

Exploring Spatiotemporal Patterns of Pedestrian Movements in Shopping Streets using Agent-Based Modelling

Master Thesis

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02 June 2021



Acknowledgement

Throughout the writing of this thesis, I have received a great deal of support and assistance. Therefore, I would like to thank the following people, without whom I would not have been able to complete this research, and without whom I would not have made it through my masters degree.

I would first like to thank my supervisor, Arend Ligtenberg, for providing guidance and feedback throughout the research. Arend's expertise was of great value in formulating the research questions and methodology. It prevented me from biting off more than I could chew, however in the end, I have still been too ambitious. Arend's feedback pushed me to sharpen my thinking and brought the research as a whole to a higher level. Lastly, the positive support really helped me to go on with the thesis. Despite several setbacks in working with the software, Arend always remained positive and hopeful. Even if I did not see the point of going on with the thesis or if I doubted my own qualities and abilities, Arend provided support and really drags me through, which I am really thankful for.

I would like to acknowledge Patrick Taillandier and Kevin Chapuis, developers of the GAMA software platform. While I was panicking about the software lacking functionalities I needed, they were there for me. I reached out to them in order to ask help in solving problems I encountered. They replied quickly and were very willing to help. I am really thankful for their quick and helpful support, since this made the difference between finishing this thesis with a functional simulation model or not. Without their help, I would not have got to the results I have now.

I would also like to thank Christian Booms, Eva Wijnands, and Nienke Vogelzang, friends and fellow students from the GIMA masters, for their endless support, laughs and feedback. In the difficult times of the Covid-19 pandemic, students were obligated to write their thesis from home. Social contact at the university and coffee breaks with other students were really missed, and focussing on the thesis at home was difficult. By working together online by means of video calls and by supporting each other, we dragged each other through this difficult time. My friends really provided stimulating feedback as well as happy distractions to rest my mind outside of my research.

Abstract

This report discusses the results of a masters thesis on the usefulness of dynamic modelling for simulation of pedestrian movement in shopping streets. The motivation for this research partly came from the introduction of social distancing measures in the Netherlands, due to the Covid-19 pandemic. Shopping streets are crowded locations for which it is likely that social distancing can be challenging, especially when obstacles or crowds block pedestrian flows.

Moreover, current studies on the topic of pedestrian movement patterns mainly focus on crowd management and situations such as evacuations and fastest or shortest route navigation, instead of movements under non-emergent and stress free conditions. However, research into pedestrian flows has practical value in a variety of other domains. Pedestrian movement simulation models can be useful for safety purposes, but also for the planning and design of public as well as private space, it is useful to know how people move in space.

Dynamic spatial modelling allows spatial planners to acquire an idea of future conditions or possible effects of the plans or policies they are developing, prior to implementing them. This saves time and trials, and enhances consensus among stakeholders and formulation of appropriate proactive measures. There are multiple useful methodologies that can be used to get a better understanding of pedestrian movement patterns, such as cellular automata (CA) and agent-based modelling (ABM). While CA has successfully contributed to traffic flow studies, it is criticised for oversimplifications of reality. ABM is known for the rather microscopic level of modelling, in which the movement of individuals in complex systems can be analysed, while CA is more useful for macroscopic analyses. Therefore, in order to get insights into pedestrian movement patterns at street level, agent-based modelling software, in this case GAMA, has been used.

A conceptual model for the pedestrian simulation model has been developed to describe and simulate pedestrian movements. This study explored how this conceptual model could be translated to an agent-based model using the GAMA software. The presented model is used to demonstrate how the simulated pedestrian crowds are influenced by obstacles in a shopping street. Based on the observations and computational modelling experiments, it could be concluded that pedestrian movements in shopping streets can be successfully simulated with agent-based models, and that insights into movement patterns can be gained. However, for non-computer scientists, the GAMA software lacks easy-to-use tools to be able to model pedestrian movement accurately. Additionally, the model still needs to be calibrated and validated.

To get better insights into the usefulness of the model, it is recommended for further research that such simulation models get calibrated with field observations. Then, dynamic and agent-based modelling allows urban planners, city authorities and decision makers to evaluate the impact of future urban design scenarios on pedestrian movements in shopping streets.

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At the end of 2019, a cluster of cases of "pneumonia of unknown origin" was reported in Wuhan, China. This was confirmed by the World Health Organization (WHO) and named SARS-CoV-2, also known as Covid-19 (Corona virus disease 2019). Soon, this corona virus rapidly spread worldwide, resulting in the WHO to declare a pandemic by March 2020 (De Vos, 2020; Harweg, Bachmann, & Weichert, 2020; Vingilis et al., 2020; World Health Organization, 2020; BBC News, 2020). The spread of the corona virus caused a number of protective measures taken by national governments. Amongst others, in order to prevent social contact, people should always keep physical distance from each other, so-called "social distancing" (Harweg et al., 2020; Parisi et al., 2020). This would minimise the risk of getting infected with the virus, since the liquid droplets released from the nose or mouth of an infected person cannot travel further than this distance and so will not reach other persons (Parisi et al., 2020). As long as all of the population is not vaccinated, social distancing is needed to slow down the spread of the virus (Harweg et al., 2020). Even when a vaccine is available and social distancing is no longer needed to maintain the spread of the Covid-19 virus, research into social distancing is still of relevance. According to Parisi et al. (2020), social distancing is likely to be useful for any contagious disease.

According to De Vos (2020), measures to prevent social contact and to slow down the spread of the virus are amongst others closing schools, shops, restaurants and bars, prohibiting public events and stimulating working from home. For the shops that remained open, such as supermarkets and grocery stores, authorities lowered the allowed capacity to avoid crowding and to ensure social distancing (Parisi et al., 2020). Some governments even declared lockdowns, in which nobody was allowed to leave their house other than for groceries (De Vos, 2020). According to Vingilis et al. (2020), the physical (social) distancing measures and limited customer capacity have had major economic effects, which is confirmed by a decrease of the world Gross Domestic Product (GDP) (United Nations Department of Economic and Social Affairs Economic Analysis, 2020).

1.1 Covid-19 in The Netherlands

The Dutch government announced that in public, a minimum distance of 1.5 metres must be maintained (Rijksinstituut voor Volksgezondheid en Milieu, n.d). As mentioned before, shops were closed or had a lower capacity than before the Covid-19 pandemic. The Dutch government also asked Dutch citizens to stay at home and to not go out unnecessarily (Rijksinstituut voor Volksgezondheid en Milieu, n.d).

However, due to a reduced spread of the Covid-19 virus, this advice was a bit weakened at the start of the Summer season of 2020 (RTL Nieuws, 2020a). As a result, in various city centres streets became overcrowded, especially in sunny weather conditions (Hoving, 2020; AD, 2020). In these crowded situations, it is impossible to keep distance from others, which will cause a possible bigger spread of the virus. Some cities even closed shopping streets because of the social distancing becoming impossible (AD, 2020). Closing of shopping streets and the advices for citizens to avoid busy places and to stay home as much as possible have negative consequences for (local) businesses, such as shops and restaurants, located in the city centres. For example, when less or no shopping activities take place, shops are likely to experience financial losses (Rabobank, 2020). In the Autumn season, the spread of the virus increased again and the weakened advice was reversed, resulting in restaurants having to close again, people to stay at home as much as possible, and face masks to be required in public interior spaces: a new economic blow for shops and restaurants (RTL Nieuws, 2020b).

In order to monitor and control social distancing, some cities developed applications to measure the crowdedness of the streets (AD, 2020). However, according to De Jong (2020), such crowd monitoring applications will not solve the problem of overcrowded shopping streets on its own. The problem of people not keeping distance from others is on the one hand due to overcrowdedness causing keeping distance to be impossible, and on the other hand due to people who do not respect the rules and advices, causing overcrowdedness and lack of distance between people.

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This study will try to uncover the location and duration of hotspots of crowds in shopping streets. This will be done by means of simulating the movement of pedestrians in different scenarios. The results provide insights into the usability of dynamic modelling to get a better understanding of pedestrian movement patterns, and might contribute to improvements in planning and design of urban areas. For the case of the Covid-19 virus, the aim is to contribute to get insights into the effects of different street designs on social distancing possibilities. In the introduction, the social relevance has been described. In this section, the scientific relevance is explained, after which the research goals and questions are presented.

2.1 Related Research

Pedestrian flows are an important topic within transportation research (Dijkstra, Jessurun, & Timmermans, 2001). However, compared to the car and public transport, it has received less interest in the (scientific) literature (Timmermans, 2009). Additionally, the studies on the topic of pedestrian movement patterns mainly focus on crowd management and situations such as evacuations and fastest or shortest route navigation, instead of movements under non-emergent and stress free conditions (Nasir, Lim, Nahavandi, & Creighton, 2014).

Research into pedestrian flows has practical value in a variety of domains, and knows a diverse set of possible applications (Nasir et al., 2014). Pedestrian movement simulation models can be useful for safety purposes, but also for the planning and design of public as well as private space, it is useful to know how people move in space (Bandini, Rubagotti, Vizzari, & Shimura, 2011; Nasir et al., 2014; Timmermans, 2009). According to Wang (2005) and White and Engelen (2000), dynamic spatial modelling allows spatial planners to acquire an idea of future conditions or possible effects of the plans or policies they are developing. As mentioned before, this results in more accurately and realistically presentations of future consequences of proposed actions. This saves time and trials, and enhances consensus among stakeholders and formulation of appropriate proactive measures. According to Ligtenberg, Wachowicz, Bregt, Beulens, and Kettenis (2004), this implies the need for the possibility of evaluating spatial plans prior to implementing them.

There are multiple useful methodologies that can be used to get a better understanding of pedestrian movement patterns, such as cellular automata (CA) and agent-based modelling (ABM). While CA has successfully contributed to traffic flow studies, it is criticised for oversimplifications of reality. ABM is known for the rather microscopic level of modelling, in which the movement of individuals in complex systems can be analysed, while CA is more useful for macroscopic analyses.

2.2 Research Goals

The goal of this study is to develop a pedestrian simulation model to gain insights into the usability of dynamic modelling into pedestrian movement patterns in shopping streets under different conditions, especially different planning and sociological scenarios. In this research, it is assumed that the street is a pedestrian zone and therefore no movements by bike, moped, or car will take place in the area. The research therefore does not take into account other types of mobility than walking.

The outcomes can be used to check for the "street level" effects on pedestrian movement patterns different planning and sociological situations might have. The main goal of this research is to uncover hotspots that might contribute to the spread of the Covid-19 virus. Spatiotemporal patterns such as crowd formation might lead to these hotspots. When people group together within a distance of 1,5 metres, this can be called a hotspot which will increase the chance of being infected

with the virus. From the model, it will be tried to retrieve results in which is visible where hotspots emerge and for how long they will remain active. From this, it might be possible to calculate the risk of spread of the virus among the pedestrians, however this is not within the scope of this research.

This study will take a look from an agent-based approach. Ligtenberg, Van Lammeren, Bregt, and Beulens (2010) also argue that ABM is a commonly used method to make the representation of groups of agents in dynamic spatial models possible. In agent-based models, agents are located in an environment in which they can operate and interact with other agents. In these models, self-organising properties of systems of agents can be simulated, which cannot be determined from the rules governing the individual agents. In other words, it is possible to study the movements of the agents under different conditions, without predetermining this behaviour completely. Both CA and ABM are further explained in Chapter 3, while a more detailed description of the methodology used for this research is given in Chapter 4.

It has to be noted that the Covid-19 virus is used as a case study in this research. However, it is a greater part of the motivation for this study, which is to study pedestrian movement in shopping areas. Also, due to one of the Covid-19 measures being social distancing, it is part of the study itself by researching what the effect of different scenarios is on the distance between pedestrians.

The study, model and outcomes are also applicable in other situations than Covid-19, such as the aforementioned evacuations. One can also think of road works and other events that cause changes in the spatial environment that have an effect on pedestrian movement patterns, and one can think of other locations, such as airports, train stations, offices, and shopping malls.

2.3 Research Questions

The main research question that follows from the research objectives is: *To what extent can dynamic modelling of pedestrian movements provide insights into the movement patterns at street level for different planning and sociological scenarios?*

In order to answer the main research question, four sub questions have been formulated:

- 1) What are the characteristics of pedestrian movements in shopping streets and what different modelling approaches are commonly used?
- 2) How can pedestrian movement in shopping streets be modelled using an agent-based modelling approach?
- 3) What spatiotemporal patterns do emerge, according to the modelled scenarios, in the movement of pedestrians in shopping streets, and how useful are they for modelling scenarios in times of a pandemic, in particular Covid-19?
- 4) What is the validity of the modelling results?

This study attempts to answer the research questions as follows. At first, scientific literature will be reviewed in order to get a better understanding of pedestrian movement patterns in shopping streets and dynamic (agent-based) modelling to identify the right methodologies to achieve the goals of this study. This will allow the first sub research question to be answered. Based on the literature review, methodologies on how to construct a dynamic model of a shopping street will be described in Chapter 4. Additionally, the methodologies for calibration of the model and for the sensitivity analysis for validation of the model will be described. Altogether, this will be the answer to the second sub question. For the third sub question, the outcomes of the model for the different scenarios will be described and compared in Chapter 5. Next to this, the outcomes of the sensitivity analysis for validation will be described in order to answer the fourth sub question. Based on a comparison and summary of the results, in Chapter 6 a conclusion and discussion covering the main research question will be given.

In this section, scientific literature is reviewed in order to get a better understanding of pedestrian movement patterns in shopping streets and dynamic (agent-based) modelling, and to identify the right methodologies to achieve the goals of this study.

3.1 Pedestrian Movement

Simulation of traffic flows is a traditional topic that plays a central role in transportation research (Dijkstra, Jessurun, & Timmermans, 2001). Transportation research focuses mainly on the transportation system, which among other things covers physical elements such as the infrastructure and vehicles, and social elements such as the movement and behaviour of human beings. Pedestrians are an integral part of the transportation system, and pedestrian flows are an important topic within transportation research (Blue & Adler, 2000; Dijkstra et al., 2001). However, current research focuses more on vehicular flows, which is likely caused by the complexity of pedestrian movement and behaviour. Weifeng, Lizhong, and Weicheng (2003) argue that pedestrians being more flexible than cars might cause studying pedestrian behaviour being more complex. As a result, modelling pedestrian flows is different from modelling vehicular flows (Blue & Adler, 1999; 2001). Since people are more intelligent and more flexible than vehicles, they can adapt their behaviour to the environment constantly and are able to change their directions flexibly, whereas vehicles are attached to lines or borders of roads (Weifeng et al., 2003). Other differences are, amongst other things, that slight bumping is allowed under pedestrians, and that it is not uncommon for pedestrians to walk side-by-side, in pairs, or in groups, whereas vehicles are more common to move individually (Blue & Adler, 1999; 2001; Weifeng et al., 2003). Because of these differences, simulation of pedestrian flows should not be based on the rules of vehicular flows, but on the special characteristics of pedestrian movement itself (Hoogendoorn & Bovy, 2003; Weifeng et al., 2003).

