DETERMINING EFFECTIVE EVACUATION STRATEGIES BASED ON WIFI DATA IN BUILDINGS

AN EXPLORATORY DATA-DRIVEN AND AGENT-BASED EVACUATION MODELING APPROACH

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Marceau Mertens

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https://github.com/marceaau/EvacuationStrategiesThesis

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Supervisor:	Dr. C.N. van der Wal, TU Delft
Second supervisor:	Dr.ir. W.L. Auping, TU Delft
Chairperson:	Prof.dr. F.M. Brazier, TU Delft

Faculty of Technology, Policy, and Management,
Delft University of Technology, The Hague and Delft, Netherlands.

Science is a wonderful thing
if one does not have to earn one's living at it.

Albert Einstein

Executive Summary

Evacuation strategies are critical in preventing casualties during emergency evacuations in buildings. As large-scale gatherings and high crowd densities in buildings occur more often, the need of relevant and effective evacuation strategies emerges. However, the domain of research that tries to identify possible ways to improve evacuation, i.e. prescriptive domain, is underlooked. Several studies successfully improve evacuation by optimizing existing evacuation scenarios in buildings. A shortcoming of these studies is that they often focus on one strategy and scenario in particular. Therefore, one should opt for a more generic approach to evaluate the effectiveness of evacuation strategies under different circumstances.

A way to mitigate uncertainties in evacuation is by using data. Recent studies use a data-driven approach, in which data is used as an input to calibrate and enhance the evacuation strategy. A promising source of data is WiFi data. WiFi data captures movement patterns of building occupants and can be translated to population and building characteristics. Therefore, WiFi data offers the creation of evacuation scenarios in which evacuation strategies can be practically tested.

This study aims to (1) evaluate the efficiency of evacuation strategies in buildings under different circumstances, and (2) determine effective evacuation strategies given WiFi data as an input. Therefore, this study presents a new exploratory agent-based approach to evaluate evacuation strategies, and moreover, presents an approach to incorporate input data to practically test evacuation strategies in a given building. To do so, this study used three methodological approaches, namely Exploratory Modeling and Analysis (EMA), Agent-Based Modeling (ABM) and Data Mining. EMA is used to experiment with the created agent-based evacuation model. EMA addresses the effect of uncertainties on the evacuation time, and if evacuation strategies are effective and robust in different circumstances.

This study showed that in the created model of the TU Delft TPM faculty building, guiding evacuation strategies, such as dynamic signs and using evacuee staff members turned out to be an effective option if the familiarity in the building is low. However, as the familiarity increases the relative effectiveness of these strategies becomes negligible. In case of increasing familiarity, bottleneck improvement strategies, such as wider exits or stairs and obstacle placement, decrease the total evacuation time consequently. Moreover, this study concluded that an exploratory approach for evacuation models is promising, as the effectiveness of evacuation strategies is very dependent on the evacuation scenario. As a result, this study is able to evaluate these scenarios beforehand and to determine the effect on the total evacuation time. In this study the uncertainties crowd density, familiarity with the building, compliance with given instructions, and the exit capacity are leading in influencing the total evacuation time. The latter was found as a newly modelled uncertainty for evacuation scenarios.

Furthermore, it can be concluded that WiFi data provides promising results and insights for the evaluation of evacuation. Based on WiFi data, the population size and familiarity of a building can be determined and the evacuation can be simulated based on these inputs accordingly. In the case study of the TPM faculty building of the TU Delft, dynamic signs and evacuee staff members were proven to be the most effective evacuation strategies, as the WiFi data derived a low value of familiarity in the building.

All in all, this study presented a stepping stone for an exploratory and agent-based approach for the evaluation of evacuation and its uncertainties. Moreover, it showed that WiFi data can be used to supplement the model, and to practically determine effective evacuation strategies for a building. Future studies should aim at increasing the span of uncertainties, and taking other influences of evacuation in to consideration, such as social influence, contagion and group behaviour.

