37 |
| 5 | 59,92 | 25,79 | 6,18 | 6,18 | 0,58 | 0,58 | 0,39 | 0,39 |

| STAGE 4 (STRICT LOCKDOWN) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Age | 0 d | 1 d | 2 d | 3 d | 4 d | 5 d | 6 d | 7 d |
| 1 | 60,66 | 21,88 | 7,65 | 7,65 | 0,69 | 0,69 | 0,39 | 0,39 |
| 2 | 60,66 | 21,88 | 7,65 | 7,65 | 0,69 | 0,69 | 0,39 | 0,39 |
| 3 | 56,51 | 24,49 | 8,38 | 8,38 | 0,75 | 0,75 | 0,38 | 0,38 |
| 4 | 66,82 | 21,26 | 5,02 | 5,02 | 0,61 | 0,61 | 0,34 | 0,34 |
| 5 | 69,47 | 18,72 | 4,77 | 4,77 | 0,68 | 0,68 | 0,47 | 0,47 |

**EDUCATION ACTIVITY**

| STAGE 0 (PRE-PANDEMIC) | | | |
|---|---|---|---|
| Age | Full online | Partial | Full on campus |
| 1 | 5,00 | 20,00 | 75,00 |
| 2 | 10,00 | 15,00 | 75,00 |
| 3 | 25,00 | 25,00 | 50,00 |
| 4 | 25,00 | 25,00 | 50,00 |
| 5 | 20,00 | 15,00 | 65,00 |

| STAGE 1 (INTELLIGENT LOCKDOWN) | | | |
|---|---|---|---|
| Age | Full online | Partial | Full on campus |
| 1 | 46,67 | 33,33 | 20,00 |
| 2 | 61,67 | 33,33 | 5,00 |
| 3 | 61,67 | 33,33 | 5,00 |
| 4 | 61,67 | 33,33 | 5,00 |
| 5 | 61,67 | 33,33 | 5,00 |

| STAGE 2 (SUMMER RELAXATIONS) | | | |
|---|---|---|---|
| Age | Full online | Partial | Full on campus |
| 1 | 33,01 | 57,49 | 9,50 |
| 2 | 78,50 | 11,95 | 9,55 |
| 3 | 78,50 | 11,95 | 9,55 |
| 4 | 78,50 | 11,95 | 9,55 |
| 5 | 78,50 | 11,95 | 9,55 |

| STAGE 3 (SEMI LOCKDOWN) | | | |
|---|---|---|---|
| Age | Full online | Partial | Full on campus |
| 1 | 56,51 | 36,25 | 7,25 |
| 2 | 84,25 | 10,98 | 4,78 |
| 3 | 86,75 | 8,48 | 4,78 |
| 4 | 86,75 | 8,48 | 4,78 |
| 5 | 89,25 | 5,98 | 4,78 |

| STAGE 4 (STRICT LOCKDOWN) | | | |
|---|---|---|---|
| Age | Full online | Partial | Full on campus |
| 1 | 80,00 | 15,00 | 5,00 |
| 2 | 90,00 | 10,00 | 0,00 |
| 3 | 95,00 | 5,00 | 0,00 |
| 4 | 95,00 | 5,00 | 0,00 |
| 5 | 100,00 | 0,00 | 0,00 |

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