Applications of Research

As mentioned before in Chapter 1, research into pedestrian flows has practical value in a variety of domains, and knows a diverse set of possible applications (Nasir, Lim, Nahavandi, & Creighton, 2014). Pedestrian movement simulation models can be useful for safety purposes, but also for the planning and design of public as well as private space, it is useful to know how people move in space (Bandini, Rubagotti, Vizzari, & Shimura, 2011; Nasir et al., 2014; Timmermans, 2009).

Concerning safety, understanding pedestrian movement patterns offers insights into capacity, potential safety hazards, and evacuation of buildings, outside areas, and events (Koh & Zhou, 2011; Löhner, 2010; Timmermans, 2009; Weifeng et al., 2003). Duives et al. (2013) state that assessing the safety of pedestrian crowd events is difficult. Since in situations with high-density crowds hazardous situations might arise, according to Duives et al. (2013), "simulation models calibrated and validated for pedestrian movement in crowds are necessary to predict and manage large-scale crowd movements". Other examples of pedestrian movement research related to safety and especially evacuation are mentioned in Helbing et al. (2005), such as research into intersecting pedestrian streams with and without guidance through obstacles and railings, the movement of pedestrians through a waiting crowd, the escape of students from a room with a narrow exit, and the escape of disoriented people from a room.

In studies with an evacuation purpose, pedestrian movement in a panic situation is observed and modelled. However, panic situations are not representative for "normal", stress free conditions. During evacuation, the main goal of the pedestrians is to save their life (Nasir et al., 2014). They do not have a destination as a goal, apart from exiting the place they are, such as a building or an event. According to Nasir et al. (2014), this main goal can lead to irrational behaviour, or blind actionism as Helbing (2001) calls it, which is not comparable with the behaviour and movements of pedestrians under stress free conditions.

These studies also mainly focus on indoor activities, such as capacity or evacuation of a building. However, research into indoor situations is not representative for outdoor conditions. According to Nasir et al. (2014), in the environment as well as in the modes of travel, differences exist. Outdoor, roads and sidewalks can be found, on which not only pedestrians walk but driving and biking takes place as well. Travelling outside, one will find fewer intersections on their way. On will also pass by physical elements in the environment, such as the built environment or natural landscapes and areas. These elements determine the attractiveness of a route, the so-called scenic beauty (Elshof, Haartsen, Van Wissen, & Mulder, 2017), which is different from indoor travelling (Nasir et al., 2014). It can be assumed that indoor, only walking activity takes place and in a rather small and closed environment. Technically, for outdoor travelling, the space is larger, resulting in complex computations (Nasir et al., 2014). Weather conditions also play a role in outdoor activities, since it might influence, for example, the density, dependent on the number of pedestrians walking outside, and the walking speed, while the outdoor climatic conditions are irrelevant for indoor travelling (Löhner, 2010; Nasir et al., 2014).

Other pedestrian movement studies focus on navigation, wayfinding or route-choice of pedestrians. The distance of a destination seems to be the most important factor in the choice for a route, while factors such as levels of congestion and safety come second (Nasir et al., 2014; Bierlaire & Robin, 2009). This means that pedestrians are not likely to avoid congested routes if these are their optimal routes or the routes they are most familiar with. This is underlined by Helbing (2001), who observed that pedestrians feel a strong aversion of taking detours, even if the direct way is crowded.

Understanding pedestrian movement is essential for design and planning of public space (Hoogendoorn & Daamen, 2005; Timmermans, 2009; Weifeng et al., 2003). For city planners in general, in order to create a safe and comfortable environment for pedestrians, it is therefore useful to get insights into the relation between environmental factors and movement patterns. In collaborative planning processes, it is the role of the planner to present possible outcomes of proposed plans accurately and realistically (Wang, 2005). However, according to Dijkstra, Timmermans, and De Vries (2000) planners and architects are "often faced with the problem to assess how their design or planning decisions will affect the behaviour of individuals." Wang (2005) suggests that simulating scenarios might be a solution for this problem, since this will result in (1) the ability of people to envision the future consequences of a proposed development, (2) a possible consensus among stakeholders, and (3) possibilities to formulate appropriate proactive measures. Simulation models will function as an effective planning support system, which supports collaboration and agreement among stakeholders by offering possibilities to analyse and evaluate plans and designs (Wang, 2005; White & Engelen, 2000).

More specifically, according to Timmermans (2009), research into pedestrian flows is essential for inner city shopping areas. Helbing (1998) even argues that pedestrians walking in shopping areas is the most relevant case for town- and traffic planning. The viability of stores is dependent on pedestrians, which makes the behaviour of these pedestrians a critical field of interest for the store owners. Shop owners are interested in how people move to know where to locate their shops, preferably at locations with "a lot of passing trade" (Schelhorn, O'Sullivan, Haklay, & Thurstain-Goodwin, 1999; Timmermans, 2009).

Individuals and Groups of Pedestrians

In order to get a better understanding of pedestrian movements, it is important to realise that not all pedestrians move the same. Differences among individual pedestrians or groups of pedestrians need to be taken into account (Koh & Zhou, 2011). According to Koh and Zhou (2011), the differences are mainly based on personal preferences. For example, pedestrians differ from each other in the decisions they make, such as the choice between following or overtaking. This also has to do with walking speed, a personal preference that differs among pedestrians. The destination or goal of the trip might differ, and the belonging navigational or route choices are differing personal preferences and choices that influence the movements as well (Koh & Zhou, 2011). In other words, the movement of a pedestrian is influenced by the movements of other pedestrians and by the environment.

However, despite that behaviour is based on individual decisions (Helbing, 1998), assumptions will have to be made in order to be able to simulate pedestrian movements. Helbing (1998) states that "the decisions and behaviour of pedestrians are usually determined by utility maximization: For example, a pedestrian takes an optimal path to a chosen destination, and tries to minimize delays when having to avoid obstacles or other pedestrians." This means that the assumption can be made that pedestrians choose the optimal path to their destination, with respect to the environment they are walking through and events that happen along the way. However, this optimal path might differ between (groups of) pedestrians individually.

The choices a pedestrian makes can change from time to time, even during the walk or trip. While the destination is likely to stay the same, the route and movements might change. This is because pedestrians scan their surroundings constantly, and adapt their walking behaviour to the (traffic) conditions around them (Hoogendoorn & Daamen, 2005). Bandini et al. (2011) summarise this as "the dependency of individual choices on the past actions of other individuals and on the current perceived state of the system (that, in turn, depends on the individual choices of the comprised agents)".

An example of such a preference is distance, which Koh and Zhou (2011) refer to as personal space. Pedestrians keep a certain distance from other pedestrians and borders, such as walls (Helbing, Molnár, Farkas, & Bolay, 2001; Hoogendoorn & Daamen, 2005; Koh & Zhou, 2011; Moussaïd, Perozo, Garnier, Helbing, & Theraulaz, 2010). This distance is dependent on the speed of a pedestrian, and on the crowd density. The distance headways that pedestrians maintain with respect to the ones in front of them increases with the walking speeds, however when pedestrians are in a hurry the lateral distance is likely to decrease. A higher crowd density results in a lower distance between individuals as well (Helbing et al., 2001; Helbing et al., 2005; Hoogendoorn & Daamen, 2005). This is especially true for queuing situations, in which the flow slows down or stops, and impatience, mostly due to longer waiting times, causes pedestrians to get pushy and decrease the distance between each other (Helbing et al., 2005).

Another example of individual preferences of pedestrians is a comfortable and desired walking speed (Helbing et al., 2001; Koh & Zhou, 2011; Nasir et al., 2014). However, the walking speed is not a free-to-make choice that can always be applied. The walking speed depends, among other things, on the pedestrian density. At low density, people walk faster than at high density (Hoogendoorn & Daamen, 2005; Moussaïd et al., 2010). In a highly crowded area, one is not able to choose their own speed, but is likely to be forced to move at the speed of the flow. Apart from the density, other environmental factors influence the walking speed of pedestrians as well.

Löhner (2010) listed possible and likely conflicting circumstances along the way which the walking speed and direction are the result of:

- Motivation to reach a certain place at a certain time (often referred to as will force, and influenced by a variety of factors such as time constraints, importance of punctuality, location constraints, importance of reaching a place and staying there long enough, etc.).
- Physical fitness (or level of exhaustion).
- Material obstacles in the way or close to the pedestrian.
- Pedestrians surrounding a pedestrian (closeness of neighbours, density of crowd, size and velocity of neighbours, etc.).
- Geographical knowledge (i.e. dependence on signs, general flow of pedestrians, etc.).
- Climatic conditions.
- Terrain conditions (slippery, climbing, stairs, escalators, etc.).
- Signs or individuals that steer the flow of pedestrians (e.g. traffic lights, policemen, etc.).

Helbing et al. (2005) argue that obstructions and perturbations cause irregular flows, resulting in a decrease of pedestrian walking speed. Dijkstra et al. (2001) also name (behaviour of) other pedestrians as a factor influencing the speed and flow of pedestrians. According to Moussaïd et al. (2010), the walking speed is also dependent on the group size. They observed that the speed of pedestrians decreases linearly with growing group size.

Since not every pedestrian walks alone, not all pedestrians move according to their personal preferences. According to Bierlaire and Robin (2009), within a group, individual decisions are influenced by the decisions of other group members. Moussaïd et al. (2010) state that it is common for leisure areas such as shopping streets to know a higher frequency of groups than solo pedestrians. This concerns groups existing of pedestrians intentionally walking together. They studied how these groups organise and move in space, and observed that on a Saturday afternoon in a commercial walkway, 70 percent of the pedestrians belonged to a group. Next to this, groups of pedestrians, especially friends or family, have an impact in space, since they move slower than others, resulting in a barrier slowing down the crowd (Sarmady, Haron, & Talib, 2009). Since the proportion of pedestrians belonging to a group is higher than that of pedestrians walking alone, and groups slow down pedestrian movement flows, it is of importance to take groups of pedestrians into account as well.

In times of the Covid-19 pandemic and social distancing rules, the 1,5 metres distance does not have to be taken into account by members of the same household. A family is allowed to walk together, while a group of friends has to keep distance from each other. This results in that the impact of groups is assumed to be even more when members of a group have to keep 1,5 metres distance.

3.2 Spatiotemporal Patterns

By studying the movement of pedestrians, insights can be gained into spatiotemporal patterns that emerge. Hu (2014) defines patterns as "something of recurring and predictable structure or manner". An example of such a pattern is avoiding collisions with other persons or objects, by for example overtaking others with a lower walking speed. Another example is crowd formation at bottle necks. This section, describing spatiotemporal patterns in pedestrian movement, builds mainly upon the studies of Duives, Daamen, and Hoogendoorn (2013) and Helbing, Buzna, Johansson, and Werner (2005).

First of all, distinctions can be made in pedestrian motion. With pedestrian motion is meant the change of location of a pedestrian. In other words, it is only the progression from one place to another, for example walking in a straight line or a corner, and not what happens during that motion.

First of all, distinction can be made in the walking directions, between unidirectional and multidirectional flows. Secondly, according to Duives et al. (2013), unidirectional flows can be sub divided into straight flows, flows rounding corners, flows entering a bottleneck, or flows exiting a bottleneck. Multidirectional flows can either be parallel (bidirectional) and crossing flows. This results in Figure 3.1, presenting the flow types commonly recognised as a pattern of pedestrian movement (Duives et al., 2013).



Figure 3.1 Common Patterns of Pedestrian Movement (Duives et al., 2013)

Duives et al. (2013) also characterise these patterns according to the availability and use of space. For straight flows, the available space and direction of the flow does not change. When rounding a corner, the available space does not change, but since the direction changes, the use of this space does as well. For entering and exiting a bottleneck, the available space decreases and increases, respectively. The emerging patterns in a situation with crossing flows are dependent on the available space and number flows. Distinction can be made between, for example, a pedestrian square and an intersection, which are likely to offer different sizes of available walking space.

Another categorisation made by Duives et al. (2013), but also by Hoogendoorn, Van Wageningen-Kessels, Daamen, Duives, and Sarvi (2015), concerns distinct types of aggregate pedestrian movements. With movement is meant the (physical) change of position of a pedestrian. So in this case, movement describes what happens during a motion.

Self-organisation, or self-emergent, phenomena are spatiotemporal patterns that occur without intention or communication about it. Such a phenomenon emerges automatically without the need for conscious support (Helbing et al., 2005). In case of bidirectional flows, it is common for the opposing flows of pedestrians to separate, especially when space is (almost) saturated (Hoogendoorn & Daamen, 2005). Pedestrians start to follow and imitate each other, which is called lane formation and is one of the aforementioned self-organisation phenomena (Duives et al., 2013; Helbing et al., 2005; Hoogendoorn & Daamen, 2005; Robin, Antonini, Bierlaire, & Cruz, 2009). In case of crossing flows, lane formation might occur as well, but then more than two opposing flows of pedestrians walking in the same direction form. How many lanes are formed is dependent on the width and length of the walkway, and on disturbances such as obstacles or in- and outflow of other pedestrians (Helbing et al., 2005). In unidirectional flows, formation takes place, the interaction frequency and number of necessary braking or avoiding manoeuvres are minimised, resulting in the possible achievement of maximisation of walking speed and comfort (Helbing et al., 2005).

However, when entering a bottleneck, the available space decreases and lanes will have to merge, which might be the case in multidirectional flows as well. This self-emergent phenomenon is called the zipper effect: flows of pedestrians are overlapping, so pedestrians leave gaps and allow other pedestrians to merge (Duives et al., 2013; Hoogendoorn & Daamen, 2005; Hoogendoorn et al., 2015).

Apart from lane formation and the zipper effect, Duives et al. (2013) and Hoogendoorn et al. (2015) name four other self-organisation phenomena. In situations with bidirectional flows passing through narrow bottlenecks, the "faster-is-slower" effect can be observed. When density increases, the bottleneck saturates and gets clogged. If pedestrians keep pushing while the crowd is slowing down, this will increase friction and slow down the total flow even more (Duives et al., 2013; Helbing et al., 2005; Hoogendoorn et al., 2015). According to Helbing et al. (2005), groups of pedestrians are involved in, or even causing, these situations more than individual pedestrians. This is because groups take up more space, which is already scarce in a bottleneck. This results in a unidirectional flow, for which people of the opposite flow to have to wait before being able to pass the bottleneck. Pressure of these pedestrians will increase, due to impatience, and they will start to push against the flow of the opposing group, trying to stop the unidirectional flow. As a result, friction will increase, the crowd compresses, and crowd motion will slow down, due to a large number of pedestrians competing for small gaps (Helbing et al., 2005; Duives et al., 2013; Hoogendoorn et al., 2015).

Impatient pedestrians will reduce the distance to pedestrians in front of them. As time goes by and impatience grows, more pedestrians will reduce the distance. This compression in the crowd results in so-called "shock waves", which produce the impression that the crowd is moving forward, while it is not (Helbing et al., 2005).

A similar phenomenon as these shock waves are "stop-and-go waves", or in more heavy situations even referred to as turbulence. In unidirectional flows, dense crowds might cause the flow to slow down or even stop (Duives et al., 2013; Hoogendoorn et al., 2015). Due to disturbances, such as in- and outflow of pedestrians, the flow is temporarily interrupted (Helbing et al., 2005).