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INTRODUCTION

Evacuation strategies are critical in preventing casualties during emergency evacuations in buildings. According to E. Galea, Sharp, *et al.* (2008), the number of casualties of the 9/11 terrorist attack could have been smaller if relevant evacuation strategies were implemented. As large-scale gatherings and high crowd densities in buildings occur more often (J. Zhou *et al.*, 2019), the need of relevant evacuation strategies emerges. Evacuation strategies try to mitigate the number of casualties in times of emergency by proposing guidelines to guide the evacuee to safety as quickly as possible (Lujak *et al.*, 2017). The study of evacuation and its strategies focus on how to improve the evacuation efficiency of a crowd by analyzing, predicting and adjusting the crowd's behavior accordingly (Yao *et al.*, 2019).

The study of evacuation and its dynamics is very complex (Oven and Cakici, 2009; Koo *et al.*, 2013; Aleksandrov, 2018). The large number of people, the non-linear behaviour, the different technologies and the external factors involved makes the research an interdisciplinary topic (Schadschneider, Klingsch, *et al.*, 2008; Vermuyten *et al.*, 2016a). As a result, the topic receives attention from researchers in different fields, including psychologists, sociologists, physicists, computer scientists and traffic scientists (Helbing and Johansson, 2013). All of these fields try to mitigate the number of casualties by enhancing the evacuation strategy to ensure the crowds' safety, which makes the role of evacuation management indisputable.

As real evacuations can not be replicated, experiments and simulation are the main methods to evaluate evacuation and its behaviours (B. Liu *et al.*, 2018). In evacuation models, evacuation behaviour can be reproduced and evaluated. In these experiments and models, evacuation strategies can be applied to determine the effect of the evacuation strategies accordingly. Multiple research has been done to improve evacuation strategies to ultimately increase the evacuation efficiency (Vermuyten *et al.*, 2016a; Aleksandrov *et al.*, 2019; Haghani, Sarvi, Shahhoseini, and Boltes, 2019). Vermuyten *et al.* (2016b) identified three categories of evacuation strategies that aim to improve the evacuation efficiency: (1) architectural design and infrastructure adjustment, (2) mathematical programming and optimisation of path/departure-schedule planning, and (3) behavioural modification, training and active instructions. Evacuation strategies that improve the evacuation efficiency are for example based on the division of occupancy rates of lifts and elevators during evacuation (Aleksandrov *et al.*, 2019), the optimal velocity on stairs (Ding *et al.*, 2017), the departure time of evacuee by means of phased- or simultaneous evacuation (Koo *et al.*, 2013) or by placing division walls at bottlenecks which creates “zipper” queues (S. P. Hoogendoorn and Daamen, 2005). The strength of these evacuation strategies is that they successfully enhance the evacuation efficiency in their scenario. However, the evacuation scenario can be prone to uncertainties, which may devalue the outcome of these studies. Ibrahim *et al.* (2016) argue that the uncertainties of evacuation scenarios may worsen the crowd calamity circumstances, and therefore, the evacuation strategy may become less relevant. Furthermore, Vermuyten *et al.* (2016b) also emphasizes that “different approaches in evacuation optimization of pedestrians have not been distinctly differentiated and the extent of their relative effectiveness and practicality are yet to be evaluated”. Ofcourse, the application of one strategy that is fit for one evacuation scenario is promising, nevertheless it emphasizes the fact that the application of generic effectiveness is unknown and should be investigated further.