Herding, also called the "leader-follower" effect, is a self-emergent phenomenon commonly observed among pedestrians in an unfamiliar environment, such as tourists. These pedestrians have little to no observation and therefore are likely to follow other people who are believed to know the best way. In general, unclarity of a situation causes individuals to follow each other instead of taking the most optimal route (Helbing et al., 2005). This means pedestrians will attempt to move in the same direction as where most of the other pedestrians are moving (Koh & Zhou, 2011). However, it needs to be said that this phenomenon is mainly observed during stressful situations, such as evacuations, rather than under stress free conditions.

An example of a non-self-emergent pattern related to the shock waves is the interaction with the physical environment. Apart from obstacles or other pedestrians, the movements of pedestrians can be influenced by visual objects, such as signs or advertisements. Concerning the latter, for example posters or shop windows, these are designed to attract the attention of pedestrians. According to Bierlaire and Robin (2009), pedestrians will react in three possible ways: they can stop in order to look in detail at the displayed elements, they can slow down to glance at it, or they can ignore it and continue walking. The choice they make will influence pedestrians walking behind. If one pedestrian decides to slow down or stop, the pedestrian behind will have to decide to overtake, or to slow down or stop as well, in order to avoid collision.

3.3 Modelling Approaches

To better understand how pedestrian movement can best be researched, it is useful to analyse and compare different methodologies. As mentioned before, simulation models are helpful in order to get insights in pedestrian movement patterns. Duives et al. (2013) argue that they are even necessary for research into large-scale crowd movements. Visualising (future) developments by means of simulations offers possibilities to analyse and evaluate results, resulting in these models to be helpful in bringing those involved together (Wang, 2005). Wang et al. (2014) underline this by arguing that modelling pedestrian movement is interesting since simulations offer a diverse set of tools and options for analysis and research. Concerning the spread of the Covid-19 virus, Harweg et al. (2020) argue that simulations can help to make the social distancing rules easier to understand, by simulating different scenarios and thereby suggesting recommendations for how to ensure social distancing.

There are two common types of simulation models: macroscopic and microscopic models (Harweg et al., 2020; Teknomo, 2006). According to Harweg et al. (2020), the difference between the types of models is what is considered the smallest entity. In macroscopic models, this is assumed to be a crowd, while for microscopic models one individual (pedestrian) is assumed to be the smallest entity. Macroscopic models therefore allow the representation of high density crowds, but are not suitable to model the interaction between (pairs or groups of) pedestrians (Harweg et al., 2020).

The majority of the simulation models of pedestrian movement (Borgers, Smeets, Kemperman, & Timmermans, 2006; Dijkstra et al., 2001; Teknomo, 2006; Teknomo, Tekayama, & Inamura, 2000) and of the spread of diseases (Harweg et al., 2020) is at the macroscopic level. However, Teknomo and Gerilla (2005) argue that microscopic models give "a more natural way to represent real-world pedestrians". In these models, each pedestrian is modelled as an agent separately (Hoogendoorn & Bovy, 2000; Robin et al., 2009). This scale allows for detailed simulation and analysis of movement of and interactions between individuals (Seer, Rudloff, Matyus, & Brändle, 2014; Teknomo, 2006; Teknomo & Gerilla, 2005). This makes that Nasir et al. (2014) argue that agent-based models of pedestrian movement belong to the microscopic scale. Additionally, this scale allows for self-organisation phenomena such as lane formation, overtaking, and intersecting to be simulated (Wang, Lo, Liu, & Kuang, 2014). The detailed level of microscopic models makes them useful for design and planning of (pedestrian) infrastructure (Seer et al., 2014). As a result, in the last 15 or 20 years, microscopic modelling has received more attention in research focussing on pedestrian movement (Robin et al., 2009).

According to Wang et al. (2014), to get a better understanding of pedestrian movement patterns by means of simulations, cellular automata (CA) and agent-based models (ABM) can be useful to create a simulation model. These modelling methods will be explained in more detail in the next sections.

3.3.1 Cellular Automata

CA has been widely used in transport and mobility related research. It has been successfully used for traffic flow studies, after which it has been introduced to pedestrian movement (Bandini et al., 2011; Weifeng et al., 2003).

CA are characterised by five components, which are a spatial framework, states, a defined cell neighbourhood, transition rules, and time steps (Abolhasani & Taleai, 2020). The spatial framework, or environment, exists of cells. All cells that are part of this spatial framework are located within a neighbourhood, which consists of the cell itself and adjacent cells (Ghafari, Shah, Saadatian, &

Salleh, 2012). Shortly summarised, the spatial framework is formed by all cells, while a neighbourhood only exists of a limited number of cells within the framework.

Within a network of cells, the cells represent locations that can be occupied by a single entity (Blue & Adler, 1999). If this entity is a pedestrian, an occupied cell means that a pedestrian is at the location the cell represents, and if it is vacant, the space is still free to be filled by a pedestrian. It is also possible that the entity concerns (physical) environmental elements, such as buildings, walls, trees, or other obstacles.

Cells within the modelled environment can be characterised by states. In the most traditional form, CA will have binary states. This is also true for pedestrian movement simulations by means of CA. According to Blue and Adler (1999), during a single iteration, or time step, of a simulation, cells are assigned one of two properties: occupied by a single automaton or unoccupied. Time progresses step-by-step, and it is determined for all cells simultaneously whether they will change state or not during each time step (Engelen, White, & Uljee, 1997). For the pedestrian entities it is likely that status of cells they visit change in time, since they are able to move. For more static elements such as walls, it is likely that cell status remains the same for every iteration. Local rules define the movement of automata such as pedestrians, with respect to the status of neighbouring cells (Blue & Adler, 1999; Engelen et al., 1997; Ghafari et al., 2012). If a neighbouring cell is already occupied, and remains occupied during the iteration, the automaton will check the status of other neighbouring cells.

According to Clarke (2014), "CA models have been criticized as oversimplifications of reality". One of the most important limitations of CA is that it is not able to accurately represent the impacts of (autonomous) human decision making (Parker, Manson, Janssen, Hoffmann, & Deadman, 2003; Ghosh et al., 2017; Noszczyk, 2019). This results in the inaccuracy to reflect real-world spatial relationships and the feedbacks that are part of the real-world system. However, despite CA often concerning simplified models, according to Engelen et al. (1997), it is still able to reproduce complex behaviour and spatial patterns, albeit mainly on a macroscopic scale.

In CA the cells are fixed, which means they will not move, and there are no flexible and freely moving agents (Clarke, 2014; Crooks & Heppenstall, 2012). In agent-based models however, the environment is not static. Agent-based models exist of a dynamic modelling environment in which agents have the ability to interact with each other and their environment, and to move freely and in more complex ways than in CA (Clarke, 2014; Crooks & Heppenstall, 2012). In the next section, this simulation modelling method is further explained.

3.3.2 Agent-Based Modelling

Agent-based modelling (ABM) is a modelling method used to understand complex systems. Such systems can be found in the field of geography, making ABM possibly of significant relevance in geographic studies. Through both time and space, geographical systems are exposed to the impacts of interactions between agents and with their environment (Heppenstall, Crooks, See, & Batty, 2011). Agents are often defined as interacting (social) entities (Bretagnolle, Daudé, & Pumain, 2006). The actions of agents can take place synchronously, for example, every second, or asynchronously, for example only in response to other activities in the model. Castle and Crooks (2006) described that ABM is an approach that models in the most realistic way, compared to other approaches, since it includes autonomous individuals. Thereby, they state that ABMs are flexible, especially in geospatial modelling, since they can be defined within any given environment. Ligtenberg (2006) mentions the concept of a social-spatial system, in which social entities such as humans are coupled with a spatial environment. In other words, ABMs are able to put social actions in a spatial

perspective (Ligtenberg, 2006; Ligtenberg et al., 2010). This ability to model (interactions between) autonomous individuals and an environment makes multi-agent models ideal for simulating pedestrian movement and analysing spatiotemporal patterns (Dijkstra, Timmermans, & De Vries, 2000; Dijkstra et al., 2011).

A real-world system with human beings as agents will likely include humans with irrational or subjective behaviour (Crooks, 2015). This is underlined by Koh and Zhou (2011), who argue that for simulations of pedestrian movement to be realistic, it is important to understand and take into account the differences among individual pedestrians. Therefore, they suggest to take into account factors such as walking speed, and actions such as overtaking, waiting, side-stepping, and laneforming (Koh & Zhou, 2011). According to Crooks (2015), calibration and validation of the irrational behaviour or individual differences might cause difficulties with interpretations of the outputs of the model. However, the outcomes can still help to broaden knowledge on the specific subject (Blue & Adler, 2000; Crooks, 2015). Section 3.3.4 elaborates further on calibration and validation.

For complex social phenomena, Edmonds et al. (2019) argue that it is interesting to understand why certain activities occur. According to Edmonds et al. (2019), for social systems it is often not possible to predict events, however it is possible to explain it afterwards. It is therefore important to realise that agent-based models should be interpreted as simulations of situations rather than predictions (Crooks, 2015; Matthews, Gilbert, Roach, Polhill, & Gotts, 2007).

For example, in the case of Covid-19, it is interesting to understand why social distancing sometimes is neglected by pedestrians in shopping streets. By constructing a simulation of the pedestrian flows based on real-time data, and comparing the simulation with the real world, the model is able to support explanation of the social distancing problems. Edmonds et al. (2019) add that such a simulation model is an environment in which it is possible to test other conditions and cases for which the explanation works.

Subsequently, this simulation takes on the role of illustration as well. Since complex social phenomena can be difficult to describe, illustrating a concrete example might help in understanding the phenomenon, in this case, social distancing (Edmonds et al., 2019). The main difference between the roles of explanation and illustration is that the latter only communicates simplified examples and does not make claims, whereas an explanation does. This difference can be described by a simple example: an illustration shows that the sky is blue, but does not make claims why that is. An explanation however explains why the sky is blue by simulating it based on data. Another characteristic of the illustration role described by Edmonds et al. (2019) is that the role of illustration is often true for an idea rather than an observed process. Therefore, illustration is useful in case of testing other conditions of the earlier explained phenomenon. For this role, however, it has to be noted that as well as the role of explanation, it is not a predictor role. It does not predict, nor does it explain, it only illustrates a possible future (Edmonds et al., 2019). By simulating pedestrian movement in a shopping street, it is aimed to explain and illustrate (opportunities to ensure) social distancing under different conditions.

3.3.3 Development of the Model

In this section, the development of the model will be described by means of a short literature review on calibration and validation of simulation models. The development of the model for this study itself, and its parameters, will be described in more detail in Chapter 4.

First, a conceptual model will be created. This is a model that simulates a shopping street without real-world data. The parameters will be mainly based on a literature review, and no simulation of real-world situations take place. Once this model delivers outputs that match the inputs and rules, the next phase can be started.

This next phase is the calibration process. The main purpose of calibration is to most accurately represent the real-world system (Santé, García, Miranda, & Crecente, 2010). Löhner (2010) argued for future research to make use of real-time data for modelling pedestrian movement, especially for comparison of the simulation model and real situation. Löhner (2010) also argues that "video footage obtained from large-scale pilgrimage events" can be used for such a comparison.

After the model is calibrated, it should be validated. The main purpose of the validation process is assessing the accuracy of the simulation model and its outputs. However, White and Engelen (2000) and Edmonds et al. (2019) argue that when it comes to the validity of a model, it should not be expected that the model output exactly matches real-world data. The model is likely to only represent a limited number of possible outcomes that can result from the same initial situation. Therefore, according to White and Engelen (2000), assessing the similarity of map patterns is a more relevant assessment method. Such an assessment can be made by means of a sensitivity analysis, which will be further elaborated on in the next section.

By analysing the sensitivity of the simulation model it is aimed to analyse the validity or plausibility of the model and its outcomes. According to Thiele, Kurth, and Grimm (2014), a sensitivity analysis is considered to be an important part of both the development and analysis of simulation models. It is used to analyse the sensitivity of the model outputs by varying parameter values in the model. In this way, one is able to identify which parameters have a strong influence, and which are of lower importance. By doing this, the robustness of the model to parameter uncertainties can be analysed. This is especially helpful if inputs of the model are uncertain, in order to explore the importance of the uncertain values. If the output does not vary after changing parameter values, the importance can be considered low. However, if there is a significant variance, the parameter values should be well-founded on empirical values (Thiele et al., 2014). This sensitivity analysis takes place for the conceptual model as well, in order to assess if that model works properly, before calibrating and validating it with real-world data.

3.4 Summary of the Literature Review

Simulation of traffic flows is a traditional topic that plays a central role in transportation research. This covers mainly the transportation system existing of physical elements such as the infrastructure and vehicles, and social elements such as the movement and behaviour of human beings. Pedestrians are an integral part of the transportation system, and pedestrian flows are an important topic within transportation research.

Research into pedestrian flows has practical value in a variety of domains, and knows a diverse set of possible applications, such as evacuations, planning and design of space, and a better understanding of route choices. More specifically, since the viability of stores is dependent on pedestrians, insights into the movement of pedestrians and flows is essential for shopping areas.

In order to get a better understanding of pedestrian movements, it is important to realise that not all pedestrians move the same. The differences are mainly based on personal preferences, such as walking direction, walking speed, and group size, and should be taken into account. Since pedestrians continuously scan the environment, the choices pedestrians make can change from time to time, even during the walk or trip, based on what is present or what happens around them.

By studying the movement of pedestrians, insights can be gained into spatiotemporal patterns that emerge. Patterns that occur without intention or communication about it are called self-emergent phenomena, such as lane formation, the zipper effect, or shock waves. These phenomena have an impact on different aspects of pedestrian flows, such as the walking speed.

Agent-based modelling (ABM) is a dynamic modelling method that has been proven to be helpful regarding pedestrian and crowd management. It is mainly used to understand complex systems. Through both time and space, geographical systems are exposed to the impacts of interactions between agents and with their environment. This results in ABMs being able to put social actions in a spatial perspective. Another important characteristic of ABMs is that they are flexible, due to the fact that they can be defined within any given environment.

To realise an agent-based model, a spatial environment and agents should be modelled. In ABMs, agents are often defined as (social) entities that have different internal characteristics, and are capable of interacting with other agents and their environment. The latter is of importance in order to create the social-spatial system, coupling the agents with a spatial environment. In the next chapter, the development of the agent-based model is described in more detail.

Methodology

4

In this chapter, the methodology used to develop the simulation model of a shopping street is outlined. The literature review, presented in Chapter 3, suggests agent-based modelling (ABM) as a method that could be used for this study. To realise an agent-based model, a spatial environment and social entities, or agents, should be modelled (Willis, Kukla, Hine, & Kerridge, 2000). Therefore, knowledge of the shopping street as environmental context, and the pedestrians as social entities, is required. Next to these two components, a set of rules is necessary to let the entities interact with each other and the environment (Willis et al., 2000). The goal of this simulation model is to recognise pedestrian movement patterns in a shopping street, in order to be able to explain the movement of pedestrians in different planning and sociological scenarios. As explained in Chapter 2, the goal is not to predict pedestrian movement. As Edmonds et al. (2019) state: it is hard to model any complex social system with a goal of prediction, but simulations that involve complicated processes can support complex explanations.

Cegielski and Rogers (2016) visualised the process of creating an ABM, from the conceptualisation to results. A slightly edited version of this visualisation is presented in Figure 4.1, showing the relationship between the system, model development, data sources, and model output. The key actions of the process are indicated by directional arrows. For this model, the process will be the same, and the contents of this chapter are in the same order. This means that in Section 4.1, the social and spatial system are described. This concerns the base of the simulation model, in which no real world data is used yet and the street and pedestrians are only theoretical entities, not representing a real world situation. The use of real world data for the simulation would take place after the conceptual model delivers outputs that match the inputs and rules. This is called the calibration process, which is discussed in Section 4.2, while validation of the simulation model is discussed in Section 4.3. In Section 4.4, the scenarios that are modelled are described. Lastly, in Section 4.5 the implementation of the simulation model is presented.

However, given the time available for this research, the process could not be completed. Therefore, in the first part of this chapter, a conceptual model is described. This model conceptualises the model as it should be according to the studies and models that were researched by means of a literature review. Calibration and validation are described as well, but given the time, these processes could not be completed. Due to the time constraints, the conceptual model differs from the actual simulation model. This becomes clear in Section 4.5, in which is described how the model has been simplified, which parts from the conceptual model and modelling process have been included, and which not.



Figure 4.1 Agent-Based Modelling Process (Adapted from Cegielski & Rogers, 2016)

4.1 Conceptual Model

In order to achieve the goals of this study, a dynamic, agent-based model will be developed to simulate a shopping street including pedestrians. First, a not in the real world existing shopping street environment with pedestrians represented by agents will be developed. The characteristics and initial movements of the agents are based on a literature review. This simulation functions as a base model, which is described in this section.

4.1.1 Overview of the Model

The shopping street simulation model exists of two components: the spatial environment, and the agents, or social entities. This is based on a study of Willis et al. (2000), according to whom an agentbased simulation model exists of the so-called environmental context and the agent parameters. The variables that are considered to be of importance to take into account are shown in a schematic overview in Figure 4.2. The contents of the main components are described in Section 4.1.2 (Spatial Environment) and Section 4.1.3 (Social Entities).



Figure 4.2 Schematic Overview of the Model Components

4.1.2 Spatial Environment

The spatial environment or context is the virtual space where the movement of the pedestrians as agents takes place. In this environment, the space can be filled with a number of different entities (Willis et al., 2000). Examples of these entities are stationary physical objects such as street furniture or greenery, and other pedestrians, which may be stationary or moving. According to Willis et al. (2000), this allows for pedestrian movement to be simulated within a complex virtual environment constructed according to the preferences of the operator, and it allows for simulation of different scenarios by adjusting the number and types of entities.

Concerning the spatial environment, Schelhorn et al. (1999) argue that pedestrian activity is the combination of a street network and attractions such as shops or public buildings along this network. Willis et al. (2000) make a distinction between the macroscopic and microscopic levels for the classification of urban environments. At the macroscopic level, distinction can be made between

two factors: the predominant 'function' of an environment, and their physical layout. For the former, shopping, route to school, and transport interchange are given as examples, while for the latter a pedestrianised street and a pavement skirting a road are named. At the microscopic level, the surroundings of pedestrians are dependent on the nature, location and density of other entities. As examples, street furniture and other pedestrians are named (Willis et al., 2000).

Since this study focuses on pedestrian movement in shopping streets on a microscopic level, the environment will represent a street, existing of a pavement, and attractions such as shops and possibly restaurants or cafés. Each shop or restaurant has its own facade with an entrance and / or exit. The walls or windows of the facades are a burden for pedestrians, while the entrances offer agents the ability to leave and (re-)enter the street environment at multiple points. Next to this framework of a pavement, walls, and shops, the street might contain obstacles. Examples of street furniture that can be found are greenery, such as trees or flowers, but also benches and posts for signs or lamps are likely to be present in a shopping street. Additionally, shops might have some of their interior stalled outside, such as racks with clothes, or advertisements displaying discounts. Also vehicles such as bikes can be a burden for pedestrian flows, in case they are parked in front of stores, next to posts, or anywhere else in the street. Lastly, pedestrians themselves are able to take on the role of an obstacle for other pedestrians, especially when they are walking against the flow or standing still in the street.

In this simulation model, the street is an inner-city pedestrian zone. The layout of the environment is visualised in Figure 4.3. In this base model, the simulated street is not modelled according to realworld data and therefore does not have the exact dimensions and properties of a real street. As a consequence, the simulated street is given a random size, of about 80 metres long and approximately 10 metres wide. The street it is fully straight, which means does not contain corners or bends. To keep the conceptual model simple, connections with adjacent streets are not modelled in the conceptual model as well. Altogether, this results in the simulation of only one vertical street, rather than a complete street network. This also means that the shopping street has just two main gateways, one at the west and one at the east of the street. Gateways are exit and entry points in the simulated environment, of which Schelhorn et al. (1999) describe the function as "simply 'release' pedestrians at a predetermined rate". Apart from the two main ports, the entrances of shops are gateways of the street as well. As mentioned before, apart from the entrances, shops exist of facades, which pedestrians are not able to directly go through. This is true for other types of physical obstacles and other pedestrians in the environment as well This means that there are basically three moving characteristics for agents in the shopping street. Pedestrians are not able to move through a wall or façade, through other pedestrians, or through any other physical obstacles (1), but they are able to enter and exit a shop via the entrance (2), or they can move to a main gateway and exit the street (3).





In a shopping street, a diverse number of shops and possibly restaurants or cafes are present. However, a representation of each individual shop is too complex and not realistic to model for this study and its goals. Therefore, it is chosen to only divide the shops into the attractiveness or popularity of a shop. The choice to take into account the attractiveness of a shop is based on that pedestrians might not have had the goal to visit a certain shop beforehand, but are attracted and therefore end up visiting it. Subsequently, it is assumed that the more attractive a shop is, the more pedestrians visit it, whether or not intentionally (Teller & Reutterer, 2008). In this study, the attractiveness will not be based on real world data, so random 'chances of visit' are given to shops to represent the popularity. The given chances are presented in Table 4.1.

Shop ID *	Attractiveness (*(1/10))		Shop ID) *	Attractiveness (*(1/10))
0	0.1		12		0.9
1	0.2		13		0.2
2	0.1		14		0.3
3	0.7		15		0.8
4	0.3		16		0.9
5	0.9		20		0.3
6	0.5		21		0.6
7	0.7		22		0.8
8	0.2		23		0.1
9	0.6		24		0.3
11	0.8		25		0.1
0 2 4	6 7 9	12	14 16	2	2 23 25
1 3	5 8 11		13 15 20	21	24

Table 4.1	Popularity	per shop
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* When creating the shop polygons, some were misdrawn and had to be recreated. When deleting and recreating, the Shop ID is removed but not replaced. Therefore, the numbers 10, 17, 18, and 19 are missing in the list.

Teller & Reutterer (2008) discussed the results of a survey set out in shopping streets Vienna, Austria. These results show an average number of 3.71 shops visited per trip, with a standard deviation of 3.17. Since there were 1066 respondents to this survey, it is allowed to assume the distribution to be normal. This means that for 68,27% of the respondents, a value within the mean value plus at most one time the standard deviation is true. Therefore, it can be assumed that pedestrians visit a number of shops in between 0.54 and 6.88, rounded to 1 and 7.

The obstacles will not be modelled in detail and not be based on real world data as well, due to complexity and lack of added value for the scope of this research. Therefore, in the simulation model, the obstacles will be no representation of a real situation, but rather hypothetical "what-if" situations, in which obstacles such as greenery, posts, or even parked bicycles would be present.

4.1.3 Agents: Social Entities

There are several factors in which the agents differ, however some are the same for every agent. According to Schelhorn et al. (1999), the characteristics of agents can be categorised as socioeconomic and behavioural characteristics. This distinction is made for this study as well, however the behavioural characteristics are subdivided into walking direction, walking speed, personal space, and distance to obstacles. The socio-economic characteristics are renamed to personal characteristics. According to Willis et al. (2000), "all these variables may affect how individual pedestrians behave within their environment and interact with other entities within it. This presents a considerable challenge for the behavioural scientist: the empirical study of pedestrian behaviour must aim to capture the important aspects of this complexity without severely compromising the simplicity and the flexibility of the model". Therefore, to prevent the model to become too complex and computations to take too long, it is chosen to only model the aforementioned limited number of factors.

Walking Direction

The walking direction is not the same for every pedestrian, however it is likely that the majority of pedestrians will be separated into two opposite flows (Hoogendoorn & Daamen, 2005). Since this model simulates a shopping street, it is also possible people walk in other directions, joining, leaving, or crossing the flow(s), in order to reach their (next) destination.

As mentioned in Chapter 3, these opposing flows arise due to lane formation (Duives et al., 2013; Helbing et al., 2005; Hoogendoorn & Daamen, 2005; Robin, Antonini, Bierlaire, & Cruz, 2009). This is a so-called self-emergent phenomenon, in which pedestrians start to follow and imitate each other. Another self-emergent phenomenon takes place in the shopping street when pedestrians join the flow. In this case, it might be possible to observe the zipper effect, in which pedestrians in the flow have to leave a gap for pedestrians from outside the flow, for example exiting stores or joining from an adjacent street, in order to let them join the flow.

Walking Speed

Pedestrians prefer to walk an individual desired speed, which corresponds to the most comfortable speed, however this is dependent on the situation around them (Helbing et al., 2001; Löhner, 2010). According to Rastogi et al. (2011), characteristics such as the width of the street, type of facility, and environmental factors have an impact on the walking speed. Personal characteristics such as age and group size are found to be of influence as well (Rastogi et al., 2011). In their study, Moussaïd et al. (2010) focussed on group size, and observed that pedestrian walking speeds decrease linearly with growing group size. This corresponds with the study of Rastogi et al. (2011). The density of an area is a factor as well, as in crowded places, when approaching obstacles or other pedestrians, and for example in bottleneck situations, the speed of the flow will change and is most likely to decrease (Helbing et al., 2005). An example has been mentioned before: compression of the crowd might cause shock waves. However there are situations in which the walking speed might increase, for example when overtaking other pedestrians or when the density decreases.

According to Helbing et al. (2005), in normal situations, the desired speed is approximately 1.3 metres per second, with a standard deviation of around 0.3 metres per second. Rastogi et al. (2011) observed that pedestrians in shopping areas walk at a speed of 55.4 metres per minute, which comes down to approximately 0.9 metres per second. Precincts are wider pedestrian zones, which means they are free of vehicles, located within a specified land use (Rastogi et al., 2011).

Since Rastogi et al. (2011) especially mention shopping precincts, it is decided this study will be leading for the desired walking speed of the agents in the simulation model. They also observed different walking speeds for different ages in shopping areas, with a range from 48 metres per minute to 70 metres per minute (Figure 4.4). For the conceptual model, a random distribution is acceptable, however for the calibration it is not, since that process tries to simulate real-world situations as correct as possible.



Figure 4.4 Effect of Age on Walking Speed in Shopping Areas (Rastogi et al., 2011)

Personal Space

The desired distance, the so-called personal space, between each other will be the same for every pedestrian. The desired distance between pedestrians and physical elements, objects or walls for example, is the same for all pedestrians as well. The distance is likely to decrease when pedestrian density increases, and vice versa (Helbing et al., 2001; Helbing et al., 2005; Hoogendoorn & Daamen, 2005).

According to Hoogendoorn & Daamen (2005), the lateral distance between the pedestrians of high-density flows in bottleneck situations is less than the width of an average shoulder, approximately 45 centimetres, while the effective width of a single pedestrian is around 55 cm. Kim, Choi, Kim, and Tay (2014) estimated that pedestrians keep a personal space of a mean lateral distance of 0.49 metres, which is close to that observed by Hoogendoorn & Daamen (2005). This would also mean that a move from the agent is expected when it is within these distances of another agent. However, since the simulation model focuses on the Covid-19 situation, social distancing rules are applied in the simulated shopping street. As a result, the agents are expected to keep 1.5 metres distance from others. This is not always the case, since not all pedestrians respect the rules and keeping distance is no longer possible if the number of pedestrians exceeds the maximum capacity of the street.

Distance to Obstacles

The average size of the personal space of a pedestrian does not apply to physical objects. Especially the social distance does not, since objects do not pose such a danger in the spread of the virus. In order to create a simulation model that is realistic for the situation in the Netherlands, a report from the Municipality of Amsterdam, published in February 2020, and a report from Transport for London (2010) are leading. These are both reports setting standards for the space pedestrians need in a street.

According to Gemeente Amsterdam Verkeer & Openbare Ruimte (2020), the width of a pedestrian itself is roughly 60 – 90 centimetres, which makes a space smaller than 90 centimetres impossible to walk through. Despite this does not exactly match the standards of Hoogendoorn & Daamen (2005), it is still used as a standard for the width of a pedestrian in the simulation model.

Especially the fact that in this study a shopping street is modelled, and it is assumed that shopping pedestrians are likely to carry bags with them, is a deciding factor to hold on to the widest standard. In Figure 4.5, a visualisation of the pedestrians widths, copied from the report of the municipality of Amsterdam, is shown.

Figure 4.5 Pedestrian Widths (Adapted from Gemeente Amsterdam Verkeer & Openbare Ruimte, 2020)



In a space up to 180 centimetres wide, it is possible for shopping pedestrians to walk in multiple flows, however it is not comfortable. An approaching pedestrian is always asked to make a change if pedestrians want to pass each other without (slight) collision. This is because Gemeente Amsterdam Verkeer & Openbare Ruimte (2020) argues that pedestrians like to keep 10 - 20 centimetres distance from obstacles and walls, and 30 centimetres distance from other pedestrians. As a result, Gemeente Amsterdam Verkeer & Openbare Ruimte (2020) sets the minimum required space at 200 centimetres (2 metres), in which they take 60 centimetres as the average width of a pedestrian. If more space than this minimum is required is dependent on the expected maximum number of pedestrians per minute passing through the street, and on if these pedestrians carry bags or ride a wheelchair.

Gemeente Amsterdam Verkeer & Openbare Ruimte (2020) clearly states that this minimum required space concerns 'free passage space', which means that constantly recurring obstacles such as greenery, benches, bikes, posts, or outside store equipment are not included in this space. The free passage space is the space a pedestrian is able to walk through without having to move from their line in order to avoid any obstacles. Still, the space is not fully useable because of the aforementioned distances pedestrians like to keep from objects, walls, and shop facades. When this all is taken into account, what remains is called the 'clear footway'. The kinds of spaces are visualised in Figure 4.6, which is copied and translated from the report of the Municipality of Amsterdam.