To analyze the above mentioned complexities and uncertainties of evacuation, Exploratory Modeling and Analysis (EMA) can be used (Kwakkel and Pruyt, 2013; Kwakkel, 2017). EMA can be used to address 'what if' questions, such as "Under what circumstances would this evacuation strategy perform well? Under what will it fail?", "What are the most sensitive factors in regards to the total evacuation time?" or "What are extreme cases for the evacuation efficiency?". EMA is able to answer such questions and derive insights by performing multiple computational experiments and analysing the results accordingly. For example, Karampekios (2019) used an EMA approach to evaluate uncertainties that are of influence on the Greek Economy, Havelaar *et al.* (2019) determined long-term infrastructure planning that is able to cope with a dynamic environment and Fraiture (2020) evaluated impacts on the robustness of Energy Systems. However, the author believes that the EMA approach has not been evaluated in evacuation studies yet, which introduces a new approach for the evaluation of evacuation modeling.

Besides an EMA approach to cope with uncertainties, recent researches use a data-driven approach, in which data is used as an input to calibrate and enhance the evacuation and to make the evacuation more realistic (B. Liu *et al.*, 2018). Based on input data, the aforementioned uncertainties of evacuation scenarios can be reduced. For example, B. Liu *et al.* (2018), Yao *et al.* (2019), Lee, S. Jain, *et al.* (2021) and Wal, Robinson, *et al.* (2021) use video footage to evaluate and observe human behaviour in buildings during evacuation, and use this as an input for the evacuation model to better reproduce real-life behaviour. Wachtel *et al.* (2021) used Bluetooth sensor data in order to identify and improve different types of evacuee movements. Martın *et al.* (2020) used Twitter and survey data to investigate whether evacuation behavior differs by race to use this in future models. Other studies also used other data sources, such as GPS signals, radio frequencies, questionnaires and surveys (Schadschneider, Klingsch, *et al.*, 2008; Van der Wal, 2019; Mohottige *et al.*, 2020; Santana *et al.*, 2020)

Another promising new source of input data is in the form of WiFi traces. Almost everyone in the world carries a Wifi-connected device, which can be traced by the building you are in. WiFi traces can indicate when "individuals are entering/exiting the building and/or moving across floors, which can be immensely helpful in evaluating evacuation events" (Mohottige *et al.*, 2020). Furthermore, the data collected by such technologies and smart devices can be used to determine user profiles of people present in the crowd (Boukerche and Coutinho, 2019). These profiles can be used as an input to design evacuation events, buildings or even critical infrastructures more efficiently and effectively. In this regard, evacuation management seems to be one of the fields that benefits from the rapidly increasing amount of connected technologies (Santana *et al.*, 2020), however studies that evaluate evacuation behaviour based on WiFi traces are yet to be written. Therefore, using WiFi data as an input for evacuation models introduces new possible ways of evacuation management.

In this study, the above mentioned approaches will be combined. By doing so, this study introduces a new methodological approach to evaluate effective evacuation strategies under different circumstances. Moreover, this method will be extended with the possibility of incorporating WiFi input data, to analyse the effectiveness of evacuation strategies not only theoretically, but also practically. First, an evacuation model will be created to implement and test multiple evacuation strategies under different scenarios by using the EMA approach. This model will be used to determine how building occupants and their characteristics are of influence on the effectiveness of evacuation strategies. Next, the evacuation model will be supplemented with input data derived out of WiFi traces. This data consists of information about the building occupants and their characteristics, for example which exits they take, if they are familiar with the building and the population size. By using this data as an input, we are able to evaluate if effective evacuation strategies can be determined for a specific scenario. This generic and data-driven approach increases the potential practicality of effective evacuation strategies by making trade-offs between the feasibility, uncertainty and adaptability of the evacuation strategy, which can be of assistance for evacuation managers to determine robust evacuation policies for their buildings. To do so, the following research question will be central:

"How can effective evacuation strategies in a large building be determined based on WiFi data?"
Substantiated with the following sub questions:

1. What are evacuation strategies, which evacuation strategies are relevant for large buildings and how can their effectiveness be measured?
2. What are user profiles and how can they be used to model evacuation behaviour and improve evacuation strategies?
3. For this case study, which users profiles and other characteristics can be derived and are important in WiFi data?
4. How to model an evacuation and its possible strategies in a large building?
5. How do different scenarios influence the effectiveness of evacuation strategies?