Figure 4.6 Kinds of Spaces (Adapted from Gemeente Amsterdam Verkeer & Openbare Ruimte, 2020)



Transport for London (2010) studied the impact of street furniture on the clear footway for pedestrians in streets as well. Apart from the size of the furniture itself, pedestrians keep distance from these objects. The sizes and distances of several objects are listed in Table 4.2. It can be noted that the distance of 20 centimetres to obstacles and walls and the distance of 30 centimetres to other pedestrians mentioned in the report from the Municipality of Amsterdam can be found in the report from Transport for London as well.

Furthermore, the impact of benches differs depending on the side of the bench. The size of the bench itself already reduces the clear way. As mentioned before, pedestrians keep 0.2 metres distance from obstacles, however in case of a bench this only concerns the non-seating side. The side of seating has an impact of 0.5 metres on the footway. If a bench allows sitting on both sides, this means 1 metre has to be added to the size of the bench itself in order to calculate the total impact on the footway (Transport for London, 2010).

For terraces of restaurants and cafés, for trees, and for posts or signs it is also true that the impact is dependent on the size of the object, and 0.2 metres have to be added for pedestrians to pass by comfortably.

When bicycles are parked parallel in the street, against walls, they are treated like a wall by pedestrians. This means that the clear footway is reduced by the width of a bicycle. According to Hoogendoorn and Daamen (2016), Dutch design guidelines indicate that all bicycles have handlebars that are less than 0.75 metres wide. Pedestrians like to keep 0.2 metres distance to a parked bicycle when passing it, which results in an impact of almost a metre.

Queues around an ATM can reduce the clear footway width by between 1.5 and 3 metres of space, however dependent on the type of area and number of machines within that area. It is also possible that people will not queue in front of the ATM, but next to the ATM alongside a facade. In this case, there is less impact on the clear footway.

In a relatively big city like Amsterdam it is likely map-based wayfinding signs are placed in or near much-visited places. According to the report from Transport of London (2010), these kind of signs have a rather big impact on the clear footway. It will take up to 2 square metres of space, used by pedestrians reading the sign on both sides, causing an increase of bumps and deviations at busy sites.

Object	Impact on Clear Footway
Wall / Facade	0.2 metres
Bench – seating side	Size of Bench + 0.5 metres
Bench – non-seating side	Size of Bench + 0.2 metres
Terrace	Size of Terrace + 0.2 metres
Tree – all sides	Size of Tree + 0.2 metres
Bicycle	Size of bike (max 0.75) + 0.2 metres
ATM	1.5 to 3 metres
Wayfinding Map Sign	2.0 square metres
Single Post* – all sides	Size of Post
Multiple Posts* – all sides	Size of Post + 0.2 metres
Person – unfamiliar	0.3 metres
Person – familiar	0.1 metres

Table 4.2 Distances to Obstacles (Transport for London, 2010)

* The rules for posts are applicable to similar obstacles such as garbage bins and flower pots as well

According to Gemeente Amsterdam Verkeer & Openbare Ruimte (2020), one of the solutions to achieve an appropriate clear footway within a street is to delete or reposition obstacles. It is also argued that the planned moments of redecoration of streets are the best moments to plan a street according to these standards. However, deleting, adding, or repositioning obstacles is often possible without completely redesigning the whole street. Therefore, one of the scenarios in this research, as described in Section 4.4, deals with the possible variances of obstacles, in positions and numbers.

Personal Characteristics

The agents are divided into groups, which each have certain needs and beliefs (Rounsevell, Robinson, & Murray-Rust, 2012). The groups can be based on for example walking speed, trip purpose, group size, patience, or else. According to Willis et al. (2000), agents classify entities within the environment into categories themselves as well. They argue that agents classify other agents based on their walking direction (same or opposite) or walking speed (same, slower, or faster), and that various objects are classified by agents as well. Based on interaction with other (groups of) agents and their environment, they are able to adapt their beliefs (Rounsevell et al., 2012).

How the agents move and behave is dependent on their beliefs and represented by parametrised attributes. According to Rounsevell et al. (2012), these attributes are crucial due to three reasons. First, they may constrain or enable behaviour. Secondly, changes that can be made in the attributes can alter the decisions that are made. Lastly, agents can communicate with each other what might alter the effects of the agent attributes. An example of an attribute is the walking speed, which differs for different agent groups and which can change due to communication with other agents and the environment.

Pedestrians often move in space according to a predefined plan (Schelhorn et al., 1999). The movement of a pedestrian therefore is dependent on how fixed it is to its own plan. Schelhorn et al. (1999) argue that high fixation and low fixation differ in if a pedestrian is easily distracted. A pedestrian with low fixation to their own plan is more likely to be attracted by objects or activities along the way, which according to Schelhorn et al. (1999) might result in for example "visiting shops which they never 'intended' to visit, and even dropping whole sections of their original plan".

Fixation is not the only attribute that influences the movement of a pedestrian. Trip purpose is an example of another personal characteristic. First of all, the trip purpose has an impact on the walking speed of pedestrians. Rastogi et al. (2011) observed different mean walking speeds in areas with different types of land uses. They assume that the effect of trip purpose is indirectly defined by the land use of an area. Next to this, the aforementioned fixation is likely to be dependent on the goal of a pedestrian. A pedestrian that is on its way to work is less likely to be distracted than a pedestrian that is in the street with the purpose of shopping or to socialise. According to Borgers and Timmermans (2005), not all pedestrians have a predefined plan. It is also possible that the goals of pedestrians are unknown or that pedestrians do not have a clear goal themselves. For example, it might be the case that a pedestrian goes to the area for shopping without a fixed plan, or that it just goes there to stroll around. In that case, the fixation would be low. It could be said that fixation and trip purpose are partly related, since not having a clear goal is likely to cohere with a low fixation, and vice versa.

Group size is another characteristic with impact. According to Willis et al. (2000), the pedestrian population is not only heterogeneous in terms of the variety of reasons to walk through the shopping street, but it also differs in if pedestrians walk alone or with others, and in case of the latter the group size. The size of the group has effect on the walking speeds, for which is true that an increase of group size results in a decline of the walking speed (Moussaïd et al., 2010; Rastogi et al., 2011).

Furthermore, Rastogi et al. (2011) argue that age of a pedestrian has an impact on the walking speed. In the section about walking speed is already explained what this impact is and how it is tried to be modelled. As mentioned in that section as well, it is not clear how the age of pedestrians will be distributed among the agents, since this is dependent on the success of data gathering.

Lastly, since pedestrians need to adopt a variety of manoeuvres such as following, overtaking, and evading to be able to reach their destinations, patience is a characteristic influencing the movement and behaviour of pedestrians as well (Koh & Zhou, 2011). As mentioned before in Chapter 3, impatience is mainly present in queuing situations and bottlenecks. In a queue, the flow slows down or stops, resulting in impatience, mostly due to longer waiting times (Helbing et al., 2005). In bottleneck situations it is possible that a unidirectional flow is formed, for which people of the opposite flow have to wait before being able to pass the bottleneck. Impatience due to waiting times might cause pedestrians to start to push against the flow of the opposing group, trying to stop the unidirectional flow, resulting in an increase of crowd compression and decrease of crowd motion (Helbing et al., 2005; Duives et al., 2013; Hoogendoorn et al., 2015).

4.2 Calibration and Validation of the Agent-Based Model

When the base of a simulation model is finished, works properly and does result in logical outcomes, the calibration process follows. Since the main purpose of calibration is to most accurately represent the real-world system, it would be best to add real world data to the model. For example, this can be environmental data from a real shopping street, such as the size of the street, the type of obstacles, and the number of shops. It is also possible to add real world data from the visitors of the street, such as the number of pedestrians, the shops they visit the most, and how long they stay in the shop on average. These data are likely to come from video footage from cameras in the streets, but it is also possible that it comes from surveys.

Concerning calibration of pedestrian agents and social distancing from video footage, it may be difficult to determine objectively whether or not individuals in a cluster are walking together (Willis et al., 2000). According to Willis et al. (2000), if they keep a certain distance and move at the same speed at all times, it can be assumed that these pedestrians form a group. However, one cannot be sure unless this is confirmed by the individuals themselves. If it is already difficult to recognise groups, it is even more difficult to recognise if people are allowed to be closer than 1.5 metres to each other. People do not have to keep a social distance if they are part of the same household. However, from video footage, it is difficult to see if people belong to the same household.

When calibration of the model using real world data has taken place successfully, the model would be validated. According to Teknomo & Gerilla (2005), validation of agent-based pedestrian models is difficult to the relatively large set of parameters, and the required understanding of the behaviour of the parameters. Therefore, they suggest to base the validation on a sensitivity analysis. Despite it being possible to validate the model before calibrating it, the given time for this research did not allow for this process to be performed. In the discussion in Chapter 6, recommendations for calibration and validation in further research are given.

4.3 Scenarios

As mentioned before, different scenarios are modelled. One scenario focuses on the effects of physical design, which encompasses the layout of the street with a focus on the number and type of physical obstacles. Another scenario focuses on sociological effects, in which the number of pedestrians plays the main role. For all scenarios, it is aimed to analyse where hotspots emerge and for how long these hotspots exist, in order to get insights into the potentially most crowded locations in a shopping street.

4.3.1 Planning Scenarios

Since modelling pedestrian movement is useful for planning and design purposes, as mentioned before in Section 3.1, this scenario will focus on the physical environment. On the one hand, this is based on basic physical objects that can be present in a shopping street, such as walls, (lamp) posts, trees, benches, terraces, racks of stores, bins, (parked) bicycles and mopeds, and (parked) cars. On the other hand, this is based on measures taken to ensure people of social distancing, such as one way pedestrian lanes, but also a maximum number of customers in stores, which might lead to passage blocking waiting lines. The scenarios are shortly described below and visualised in Figure 4.7.

The first scenario, called 'Basic', deals with an environment without obstacles in the street. This means that pedestrians walk through the street and visit shops without limitation, apart from the walls and other pedestrians which are always present. The second scenario, called 'Flowers', deals with an environment with flower boxes in the centre of the entire street, separating the street in two vertical parts. The third scenario, called 'Bicycles', deals with bicycles parked in front of the facades of the shops, located at both sides of the street, causing the free passage way to be limited. The fourth scenario, called 'Furniture', deals with street furniture such as lamp posts, benches, or greenery located all over the width of the street, causing the free passage way to be more limited than in the other scenarios. The name of the scenarios and their obstacles are only an example of what they could represent. A flower box could also be a lamp post, a bicycle could also be a bench, and a bench could also be a flower box. The shapes and sizes of the obstacles are not based on real world data, so a disclaimer has to be placed that the obstacles might be too big or too small and wrongly shaped. The main goal of these scenarios is to analyse what the impact is on pedestrian movement patterns when the obstacles are organised and located in the middle of the street, when they are organised and located at the sides of the street, and when they are more or less unorganised and located all over the street.



Figure 4.7 Planning Scenarios

4.3.2 Sociological Scenarios

This scenario mainly focuses on the impact of the number of pedestrians in the street. The aim is to analyse what happens concerning the social distancing measures if more or less people enter the street, and where and for how long the rules are being neglected. Next, it is aimed to analyse the emergence of hotspots of crowdedness in the street, to check if the location and duration is different when more or less pedestrians are present in the street. There might be correlation with the planning scenarios, such as less people respecting the rules if crowdedness increases, bottlenecks due to obstacles.

4.4 Implementation of the Model

For the development of the dynamic spatial model, the GAMA software will be used. GAMA (GIS Agent-based Modeling Architecture) is a modelling and simulation development environment for building spatially explicit agent-based simulations. GAML is the language used in GAMA, coded in Java. It is an agent-based language, that provides the possibility to build a model with several paradigms of modelling. It is possible to import a large number of data types, such as text, files, CSV, shapefile, OSM (open street map data), grid, images, SVG, but also 3D files, such as 3DS or OBJ, with their texture.

In the GAMA environment, a spatial environment and agents can be created, in order to analyse different scenarios. The most convenient approach for modelling social systems, explained by Rounsevell et al. (2012), is the heuristic method, which uses a decision tree that reflects human behaviour by representing the agents attributes. In short, certain actions are prescribed to groups of agents. As a result, agents will react to obstacles or events in the environment according to their own parameters, or attributes. The output is likely to be either a change of direction, speed, or both (Willis et al., 2000). This decision tree is incorporated in the model using 'if... then... else...' statements, resulting in transparency of the decision making process. This transparency helps to understand the modelled human-environment relationships (Rounsevell et al., 2012). In Figure 4.8, the decision tree for the pedestrian simulation model is shown in a flow diagram.





Due to time constraints, several details that are present in this diagram could not be added to the model. These time constraints mainly come from issues with the software, which are explained in more detail in the discussion in Chapter 6.

Simplification of the Model

The modelling process was divided into several main steps, to get to a general conceptual pedestrians simulation model, without details such as personal characteristics or real world data. The checkmarks (\boxdot) and crosses (\boxdot) indicate if the step has been executed successfully or not.

- 1) I Create a shopping environment, existing of a street and buildings;
- 2) Z Create pedestrian agents and let them move through the street;
- 3) Z Let pedestrians avoid each other with appliance of social distancing;
- 4) 🗹 Let the pedestrians enter the street, visit several shops, and leave the street;
- 5) 🗹 Let the shops to visit be based on popularity;
- 6) E Let the shops have a customer maximum and let pedestrians queue outside;
- 7) 🗹 Analyse the pedestrian density in the street;
- 8) I Analyse the density for different planning scenario's;
- 9) Analyse the density for different sociological scenario's;

Because of the time it took to get to the first model version that worked properly, there was no time to add more details or run different simulations of the model. A detailed description of the missing aspects is given in the discussion in Chapter 6, and in this section, the attributes of the pedestrians and the environment that have been included in the model successfully are described. In Table 4.4, the main attributes of the pedestrians are listed, while the main components of the physical environment are given in Table 4.5.

Attribute	Description	
Start Location	Each pedestrian will enter and leave the street at one of the main gateways, which a	
	in the west and the east of the street.	
Walking Direction	n Each pedestrian follows the shortest path to the next shop they are going to visit, or to	
	the exit. The direction of this path is dependent on the start location.	
Walking Speed	Each pedestrian has an individual speed between 0.8 and 1.2 m/s, which will no	
	change during the trip.	
Personal Space	Each pedestrian will always keep a distance of 1.5 metres to other pedestrians, except	
	in shops, where no distance is applicable.	
Size	Each pedestrian has a shoulder length of 0.9 metres, since it is assumed that people in	
	the shopping street are likely to carry bags, and to take into account people riding a	
	wheelchair or holding a bike.	
Trip Purpose	Each pedestrian will visit a number of shops, or moves straight to the exit.	
Shops to Visit	Each pedestrian gets a list with a number of shops, random between 1 and 7, they are	
	going to visit. The shops are assigned to a pedestrian based on the attractiveness.	
Target	Each pedestrian gets a target, which is the next shop on the list of shops to visit. If the	
	list is empty, the target will be one of the main gateways to exit the environment.	
Staying Counter	Each pedestrian has a staying counter. This attribute counts the number of seconds a	
	pedestrian is in a shop. When it has achieved a value of 900, the pedestrian gets	
	assigned a new target.	
Fixation	Each pedestrian has a fixed, predefined plan, and will not get attracted by other shops,	
	pedestrians, or events.	

Table 4.4 Attributes of the Pedestrians

Component	Description	Illustration
Street	The shopping street in which pedestrians walk from shop to shop.	
Building / Shop	The buildings in which shops are located. Each building is one shop, with a random attractiveness attached to it.	
Walls	Function as the facade of the buildings and as obstacles. Pedestrians cannot move through walls.	
Exit – Entrance	Exits and entrances are the same, located at the main gateways in the west and east of the street. They have a chance attribute, which is the chance of releasing a pedestrian into the environment. Each cycle, a virtual coin is flipped to determine if new pedestrians will enter the street.	
Pedestrian Path	The network of lines pedestrians can move on to get to a target. Generated with the GAMA software. Displayed in purple.	
Free Spaces	The free spaces are the buffered segments of the pedestrian path, which results in pedestrians being able to move on polygons instead of lines, and therefore make use of a wider space than wit the original line network. Generated with the GAMA software. Displayed in pink.	
Fishnet	A shapefile with raster pattern to get insights into the density of pedestrians in the street. Counts the number of passages by pedestrians and saves this as a heatmap for every hour and for the total of the simulated day.	

 Table 4.5 Attributes of the Physical Environment

From the literature review, it was learned that in order to get a better understanding of pedestrian movements, it is important to realise that not all pedestrians move the same. The differences are mainly based on personal preferences, such as personal space, walking direction, walking speed, and group size. From these personal characteristics, only modelling personal space, walking direction, and walking speed was successful. The personal space has been set to 1.5 metres, following the social distancing concept that has been explained before. The walking direction has been set by numbering the shops and letting the pedestrians choose the shops to visit in the order from west to east or vice versa, dependent on their location of arrival. The walking speed has been set to random values between the minimum and maximum speed that was found in the literature review. This resulted in pedestrians having slightly different speeds. Group size is a complex factor, and has not been taken into account in the model, which results in all pedestrians to operate individually.

Concerning the shopping activities, each pedestrian gets an own list of shops that they are going to visit. The length of this list is between 1 and 7 shops. The shops get assigned by means of virtually flipping a coin which tells if a shop is getting visited or not. The chance of getting chosen is based on the attractiveness of a shop, which in its turn is a random predefined value which does not change during the simulation. There are also pedestrians who do not visit shops, and only walk straight through the street and leave it. To determine who is not visiting a shop at all, a virtually coin will be flipped as well, with a chance of 0.5 (on a scale of 0 to 1) to be characterised as a pedestrian that will walk straight to the exit. When a pedestrian enters a shop, a staying counter will start to count the number of seconds the pedestrian is inside the shop. When it achieves the value of 900 (15 minutes), the pedestrian gets the task to leave the shop and walk to the next shop, or if the list of shops to visit is empty, to go to the exit.

Concerning the shopping environment, a street of 80 metres long and 10 metres wide has been developed. Next to this street, relatively small buildings have been added. These buildings have a certain, predefined attractiveness, which is the base of the chance to be chosen by a pedestrian. In the model script itself, it is not possible to add obstacles. This has been done by creating shapefiles of walls, which function as obstacles as well. The buildings are surrounded by walls (facades), and to add obstacles in the middle of the street, for example, walls have been drawn in the shapefile, to function as obstacles. This reduces the complexity of the model, since pedestrians now only get the task to avoid walls.

Next to the attractiveness, a maximum number of customers can be attached to the buildings. When the maximum number of pedestrians is inside a building, other pedestrians that want to visit it have to wait and queue outside. However, due to time constraints, this waiting or queueing task for pedestrians has not been added successfully. This causes shops to be allowed to be overcrowded, resulting in clogging in the street. Pedestrians do not wait in line, but keep trying to enter the shop, which blocks the pedestrians inside from leaving the shop.

Lastly, in order to calculate the density of the pedestrian crowds moving through the street, a 'fishnet' is created, which is visualised in orange in Figure 4.9. This is an overlay existing of cells in a raster pattern. In this case the cells have a size of 1x1 metres, which means that one pedestrian with a shoulder width of 0.9 metres can fit in one cell. As a result, each cell can only be occupied by one pedestrian at a time. It is even likely that the neighbouring cells cannot be occupied at the same time, due to the social distancing rules. Every time a pedestrian moves through a cell, the cell saves the passage. Each cycle, the fishnet checks for each cell if it is occupied. If this is true, it will increase the 'number of passages' for that cell by 1. The amount of time a single pedestrian is at a certain location is not calculated and saved for each pedestrian. However, since the fishnet checks the occupancy of the cells for each cycle, it is still possible to get insights into how intensively a single cell is used. Reasons for intensive use can be twofold: on the one side that a pedestrian is standing in that cell for a longer time, or on the other side that many pedestrians pass this cell. By means of heatmaps, which are created for each simulated hour and for the total simulation, insights can be gained into which locations in the street are intensively used. From these heatmaps, the hotspots of crowdedness can be identified. By doing this for multiple scenarios, which differ in the number and location of obstacles and the number of pedestrians, it is possible to check for the effects of possible plans concerning the physical environment.



Just before the first model run starts, the two main components of the model, the spatial environment and social entities, are loaded. An environment is created and enriched with entities, such as the shops, walls, physical obstacles, and gateways. The shops are given a random attractiveness or popularity. Subsequently, the social system is loaded by creating agents and prescribing them certain parameters, dependent on to which division they belong. These divisions can be based on personal characteristics such as age, trip purpose, and group size.

If the environment, agents, and all parameters are loaded, the model run can start. Starting a model run will result in pedestrians entering the environment as agents via the gateways. These agents walk at their predefined desired walking speeds, along the shortest path trajectory, towards their destination. If they reach their destination in a straight line at a constant walking speed is dependent on the aforementioned fixation of an agent, the location and number of obstacles in the environment, and the pedestrian density, which might cause other agents to be perceived as obstacles as well.

During their walk, the agents constantly scan their environment (Hoogendoorn & Daamen, 2005; Willis et al., 2000). The agents have the option to keep up with their original plan, or to deviate from it in response to entities in the environment, such as obstacles, events, or other agents (Schelhorn et al., 1999). According to Willis et al. (2000), when an agent is confronted with an entity, it will take action. There is a confrontation if the entity is within the personal space of an agent, which in this model is set at 1.5 metres for other pedestrians, and no distance for obstacles. When the entity is identified by the pedestrian, some kind of action has to be taken to avoid collision (Willis et al., 2000).

In the study of Willis et al. (2000), the action that will be taken is based on "common sense judgements of what is likely to happen in a given circumstance". They give an example of an agent for whom the space ahead and on the left are blocked, while on the right another agent is walking at a lower speed. This will result in the agent deflecting its path to the right and to reduce its speed to match that of the other agent. For this model, however, slowing down or stopping until there is free space could not be simulated. Depending on the patience of an agent, if there is no free space within a certain amount of time, it would decide to ignore the social distance of 1.5 metres and look for options with a minimum distance of 0.3 metres to other agents. However, this was not successfully modelled as well, and pedestrians are forced to always keep 1.5 metres distance.

Since Helbing (2001) argues that pedestrians feel a strong aversion to taking detours or moving opposite to their desired walking direction, even if the direct way is crowded, it is decided not to give agents the ability to turn around or move to an adjacent street only because of crowdedness. The pedestrians have got a list of shops they want to visit, which are in order of their walking direction. Only when pedestrians are going to leave the shopping environment, they are able to turn around, since it is likely that they will go back to where they entered the street, for example due to their car or bicycle being parked over there. Since the environment is a shopping street, it is likely that the majority of the agents visits one or more shops. Visiting a shop results in the agent temporarily leaving the street environment. According to Schelhorn et al. (1999), the most important consideration in modelling agents entering buildings is the average time that is spent in the building. If a building is becoming crowded, the average time agents spend in the building increases (Schelhorn et al., 1999). Once agents return from the building back to the street, they will continue their journeys with the same parameters, such as walking speed, as before. In this model, however, the time pedestrians spend in a shop is predefined at 15 minutes and not dependent on the crowdedness, size, or type of the shop.

Results

In this section, the results of this research are analysed. The goals of this study were to uncover hotspots of crowds in shopping streets, and to analyse the movement of pedestrians in different scenarios. By means of a pedestrian simulation model, it was aimed to gain insights into pedestrian movement patterns in shopping streets under different conditions, especially different planning and sociological scenarios. The analysis of the results mainly focuses on the crowding hotspots, and heatmaps are used to support this analysis. These heatmaps are the outputs of running the scenarios. For the planning scenarios, different layouts of the physical environment have been used to check for the influence of the number and organisation of obstacles. For the sociological scenarios, the number of pedestrians entering the environment has been increased to analyse the capacity of the street. As mentioned before, the validation and calibration processes could not be performed for this model, so there are no results of these analyses. Comparison of the patterns of pedestrian movement that resulted from running the simplified model to the literature review takes place in the conclusion in Chapter 7. Since not all components of the conceptual model have been successfully modelled, these can also not be compared. A reflection on these missing components and details is given in the discussion in Chapter 6.

5.1 Planning Scenarios

5

Different planning designs have been set up and uploaded to the model, in order to check for changes in density, and where and for how long crowded hotspots exist. The scenarios have been described and visualised in Figure 4.7 in Section 4.3.1. The Basic Scenario does not contain obstacles, apart from the walls. The Flowers Scenario has organised obstacles in the middle of the street, while the Bicycles Scenario contains organised obstacles at both sides of the street. Lastly, the Furniture Scenario is a less organised situation of obstacles all across the street.

In Figure 5.1, the heatmaps with the total number of passages are visualised for each scenario. The heatmaps are visualised with a natural breaks classification method. In the legend, the last category has a relatively large extent. This is because of one outlier in the Bicycles Scenario (1192) and two outliers in the Furniture Scenario (1190 and 1989), which are visualised with a light blue border in the respective maps.

Each heatmap shows a different pattern, however similarities can be seen as well. In all heatmaps, there are (dark) red spots at the entrances of the shops, which means that such a particular cell is passed more frequently than other cells in the street. This shows that these shops are visited more than other, which indicates that these are popular shops. This outcome makes sense, since each shop has a predefined attractiveness, which means that the more attractive shops have a higher chance to be visited by more pedestrians.

[36]



Figure 5.1 Patterns of Total Number of Passages **Basic Scenario**

Flowers Scenario



Bicycles Scenario



Furniture Scenario





In the Basic Scenario, a straight line pattern can be seen, with branches towards the shops. The absence of obstacles causes a spread density throughout the street, with the highest number of passages being counted at the entrances of popular shops.

In the Flowers Scenario however, a meandering pattern can be seen. The line relatively strongly bends towards the more popular shops. A higher density can be seen on the 'popular side' of the obstacles, with a relatively low number of passages (less than 125) on the other side. This indicates that an obstacle in the middle of the street forces a pedestrian to choose a side, and that the majority of the pedestrians chooses the same side as where the shop they want to visit is located. This implies that an obstacle in front of or nearby attractive and popular shops might cause a dense crowd at one side of the obstacle.

In the Bicycles Scenario, a similar pattern as in the Basic Scenario is visible, albeit with little bends away from the obstacles. The crowd is focused in the middle of the street and there are no obstacles that cause a higher density at specifically the one or the other side of the street. However, it is visible that in this scenario, the density of the flow is slightly higher in the middle of the street than in the Basic Scenario. This might be due to the obstacles located at the sides, pushing pedestrians more to the middle of the street. This is especially true for the centre of the street.

Lastly, the Furniture Scenario shows a pattern of pedestrians walking in the middle of the street, except from when they encounter an obstacle. Then, the pedestrians tend to choose the southern side, especially in the eastern part of the street. This is remarkable, since there are also popular shops on the other side of the street. This means that in this scenario, different from the Flowers Scenario, no meandering from popular shop to popular shop takes place. It is also visible that the obstacles cause jams in the street, which can be seen by the dark red spots indicating a higher density around the obstacles. It is unclear why pedestrians choose the southern side of the obstacles in this scenario.

From these heatmaps, it can be concluded that obstacles that are not located alongside the facades of shops cause pedestrians to choose a side of an obstacle, with the majority choosing the side of the attractive or popular shops. This is likely caused by the pedestrians planning to visit the more popular shops and therefore have no reason to walk on the other side of the obstacle.

There is, however, a drawback to these results and conclusions. The results have not been calibrated or validated, which means the results do not tell anything about a real world situation. Without a sensitivity analysis, it is hard to tell if the model is robust and if the results are valid for differences in the population or characteristics of the street and shops. Next to that, the aforementioned lack of components and details results in uncertainty about the representativity of the modelled situation for a real world situation, however it is likely to be not representative due to missing behavioural attributes. Therefore, it has to be kept in mind that statements made in the results and conclusion sections of this report are based on the relatively few simulations that have been executed by means of this simplified model, and indicate what pedestrian movement patterns could become visible in different scenarios, but do not state anything about real world situations with certainty.

5.2 Sociological Scenarios

For the sociological scenario, only the number of pedestrians in the model has been changed. It is unsure if the model allows for changes in the population that accepted the social distancing rules. Due to time constraints, it could not be checked if there are possible ways to add such a differentiable parameters, and if not, to contact the developers to change this in the software. Therefore, changes in the percentage of social distancing pedestrians has not been taken into account.

For changing the number of pedestrians, it was assumed that the Furniture Scenario would be best. This is because of the relatively high number of obstacles, and thereby disturbed clear footway. The impact of more or less pedestrian was assumed to be likely to be the highest in this scenario. When the number of pedestrians entering the street was approximately doubled, parts of the street became overcrowded very soon, as shown in the images in Figure 5.2. It is also visible that pedestrians try to keep distance in the street most of the times, however at some locations it is too crowded and the 1.5 metres distance is ignored, which can be seen by pedestrians being inside the circle of another. When looking at these circles, it is important to keep in mind that social distancing is never applied in the shops. The first simulated hour would take more than an actual hour to complete, since a simulated second took more than one second in real life. Therefore, the simulation was stopped promptly. Pedestrians were unable to move through the street and therefore could not reach their targets. The explanation for the jams that occur in this scenario cannot be given with certainty, but it is likely that two factors play the main roles.



Firstly, the buildings have no representative size, as they are not 'deep' enough in length to house all pedestrians when the number of pedestrians entering the environment is increased. This means that pedestrians are unable to enter the building, but because they keep trying, they are blocking the entrance. This means that pedestrians inside the shop are unable to leave the building as well. This situation also occurs in the Basic Scenario, however then there are no obstacles increasing the jam (Figure 5.5). As more pedestrians enter the street, more pedestrians will try to get into the shops. At one moment, the whole width of the street is filled with pedestrians trying to enter a building, which results in the blocking of pedestrians that just entered the street and want to move on.