6. Based on the derived user profiles and WiFi data characteristics, what are effective evacuation strategies?

To answer these research questions, the structure of the study is as follows. First, an extensive literature study is performed to define core concepts and present an overview of related work (Chapter 2). Secondly, a large data set of WiFi traces of the TPM faculty of the TU Delft is acquired and used to derive user profiles and characteristics (Chapter 3). Thirdly, an agent-based evacuation model has been created to model evacuation behaviour and evacuation strategies (Chapter 4). Lastly, general and data-driven experiments using the Exploratory Modeling and Analysis (EMA) workbench are conducted to interpret (Chapter 5) and conclude (Chapter 6) the results.

2

THEORETICAL BACKGROUND

This chapter provides the theoretical background and the concepts used in this study. The key points this chapter will elaborate on evacuation strategies and its implications, state-of-the-art evacuation modeling, how data can be used in these models and the application of WiFi data in such models.

Evacuation situations and its preparedness, and strategies have been extensively studied (Pauls, 1980; Sime, 1985; Fruin, 1987; Canter, 1980; Santos and Aguirre, 2004; E. D. Kuligowski and S. M. Gwynne, 2010; Cuesta *et al.*, 2015). In order to reduce the number of casualties during evacuation situations, moving the evacuees as quickly as possible to safety is ultimately the end goal. Therefore, the understanding of crowd and evacuation dynamics has become a subject from researchers in different fields, including psychologists, sociologists, physicists, computer scientists and traffic scientists (Helbing and Johansson, 2013).

Research in the field of evacuation can be divided in two domains: (1) the descriptive or observational domain, and (2) the prescriptive or interventional domain (Chiu and H. X. Liu, 2008; Vermuyten *et al.*, 2016a; Vermuyten *et al.*, 2016b; Santana *et al.*, 2020). Descriptive evacuation studies aim to "assess, explore, describe or predict the likely evacuation behaviour either through experimentation or numerical simulation" (Vermuyten *et al.*, 2016b). On the contrary, prescriptive evacuation studies aim to recommend evacuation managers about interventions and identify possible ways to improve the evacuation, rather than predicting and evaluating the performance (Tsang, 1997; Chiu and H. X. Liu, 2008; Romanski and Van Hentenryck, 2016). The prescriptive domain is of more value for future recommendations and policy, however the domain is underlooked (Hu, X. Wang, *et al.*, 2018; Haghani, Sarvi, Shahhoseini, and Boltes, 2019; Vermuyten *et al.*, 2016b). Efficient evacuation strategies improve the evacuation time and lower the number of casualties (Schadschneider, Klüpfel, *et al.*, 2009), making the underlooked domain an important study.

2.1. EVACUATION STRATEGIES

An evacuation strategy is a blueprint for how to evacuate in times of an emergency. Nowadays, safer building evacuation strategies are an important concern (Aleksandrov *et al.*, 2019) and safety requirements are considered essential in the building plans of low-rise or high-rise buildings (E. Galea, Sharp, *et al.*, 2008). The evacuation strategy guides the escape plan of the evacuee. The escape plan is determined during the pre-movement time and defines the path and behavior of the evacuee (Oven and Cakici, 2009). Therefore, the evacuation strategy should be tailored to achieve an optimal evacuation performance (Abdelghany *et al.*, 2010; Kurdi *et al.*, 2018). The optimisation of the evacuation performance falls within the aforementioned prescriptive domain of research.