Another possible explanation is the small space between the obstacles and the facades of the buildings. This space is less than 3.5 meters wide, which means that in a situation of social distancing, only one pedestrian (with a shoulder length of 0.9 meters) can pass through that space. When two opposite pedestrians arrive at the obstacle at the same time, both are stubborn and keep trying to pass through the space, which is not possible. More pedestrians will try to get through the same space, and soon jams and clogging of the street will occur. Unfortunately, the pedestrian agents are not 'smart enough' to choose another way to get to their target. They always choose the shortest path, which in this case, leads through the smallest space. This causes a situation which is not representative, since in a real world situation, pedestrians would see that the space is too small and choose to walk past the other side of the obstacle, or they will ignore the 1.5 metres social distancing measures, or they will see that it is crowded in front of them and choose another route to walk past the crowd. Due to time constraints, it was not possible to analyse the problem more deeply and therefore no solution to this problem has been found.

The changes in the number of pedestrians were next applied on the Flowers Scenario. In this scenario, it was possible to double the number of pedestrians. When the number of pedestrians was multiplied by a factor 10, the street became overcrowded soon, which is shown in Figure 5.3. In this situation, it is clear that social distancing no longer takes place in the street, which means that the maximum capacity of the street is exceeded. In Figure 5.3.b, this is made visible by means of the 1.5 metre distance circles.



Figure 5.3 Overcrowding of the Flowers Scenario **a. Overcrowding Street**

However, in contrast to the Furniture Scenario, it was possible to complete the first hour. After the first hour, the model became too slow and was stopped promptly. Since the model saves heatmaps for each hour, it is now possible to compare the situations with different numbers of pedestrians. It has to be kept in mind that in the first hour, the chance of pedestrians to be born is To be able to see the differences more clearly, a quantile classification method has been chosen. The three situations are displayed in Figure 5.4.



Figure 5.4 More Pedestrians in the Flowers Scenario – First Hour Initial Number of Pedestrians (+/- 130)

When looking at these outputs, it is visible that with the initial number of pedestrians, a meandering pattern is visible which bends towards the attractive shops, indicated by the larger and darker spots at the entrances of these shops.

With the doubled number of pedestrians, two main differences can be seen. First, the flow of pedestrians is widened in comparison to the initial situation. Because more pedestrians are present in the environment at the same time, more space is occupied. Second, in the middle of the street, more pedestrians walk past the 'unattractive side' of the obstacle, which might be caused by the increased crowd density at the 'attractive side', but cannot be explained with certainty.

With the largest number of pedestrians, the meandering pattern is still visible, and more dense or crowded than in the other situations, but less evenly crowded. In the east of the street, it is clear that a relatively large and dense crowd has formed at northern side of the obstacle. It is likely that this crowd causes other pedestrians to experience difficulty with passing and arriving at the western side of the street, while pedestrians coming from the west struggle to reach the east. This might explain the less dense flows near the main gateway at western end of the street, although this cannot be said with certainty.

In all situations, but most clearly in the situation with the largest number of pedestrians, it is visible that jams occur in front of the second most eastern obstacle. This happens at both sides, but most clearly at the western side. In the last situation, it is visible that at one metre of the obstacle, a relatively large cluster of dark red spots is visible. This indicates a jam, likely to be existing of pedestrians who want to visit the shops at the northern side of the obstacle, or at least want to pass that already crowded side.

To be able to analyse the effect of the obstacles, the same outputs are created for the Basic Scenario. In the Basic Scenario, the higher number of pedestrians seems to have less impact than in the Flower Scenario. First, the situation of the factor 10 multiplication of the number of pedestrians is shown in Figure 5.5. The higher number of pedestrians does not result in the model becoming too slow or too crowded to finish, but the social distancing measures are ignored in this situation as well.





Since this model did not became too slow and too crowded, for this scenario, it was possible to simulate the model completely until the end. The outputs of the first hour are presented in Figure 5.6, while the outputs of total simulation time are presented in Figure 5.7.







Figure 5.7 More Pedestrians in the Basic Scenario – Full Simulation Initial Number of Pedestrians (+/- 500)

In the first hour, a more dense flow of pedestrians in the middle of the street can be seen, but no concentrated jams are visible. The full simulation, however, shows some interesting results. For the highest number of pedestrians, this resulted in a heatmap with a fragmented pattern. The flow of pedestrians in the middle of the street is no longer clearly visible, but it can be seen that the dark spots mostly concentrate alongside the facades of the buildings. This indicates that the shops have become overcrowded in such a way that the entrance was blocked and not pedestrians could enter or leave the buildings, causing pedestrians who want to enter the building to get in a jam alongside the facades and in front of the buildings.

From comparing the outputs of the Flowers Scenario and the Basic Scenario, it can be seen that obstacles have a meandering effect on the pedestrian flow. Additionally, the obstacles cause jams in front and aside of them when they are located near an attractive or popular shop. From comparing the clogging situation in the Furniture Scenario with the Basic Scenario, it can also be analysed that the (relatively small and unrepresentative) size of the shops has an impact on the hotspots of crowdedness.

5.3 Validation and Calibration

For calibration of the model, real-world data was necessary. However, given the time and due to privacy regulations, these could not be retrieved. Validation of the model, or testing the plausibility, could not take place as well, due to time constraints and the model missing components necessary for a sensitivity analysis. As a result, the simulation model remains a simplified version of the conceptual model, which is not validated or calibrated. However, it is still possible to analyse patterns of pedestrian movement in a shopping street. It has to be kept in mind that the representativity of the model has not been analysed, but a cautious statement that can be made from this simulation model, especially the planning and sociological Flowers Scenarios, is that placing obstacles in front of attractive shops causes a higher number of pedestrians walking past the 'attractive side' of the obstacle, which results in a higher density and potentially higher safety risks.

When there is more time, the missing components and details can be added, and a sensitivity analysis can be performed to validate the model. Next, if correct real-world data are added, it might be possible to do analyses for real world scenarios. In the discussion in Chapter 6, this will be explained in more detail.

6

Discussion

In this chapter, the research as a whole is analysed and discussed. It starts with going through the modelling process. The problems identified while developing the simulation model are discussed in the first section. These problems lead to time constraints, which resulted in several components of the conceptual model not being modelled in the simulated model. This gap is discussed in the second section.

6.1 Reflection on the Modelling Process

First of all, the modelling process is discussed. In Table 6.1, a summary of the problems that have been encountered during the modelling process has been listed.

GAMA Version	Main Problems	Solved Problems		
GAMA 1.8.1	No avoidance of pedestriansInability to visit shops polygons			
Pedestrian Plugin	 Inability to set distance between pedestrians Inability to visit shops polygons Maximum number of customers and queueing not respected 	Pedestrians are able to avoid each other		
GAMA 1.8.2	Maximum number of customers and queueing not respected. This is probably due to the way of allocating targets, but could not be analysed.	 Possibility to set distance between pedestrians Possibility to generate pedestrian paths 		

Table 6.1 Summary of Problems

Shopping Environment

The first goal when the modelling process started was to develop a simulation model of a shopping street with moving agents. The moving agents represented pedestrians, who were supposed to enter the street, visit several shops, and leave the street. The model was created with the GAMA software. With this software, it is possible to upload shapefiles in the environment, in which agents can move. For instance, it is possible to let agents move on a graph (line network). However, this does not show a correct representation of walking pedestrians, since they do not all move on one and the same line in a real-world scenario. Therefore, it was necessary to make use of polygon features, in order to create a more wide walking area. Next to this street polygon, polygons representing buildings were added.

The first model was developed in the GAMA 1.8.1 version. After the polygon features of the street and buildings were created in ArcGIS Pro, and saved as shapefiles, these could be added to the modelling environment. The next aspect that needed to be added to the model was the activity of pedestrians actually visiting buildings. This caused several problems, since the environment existed of closed polygons, from which the borders represented walls. This meant that if pedestrians wanted to access a building, they needed to move through the walls. Since this is not realistic, they could not access the buildings, and a solution was found in adding points just in front of the buildings. By adding this point as a target for the pedestrians, they could move to a shop, visit the shop, and leave. The situation is shown in Figure 6.1.

Figure 6.1 Initial situation of street, buildings, and shops



Now that letting pedestrians arrive at shops was successfully simulated, the selection of shops to visit could be specified. Multiple selection criteria were added. First, pedestrians had to visit shops in the order of the street, which means that pedestrians entering the street in the west walk to the east and visit shops in that order, and vice versa. Next, the selection of the shops that they had to visit had to be based on a given attractiveness for each shop. This caused more attractive or popular shops to have a higher chance to be chosen and therefore to be visited by more pedestrians than others. Additionally, the pedestrians would have to stay in a shop for an initial defined duration.

The base of the shopping environment has been developed successfully, after which the movement behaviour of the pedestrian agents had to be specified.

Pedestrian Movement

In times of the Covid-19 pandemic, the two main measures that have an impact in shopping streets and the movement of pedestrians are the social distancing measures and the limited number of customers to be allowed in buildings at the same time. The latter might cause pedestrians having to wait and queues to occur in the street. When queueing, pedestrians should keep to the social distance oof 1.5 metres distance. However, modelling a maximum number of customers and others waiting outside was not a success. It did not work perfectly due to that the maximum was not always respected. The pedestrians did not wait at the given distance from each other as well. In the original GAMA 1.8.1 application, it was not build in that pedestrians had to avoid each other. They walked right through each other, which caused several problems in terms of simulating the movement of the pedestrians. Given the time, this problem made it impossible to develop a realistic pedestrian movement model, let alone one in which pedestrians keep a certain distance from each other. Therefore, it was not possible to simulate social distancing with this software within the time.

However, a 'pedestrian plugin' was available. Besides the plugins delivered by the developers of the GAMA software, there are a number of additional plugins that can be installed to add new functionalities to GAMA or enhance the existing ones. The pedestrian plugin included predefined rules to make it possible for pedestrians to avoid each other. Now that the plugin allowed pedestrians to avoid each other, it would be likely that it would become possible to simulate social distancing. However, since the rules were predefined distance from each other, but since this was less than 1.5 metres and it could not be changes, it was still not possible to simulate social distancing. Despite the plugin offering the possibility to develop a simulation model with a better representation of moving behaviour of pedestrians in a street, it did still not meet the requirements to achieve the goals of this study. The developers of GAMA and the plugin were informed of this issue and replied quickly that they would try to deliver a solution.

After a few weeks, the developers launched a new version of GAMA (1.8.2), in which the pedestrian plugin was included and in which it is possible to change the distance parameter. Therefore, in this version, pedestrians could keep 1.5 metres distance to each other, which made simulation of social distancing possible. With this version of GAMA, a solution to the problematical situation of polygons and points concerning the buildings was found as well. By means of a "generate pedestrian paths" model which was delivered with the new version, it was possible to

create a graph which would be "buffered" so that pedestrians followed a line network, but were also able to step off the line, while still remaining within the buffer and respect obstacles such as walls. By creating a shapefile with lines as walls, and keeping parts open so that there would be entrances to the shops, it was possible to let pedestrians enter a shop and return to the street, while also respecting wall boundaries. In Figure 6.2, the graph is visualised in purple, and the buffer is displayed in pink, for the Basic Scenario and the Furniture Scenario. The pedestrians are only able to move over the pink polygons in the environment, which restrains them from moving through walls.



Time Constraints

It took the developers a few weeks to solve the issues and launch the new version. This resulted in time constraints for this study. As a consequence, not all components of the conceptual model could be added to the model. Other components had been added, but did not work perfectly, after which there was no time to analyse and solve the issues. For example, it was not tested if it is possible to set the distance pedestrians have to keep to obstacles. It was also tried to develop solutions for the waiting and queueing problem, but it did still not work perfectly, and could not be analysed extensively due to time constraints. After it had become clear that the problems could not be solved in a timely manner, the decision was taken to let go of the maximum customers in a shop, and so the waiting and queueing parts of the model. As a result, the simulation and analyses only focus on pedestrian movement and hotspots of crowdedness with social distancing measures.

Subsequently, given the time, it was not possible to change when pedestrians should keep distance, while this would be likely to be dependent on, for example, the crowd density. This resulted in that in this model, pedestrians always keep 1.5 metres distance to other pedestrians, apart from when they are in a building. This is not a fully representative situation, since in real life, people tend to let go of social distancing when it becomes crowded, however this is not confirmed. Not setting a lower distance for certain crowdedness caused jams in the streets, which did not solve due to the 'stubbornness' of the pedestrians. Especially when setting the parameter for the number of pedestrians too high, the street became soon overcrowded, with the Furniture Scenario as the relatively most 'extreme' situation.

In the simulation model, pedestrians always choose to move on the shortest path to their target. As mentioned before in Chapter 4, it is visible on these heatmaps that a relatively large number of passages is counted on the side of obstacles where attractive shops are located. These locations could be identified as bottlenecks in the street. However, since in this model the jams are caused by the inability of pedestrians to take a detour, and this movement behaviour might not be representative, the model might not be suitable for bottleneck identifying purposes. Given the time, it was not possible to analyse the representativity of the movements identified in the simulations.

6.2 Recommendations for Further Research

As mentioned before, the model had to be simplified due to time constraints. Therefore, it was not possible to add all aspects of the conceptual model such as personal characteristics, and to calibrate the model and execute a sensitivity analysis. In this section, it is explained what can be done in further research to make the model more complete. A summary of the missing components is listed in Table 6.3.

Characteristic	Missing Details		
Personal Space	• The personal space is always the same as social distancing (1.5 metres), and is not dependent on crowdedness or agent type		
Obstacles	• The size of obstacles and distance pedestrians keep to obstacles could not be modelled in detail		
Walking Speed	• Pedestrian walking speed is the same for entire trip, no increase or decrease when overtaking others or detecting obstacles		
Self-emergent Phenomena	• No self-emergent phenomena such as lane formation or the zipper effect are present, mainly due to the lack of differences in walking speed and walking lanes / flows		
Group size	All pedestrians move individually, no groups are present		
Age	• There is no difference in age between the pedestrians		
Shop Selection	• Shops are selected once, pedestrians have a predefined plan, no attractions of other shops / no unplanned visits take place		
Maximum Customers	• Shops have no maximum number of customers, shops become overcrowded, pedestrians keep trying to get inside and do not wait outside in line		

Table 6.3 Summary of Missing Details

The differences in the movement of pedestrians are mainly based on personal characteristics, such as personal space, walking direction, walking speed, and group size. In further research concerning modelling pedestrian movement in shopping streets, it has to be analysed how to model several components, which will be explained below.

First of all, the personal characteristics of the pedestrians have to be modelled. In the simulation model of this study, the personal space has been set at 1.5 metres distance, following the social distancing concept that has been explained before. However, from the literature review it was learned that pedestrians keep about 0.3 metres distance from each other. Additionally, it is assumed that in crowded situations, people ignore the social distancing measures. Therefore, it is recommended to analyse at which density rate pedestrians start to ignore the social distancing measures and to include this in the simulation model.

The same is true for distance to obstacles. In the methodology section, a relatively broad review of different kinds of obstacles and their impact on the clear footway has been presented. Given the time, this has not all been included in the simulation model of this study. However, it is recommended to model this in more detail in further research, since the impact of obstacles can be relatively large. For example, in the Bicycles Scenario and the Furniture Scenario, recurring obstacles are present. In the methodology section, it was stated that recurring obstacles have a relatively large impact on the clear footway and will function as a wall alongside the full street length. However, in the simulation model, pedestrians start to avoid obstacles when they get in touch with it, and then

after the avoidance manoeuvre return to the path they were moving on. This is a drawback of the simulation model which has to be solved in further research.