Past research has tried to optimise the evacuation efficiency by enhancing evacuation strategies. Aleksandrov *et al.* (2019) and Ding *et al.* (2017) are evidently helpful in optimizing evacuation strategies by giving advice on how to divide the occupation rate of stairs and (evacuation) lifts. Zeng *et al.* (2017) evaluate and optimise the speed of evacuees on stairs. J. Zhou *et al.* (2019) and Hu and X. Liu (2018) effectively optimises the number of people in groups and its leaders to enhance the total evacuation time. However, these studies do not take the route choice of the evacuee into consideration. Optimising route choice can be done by making the evacuation strategy more intelligent, or smart (Atila *et al.*, 2018; Solmaz *et al.*, 2019; Santana *et al.*, 2020). Smart, or intelligent, evacuation strategies are based on real-time IoT data from crowd monitoring techniques, such as cameras, sensors, smart device data and radio technologies to create dynamic evacuation routes (Nguyen *et al.*, 2019; Q. Li, Y. J. Liu, *et al.*, 2020; Santana *et al.*, 2020). And while these smart strategies are promising to improve the evacuation efficiency, these researches also state the limitations of such systems in the form of availability of sensors, limited sight of cameras and delayed or inaccurate data. Despite advancements in optimisation of evacuation (Ding *et al.*, 2017; Hu and X. Liu, 2018; J. Zhou *et al.*, 2019; Aleksandrov *et al.*, 2019), the lack of feasibility and increasing uncertainty of one evacuation strategy is worrying. Feasible, practical and generic outcomes should be essential to enhance guidelines for evacuation (Vermuyten *et al.*, 2016b). Therefore, looking at a broader spectrum of evacuation strategies for the evacuation should be evaluated.

2.1.1. TYPES OF EVACUATION STRATEGIES

As indicated before, numerous strategies to enhance evacuation exist. Vermuyten *et al.* (2016b) reviewed over 110 studies which aimed to optimise the evacuation time and categorised these approaches into three different categories: (1) architectural design and infrastructure adjustment, (2) mathematical programming and optimisation of path/departure-schedule planning, and (3) behavioural modification, training and active instructions. For each of these categories several strategies will be elaborated on.

ARCHITECTURAL STRATEGIES

The architectural design approach focuses on approaches that optimise evacuation through "making alterations to the physical space of the movement, i.e. the infrastructure" (Vermuyten *et al.*, 2016b). The architectural design of a building can cause bottlenecks because of the number of exits, hard-to-find exits, and narrow stair passages and exits (Purser and Bensilum, 2001; Koo *et al.*, 2013). Therefore, multiple studies used architectural design changes to improve the evacuation efficiency based on the spatial positions of exits, width of exits and stairs and placing obstacles in front of exits. In regards to new buildings, Aleksandrov *et al.* (2019) and Haghani and Sarvi (2018) advise to use the evacuation strategy as a basis to inform building facility planning.

A commonly studied improvement is the spatial position of exits. Tavares (2010) argues that the relative distance between exits is of more importance than the maximum travel distance in regards to the evacuation efficiency, especially in high density population scenarios. Tavares (2009), Tavares and E. R. Galea (2010) and Shao and Y.-Y. Yang (2015) claim that positioning the exit in a corner improves the evacuation efficiency, as the occurring queue for the corner exit is less wide. On the contrary, Haghani, Sarvi, Shahhoseini, and Boltes (2019) and Jianyu *et al.* (2019) state that placing the exit in the middle of the wall is more efficient. It is to say that agreement on the spatial position of the exit is lacking, the effectiveness of the positioning depends on the behaviour of the evacuee (i.e., peacefully queuing or rushing) and on the width of the exit (i.e., a wider exit results in a smaller queue).

Next to the spatial position of exits, the width of an exit has been studied as well. According to Haghani, Sarvi, and Shahhoseini (2019), the width of an exit positively correlates with the possible flow throughput of the particular exit. Other studies, such as Kretz *et al.* (2006), Seyfried *et al.* (2009) and Garcimartın *et al.* (2016), found the same positive correlation of the flow throughput and the width of bottlenecks. Rationally, this conclusion seems valid. However, increasing the width of a bottleneck or exit is not that straight-forward. Therefore, just as the spatial position of exits, this possibility of increasing the evacuation efficiency should be evaluated during building facility planning.

Another commonly studied architectural improvement is obstacle placement. Helbing, Farkas, *et al.* (2000) was the first to conclude that placing an asymmetrical pillar in front of the exit improves the evacuation efficiency. Many other studies examined the effect of obstacle placement on evacuation. Shi *et al.* (2019) found that the width and the distance of the obstacle is of influence for the relative efficiency. Jiang *et al.* (2014) indicated that an obstacle is only efficient when it is placed on the side of the exit instead of in front. X. Zheng, W. Li, *et al.* (2010) and Y. Zhao *et al.* (2017) argue that an obstacle should be in the form of a panel rather than a pillar. However, placing obstacles in front of an exit might obscure the exit (Q. Li, Gao, *et al.*, 2019) which can be troublesome for evacuees that are not familiar with the building. Moreover, a recent study by Zang *et al.* (2021) concluded that obstacles even decrease the evacuation efficiency. Therefore, the effectiveness of placing obstacles remains pretty unclear.

PATH AND DEPARTURE PLANNING STRATEGIES

The mathematical programming approach "seeks to find the optimum path planning or departure schedule planning solutions for a fixed given design of the infrastructure and the environment" (Vermuyten *et al.*, 2016b). Finding the optimum path in an evacuation is focused on choosing the nearest exit and taking the shortest route with possible congestion in mind (Z. Fang, Zong, *et al.*, 2011; Teknomo and Fernandez, 2012). However, to do so, complete information to the evacuee is necessary. For example, the evacuee should know all possible exits, corridors, shortest paths and occupancy rates in order to calculate the optimum path. Multiple optimal path planning and exit choice algorithms - e.g., Z. Fang, Zong, *et al.* (2011), Lu *et al.* (2014) and Kang *et al.* (2015) - are often calculated with the availability of complete information, which is not realistic during a real evacuation. Therefore, I will focus on strategies that facilitate providing this information to optimise the path planning and exit choice, e.g. by making use of dynamic or intelligent systems.

Evacuation strategies that facilitate complete information during evacuation have recently become a topic of study and are evidently helpful in improving the evacuation efficiency (Solmaz *et al.*, 2019; Santana *et al.*, 2020). Smart, or intelligent, evacuation strategies are based on real-time IoT data from crowd monitoring techniques, such as cameras, sensors, smart device data and radio technologies to create dynamic evacuation routes (Nguyen *et al.*, 2019; Q. Li, Gao, *et al.*, 2019; Santana *et al.*, 2020). For example, Elkhoukhi *et al.* (2018), uses real-time data to inform evacuees about occupancy rates and guide them to take the less crowded - i.e., efficient - route. Nguyen *et al.* (2019) extends this approach by implementing safety concerns based on building and disaster status. Smart evacuation systems are already being integrated, such as SmartEscape (Atila *et al.*, 2018), Hex (Hex, n.d.) and EvaGuide (Drakoulis *et al.*, 2021), and have become the yardstick for improving evacuation. However, Santana2020 and Nguyen2019 also state limitations of such systems in the form of availability of sensors, limited sight of cameras and delayed or inaccurate data, which can prevent the system from actually working. Besides, such intelligent systems will theoretically improve the evacuation efficiency, while practically being less feasible due to the implementation of such systems and costs. Therefore, one can opt for more feasible strategies that influence the path planning and exit choice, which are not dependent on complete information availability, e.g. dynamic signs, which will be elaborated on in the next subsection.