Concerning speed, it has been successful to let each pedestrian walk at an individual, predefined random speed. However, pedestrians do not slow down when they encounter other pedestrians, or increase their speed to overtake others. Concerning the walking direction, it has been successful to let pedestrians visit shops in a logical order. Group size is a factor that has not been taken into account in the model of this study, however from the literature review it is learned that this is an important factor in pedestrian movement behaviour. Since the group size influences the walking speed, directions, and the fact that groups occupy more space, makes it relevant to take them into account in further research and future models.

For all personal characteristics, it is recommended to do more research into the aspects that are necessary to be able to model pedestrian movement more accurately. As mentioned before in the literature review and methodology section, self-emergent phenomena such as lane formation and the zipper effect are common to occur in situations with (dense) crowds, such as shopping streets. It is necessary to add more details of movement behaviour to be able to detect the self-emergent phenomena in a simulation.

Next to the implementation of personal characteristics, further research into this model can improve the simulated physical environment. For example, due to time constraints, it was not possible to model the obstacles in detail. As mentioned before, The average sizes of individual obstacles and the distance pedestrians tend to keep to obstacles could not be modelled. In addition, the obstacles themselves have not been modelled in detail as well. Given the time, these were generalised, which means they are all displayed as a rectangle, have the same size, and are quite randomly located in the environment.

Something which is missing as well, is the maximum number of customers in a store, and the waiting or queueing task for pedestrians. This causes shops to be allowed to be overcrowded, resulting in clogging in the street. Pedestrians do not wait in line, but keep trying to enter the shop, which blocks the pedestrians inside from leaving the shop. In the simulation, pedestrians do not have to keep distance in the shops, because the shops do not have a representative size. This lack of accurate sizing, especially the depth of the buildings, causes the shops to become overcrowded even more quickly, and jams in the street to arise more quickly as well. Therefore, it is recommended to create buildings according to more accurate and representative sizes, and to do more research into queueing pedestrians.

Calibration & Validation

The calibration and validation processes have not been executed for this model. This could not be done due to time constraints, and it was uncertain if data could be gathered successfully, due to privacy regulations and possible costs of the data. For further research, it would be interesting to calibrate the model by means of pedestrian movement data, for example of the municipality of Amsterdam. Examples of 'large-scale pilgrimage events' in the city of Amsterdam are shopping streets, such as the Kalverstraat, or less shopping-like areas such as the Wallen area. The latter is a touristic and crowded area in the centre of the city of Amsterdam. In both areas, it is likely that difficulties in social distancing might be experienced by pedestrians due to the narrow streets. This makes it interesting areas to simulate for the Covid-19 case. Apart from the pandemic, these narrow and crowded areas are interesting to simulate for safety purposes or to analyse for the consequences spatial plans for these areas.

After the calibration process, validation takes place, in which the plausibility or the robustness of the model is analysed. Although the base model could be validated without calibrating it, given the time, validation has not taken place. Therefore, it is recommended for further research

to validate the model. The validation was planned to be performed through a sensitivity analysis by means of adjusting parameter values of the physical environment and the social entities. It is still recommended to make use of this method.

The first sensitivity analysis would be performed on the environment. It would be analysed whether an increase or decrease in the number of obstacles within a scenario has a significant impact on the pedestrian movement patterns and especially the number, location, and duration of hotspots of crowdedness. Another test can be performed by changing the location of obstacles, however this might overlap with the goal of simulation of the different planning scenarios.

The second sensitivity analysis would be performed on the pedestrians. By adjusting the percentage of agents or number of agents that respect the social distancing rules, the tipping point in the risk of spread of the virus is checked for, by means of detecting the number, location, and duration of hotspots. Other analyses can be performed on aspects such as the number of pedestrians in total, the average age of pedestrians, group size, the walking speeds, or the number of shops the pedestrians attempt to visit.

Conclusion

While the Covid-19 virus is pandemically spreading, social distancing rules are applied in most countries with a significant number of infections. Due to this social distancing, people might be less able to move safely in narrow streets. The capacity of the shopping streets reduces when people have to keep 1.5 metres distance to each other. Shopping streets are busy areas in which obstacles might cause social distancing to be difficult and therefore allow spread of the virus. Hence, the question of how to design (new) shopping areas and the effects of obstacles on pedestrian movement in these areas is relevant. Studying pedestrian movement is relevant for situations without the Covid-19 pandemic as well, for example for situations with other viruses or for safety purposes in general.

By simulating pedestrian movement in a shopping street by means of agent-based modelling techniques, this study provides a better understanding of the spatial patterns visible in such an area. Different scenarios have been modelled in order to get an understanding of how pedestrian movement changes for different layouts of the physical spatial environment. Modelling these different scenarios allows urban planners to acquire better insights regarding possible consequences of plans they are developing.

The main goal of this study was to gain insights into pedestrian movement patterns in shopping streets under different conditions, especially different planning and sociological scenarios, using a dynamic agent-based modelling approach. The main research question will be answered at the end of this section, since the four sub questions need to be answered first before the main question can be answered. These questions have been introduced in the introduction of this report, but will be repeated and answered individually in this concluding chapter.

What are the characteristics of pedestrian movements in shopping streets and what different modelling approaches are commonly used?

Pedestrians are an integral part of the transportation system, and pedestrian flows are an important topic within transportation research. In comparison to vehicular flows, pedestrian flows are more complex due to pedestrians being more intelligent and flexible. They can adapt their behaviour to the environment constantly and are able to change their directions flexibly.

It is possible to divide research into pedestrian flows in two categories, which are the two main elements of pedestrian activity: the spatial environment and social entities.

Concerning the spatial environment, pedestrian activity is the combination of a street network and attractions such as shops or public buildings along this network.

Understanding pedestrian movement is essential for design and planning of public space. For city planners in general, in order to create a safe and comfortable environment for pedestrians, it is therefore useful to get insights into the relation between environmental factors and movement patterns. In collaborative planning processes, it is the role of the planner to present possible outcomes of proposed plans accurately and realistically.

Concerning the social entities, in this case the pedestrians, the characteristics of pedestrian movements are not the same for every pedestrian. There are general characteristics, such as the desired personal space. The distances pedestrians like to keep between each other and between physical elements are the same for all pedestrians. In general, pedestrians like to keep 20 centimetres distance to obstacles and facades and 30 centimetres distance to other pedestrians. The distances are

likely to decrease when pedestrian density increases, and vice versa. In the situation of the Covid-19 pandemic however, pedestrians are required to keep a 'social distance' of 1.5 metres to each other. Another characteristic that almost all pedestrians share is taking the optimal path to their destination, and trying to minimise delays when having to avoid obstacles or other pedestrians. However, it has to be kept in mind that the most optimal route is not per se the fastest route. It might be the route with minimum congestion, or pedestrians might choose a more natural or green route, or like to walk through certain areas despite these not lying on the fastest route.

However, most of the characteristics differ among different groups. The differences are mainly based on personal preferences. The groups can be based on for example walking speed, trip purpose, group size, patience, or else. Agents classify entities within the environment into categories themselves as well, for example other agents are classified based on their walking direction (same or opposite) or walking speed (same, slower, or faster). The movement of a pedestrian can also change from time to time or even during the trip, since pedestrians are known for scanning the environment continuously. Based on interaction with other (groups of) agents and their environment, pedestrians are able to adapt their beliefs.

By studying the movement of pedestrians, insights can be gained into spatiotemporal patterns that emerge. An example of such a pattern is avoiding collisions with other persons or objects, by for example overtaking others with a lower walking speed. Another example is crowd formation at bottle necks. Spatiotemporal patterns are a kind of characteristic related to the environment rather than the individual. This is because the context pedestrians are within is of a higher influence on the emergence of patterns than individual characteristics of pedestrians. Patterns that occur without intention or communication about it are called self-emergent phenomena, such as lane formation, the zipper effect, or shock waves. These phenomena have an impact on different aspects of pedestrian flows, such as the walking speed.

There are two common types of simulation models: macroscopic models, focusing on crowds, and microscopic models, focusing on the individual. The majority of the simulation models of pedestrian movement and of the spread of diseases, however microscopic models allow for a more natural representation of real-world pedestrians. This scale allows for detailed simulation and analysis of movement of and interactions between individuals, such as the aforementioned self-emergent phenomena.

To get a better understanding of pedestrian movement patterns by means of simulations, cellular automata (CA) and agent-based models (ABM) can be useful to create a simulation model.

Despite that CA models have been successfully used for traffic flow studies, they have been criticised as oversimplifications of reality. One of the most important limitations of CA is that it is not able to accurately represent the impacts of (autonomous) human decision making This results in the inaccuracy to reflect real-world spatial relationships and the feedbacks that are part of the real-world system.

Agent-based modelling (ABM) is a dynamic modelling method that has been proven to be helpful especially regarding pedestrian and crowd management. It is mainly used to understand complex systems. Through both time and space, geographical systems are exposed to the impacts of interactions between agents and with their environment. This results in ABMs being able to put social actions in a spatial perspective. Another important characteristic of ABMs is that they are flexible, due to the fact that they can be defined within any given environment.

How can pedestrian movement in shopping streets be modelled using an agent-based modelling approach?

To realise an agent-based model, a spatial environment and agents should be modelled. In ABMs, agents are often defined as (social) entities that have different internal characteristics, and are capable of interacting with other agents and their environment. The latter is of importance in order to create a so-called social-spatial system, coupling the agents with a spatial environment.

The most convenient approach for modelling social systems explained by Rounsevell et al. (2012) is the heuristic method, which uses a decision tree that reflects human behaviour by representing the agents attributes. In short, certain actions are prescribed to groups of agents. As a result, agents will react to obstacles or events in the environment according to their own parameters, or attributes. The output is likely to be either a change of direction, speed, or both.

It is useful, or even necessary for research into large-scale crowd movements, to model different scenarios. Simulation of scenarios might function as a planning support system, since it allows people to envision the future consequences of a proposed development, which increases the chances of consensus among stakeholders. Analysing and evaluating plans and designs supports collaboration and agreement. Next to this, simulating scenarios results in possibilities to formulate appropriate proactive measures, which is useful in situations such as social distancing. In other words, visualising developments by means of simulations offers possibilities to analyse and evaluate results, resulting in these models to be helpful in bringing those involved together.

What spatiotemporal patterns do emerge, according to the modelled scenarios, in the movement of pedestrians in shopping streets, and how useful are they for modelling scenarios in times of a pandemic, in particular Covid-19?

To get an answer on this sub question, for both the planning scenarios and sociological scenarios, heatmaps have been produced. These heatmaps were presented in Chapter 5 of this report, and showed patterns of pedestrian movement in a shopping street.

The planning scenarios existed of scenarios with a different layout of the obstacles in the physical environment. From the heatmaps of these scenarios, it can be concluded that obstacles that are not located alongside the facades of shops force pedestrians to have to choose a side of an obstacle. In this case, the majority of the pedestrians chooses the side of the attractive or popular shops. This is likely caused by the pedestrians planning to visit the more popular shops and therefore to have no reason to walk on the other side of the obstacle. This pattern is clearly visible in a situation with organised obstacles that are located in the middle of the street.

Therefore, it can be concluded that obstacles that are located near an attractive or popular shop cause higher densities or compressed crowds in front of these shops, and the space is not used effectively. This results in the recommendation to planners to take into account the attractiveness of shops when placing objects in the street that might be an obstacle.

The sociological scenarios existed of scenarios with a different number of pedestrians entering the street. From comparing the outputs of these scenarios, the simulation model presented in this report seems to be unable to model pedestrian movement accurately or according to real world standards in an absolute way. In a relative way, it is useful to get insights into the effects of different scenarios.

In this model, the pedestrians always try to keep a predefined distance to each other. Only when the street (or parts of the street) become relatively highly overcrowded, the distance is ignored. However, at that moment, it is already too late to solve the occurred jams. If pedestrians would be given the task to look forward and identify relatively small jams, they could take a detour and bigger jams and clogging of the street could be prevented. For this study, however, this could not be modelled successfully.

There is a sidenote to the overcrowding situation, which could be identified from comparing the outputs of the sociological scenario. From comparing the locations of the jams or clogging situations in the street for the different planning scenarios and numbers of pedestrians, it could be analysed that the size of the shops has an impact on the hotspots of crowdedness as well. The shops are not of a relatively small and unrepresentative size, while the pedestrians are of a realistic size. This causes the shops to become overcrowded relatively quickly and easily, which results in pedestrians not being able to enter the shop. Because these pedestrians keep trying to enter the shop, due to modelling queueing of pedestrians being unsuccessful for this study, they block pedestrians inside from leaving the shop. This results in a still situation in and in front of the shop, while more pedestrians keep entering the environment and trying to enter that shop as well, developing a bigger jam and clogging of the street.

What is the validity of the modelling results?

Since validation of the model did not take place, statements about the validity, plausibility, or sensitivity of the model cannot be made. Due to time constraints and the simulation model missing components necessary for a sensitivity analysis, the validity could not be analysed. As a result, the simulation model remains a simplified version of the conceptual model, which is not validated or calibrated. Therefore, this research showed what is possible with a simulation model developed with the GAMA software in this context, but it could not confirm the validity of the outcomes.

Now all of the sub questions have been answered, it is possible to answer the main research question, in order to come to a final conclusion.

To what extent can dynamic modelling of pedestrian movements provide insights into the movement patterns at street level for different planning and sociological scenarios?

In this study, the GAMA software has been used to develop a dynamic, agent-based model to simulate pedestrian movement in a virtual shopping street. The GAMA software and language allow for specific and detailed modelling of different agents. In this research, creating pedestrian agents at different moments in time, letting them arrive at a certain location in the environment, letting them visit different locations and leave the environment has been modelled successfully. Next to that, this study succeeded in letting pedestrians move at a certain speed and avoid obstacles and other pedestrians. It was also possible to add a time component to the model, which allowed for spatiotemporal analyses. Because of the lack of calibration and validation procedures, it is difficult to make statements about the usability of the model in absolute terms. However, the analyses showed that the model is useful to get insights into the relative effects of different scenarios.

At first, the model did not include a tool to let pedestrians avoid each other. Such a functionality was essential to model pedestrian movement in a situation with social distancing measures. After the developers were involved in the study, this gap had been filled, and even a parameter for setting a distance pedestrians should keep to each other was introduced. These achievements in a relatively short time show great potential of the agent-based modelling software and the possibilities to model pedestrian movements in order to get better insights into the movement patterns at a detailed level. However, it should be pointed out that currently, for non-computer scientists, without experience in modelling pedestrian movement, the software lacks (easy-to-use) tools to model accurate and representative pedestrian movement behaviour in a relatively simple and time efficient quick way.

In the end, this study showed that dynamic modelling of pedestrian movement in the GAMA software makes it possible to develop an agent-based model of the movement of pedestrians in detail, and that it is able to provide insights into movement patterns at street level for different planning and sociological scenarios. There is a bright future ahead for pedestrian movement modellers!

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