In regards to departure planning strategies prevailing research focuses on distributing the departure time of evacuees to spread the evacuation and its congestion (Cepolina, 2009; X. Li *et al.*, 2012; Koo *et al.*, 2013; X. Chen and Zhan, 2014). A commonly used strategy in the body of this literature is the phased, or staged, evacuation. In a phased strategy the evacuation takes place vertically (floor by floor) or horizontally (segment by segment) to control the upstream density at bottlenecks and maximise the flow through it (Cepolina, 2009; Koo *et al.*, 2013). For example, Cepolina (2009) used phased evacuation per room by means of an alarm schedule, Z. Fang, Q. Li, Q. Li, L. D. Han, and D. Wang (2011) uses a waiting-time strategy to distribute the density throughout the building, Sano *et al.* (2018) uses a vertical approach by evacuating floor by floor. All of these studies concluded that a staged strategy improves the evacuation efficiency by reducing congestion at bottlenecks, hence increasing the throughput. On the contrary, several studies conclude that a staged evacuation may not necessarily improve the evacuation efficiency (Koo *et al.*, 2013; Gravit *et al.*, 2018; L. Yang *et al.*, 2021). However, these studies do conclude that a staged evacuation reduces the congestion, which can be physically safer for evacuees. Therefore, staged evacuation might be useful in certain situations in which the occurring emergency is not life endangering.

BEHAVIOURAL MODIFICATION STRATEGIES

The behavioural modification approach focuses on "how one can provide effective instructions or advice or training guides to the individuals in order to influence/modify their behaviour" (Vermuyten *et al.*, 2016b). In contrast to the path and departure strategies, behavioural modification strategies aim to modify decisions, actions and behaviour of evacuees individually rather than collectively. To do so, evacuees are influenced by people or emergency facilities, such as alarms, signs, barrier posts and arrows.

Studies that use people to influence the evacuation behaviour of individuals are commonly in the form of leaders, authority figures and (trained) employees (J. Wang *et al.*, 2015; X. Song *et al.*, 2017; Formolo *et al.*, 2018; Wal, Formolo, Robinson, *et al.*, 2021). For example, J. Wang *et al.* (2015), assigned a virtual leader during an evacuation who guides evacuees to safer and more efficient exits in case of congestion. X. Song *et al.* (2017) indicates that having authority - or security - figures during egress may calm down evacuees and direct them to the shortest path available. They also endorse the fact that authority figures are always available, while communication networks might be blocked or damaged. Formolo *et al.* (2018) employed evacuation staff - i.e. regular staff members that did not receive much training to staff members that did - to guide evacuees to the nearest exit available during egress. In all of these studies, evacuee staff were able to increase the evacuation efficiency respectively. According to Formolo *et al.* (2018), the higher the number of evacuation staff members the better, while X. Song *et al.* (2017) and Wal, Formolo, Robinson, *et al.* (2021) conclude that increasing the number beyond four will not increase the efficiency any further. The increase in the evacuation efficiency by using people to guide evacuees is promising. Moreover, this type of strategy also seems feasible, as there is no dependency on connections and availability of sensors. A possible bottleneck might be that staff members are obstructed to reach the destination in time, which mitigates the effect.

Other ways of influencing the individual behaviour of evacuees is through emergency facilities. Nowadays, all buildings should be "equipped with emergency egress facilities complying with the fire safety requirements of the respective country" (Jeon *et al.*, 2019). Emergency facilities, such as alarms, (exit) signs, barrier posts or guidance arrows, should help evacuees to rapidly escape. However, conventional facilities are rather static which might influence the evacuees perception of these facilities (M. Zhou *et al.*, 2019), e.g. according to Xie *et al.* (2012) static exit signs are only observed by 38

A promising solution to improve emergency facilities is to make the facilities more dynamic, e.g. emergency communications, dynamic signs and contraflow traffic. Dynamic signs are "intended to compensate for the complexity of an enclosure and/or where exits are not sufficiently apparent, thereby improving wayfinding efficiency" E. R. Galea *et al.* (2014). Compared to conventional signs, dynamic signs offer promising results as they improve the sensory affordance of guidance signs by means of flashing (led) lights, arrows or even text (E. R. Galea *et al.*, 2014; Duarte *et al.*, 2014; Langner and Kray, 2014; E. Galea, Xie, *et al.*, 2015; Olander *et al.*, 2017). All of these studies derive promising results, as the visibility and intention to follow these signs increases, which leads to an enhanced evacuation efficiency. Another promising strategy is to make the emergency communications - i.e. alarm - more dynamic. The conventional alarm (e.g. slow whoop) often is neglected by evacuees because of doubt - i.e., is this a drill or is this a real emergency - and social influence - i.e., nobody reacts, so I will do the same (Proulx, 2000; Nilsson and Johansson, 2009; Hofinger *et al.*, 2014). This increases the pre-evacuation time, i.e. time before an evacuee starts to evacuate, and has a negative effect on the total evacuation time. Therefore, studies that use a more dynamic alarm (e.g., a predefined spoken alarm, or spoken alarm with real information about the emergency) seems promising. Benthorn and Frantzich (1999), Nilsson and Johansson (2009) and Wal, Formolo, Robinson, *et al.* (2021) successfully use spoken alarms to reduce the pre-evacuation time. However, Wal, Formolo, Robinson, *et al.* (2021) did not reduce the total evacuation time as the immediate evacuation of evacuees increased congestion, resulting in a lower throughput of bottlenecks. A last promising strategy to improve emergency facilities is to implement different forms of traffic. In a conventional evacuation people may intersect each other's path, which slows them down or can cause casualties (Ronchi, Norén, *et al.*, 2015; Ibrahim *et al.*, 2016; J. Zhou *et al.*, 2019). Therefore, one-way traffic or contraflow traffic might be implemented during evacuation to reduce flow intersections and casualties. These flow strategies are commonly used in traffic evacuations and are evidently helpful in reducing the evacuation efficiency (Hobeika and C. Kim, 1998; Urbanik, 2000; Wolshon, 2001; Theodoulou and Wolshon, 2004). However, these strategies have not been experimented with in buildings.

A potential drawback of above mentioned types of strategies is that evacuees may not comply with the provided instructions or guidelines. Therefore, according to Duarte *et al.* (2014), compliance can be seen as the ultimate measure of the effectiveness of such strategies. Many fictional experiments have been done in regards to the compliance of evacuation instructions, such as questionnaires or evacuation drills (Wogalter, 2006; L. D. Han *et al.*, 2007; Duarte *et al.*, 2014). However, as participants of these experiments can not be exposed to real danger, the question remains how one complies during a real evacuation. Therefore, to test several strategies, the compliance should be treated as an uncertainty.

2.1.2. Evaluating effectiveness of strategies

Previous section elaborated on a broad spectrum of possible evacuation strategies within buildings, but what makes a particular evacuation strategy more effective than another one? In order to determine the efficiency of the evacuation strategy measures of effectiveness (MOEs) should be defined. MOEs assess the efficiency of the evacuation routes (space-based) and evacuation duration (time-based) (Z. Fang, Q. Li, Q. Li, L. D. Han, and D. Wang, 2011; Z. Fang, Q. Li, Q. Li, L. D. Han, and Shaw, 2013). Researchers have differentiated multiple MOEs, among which evacuation time is the most commonly used (Kwon and Pitt, 2005; L. D. Han *et al.*, 2007; Z. Fang, Q. Li, Q. Li, L. D. Han, and Shaw, 2013; X. Chen and Zhan, 2014).

Multiple studies use the average clearance time of an evacuation as the leading KPI to evaluate the evacuation efficiency (Løvås, 1995; Urbanik, 2000; Kwon and Pitt, 2005; Varas *et al.*, 2007; L. D. Han *et al.*, 2007; Z. Fang, Q. Li, Q. Li, L. D. Han, and Shaw, 2013; X. Chen and Zhan, 2014). Often, clearance time is defined as the time at which 95% of the total population is evacuated. However, this simplistic method of measuring the efficiency can overlook certain aspects of the evacuation. Figure 1 illustrates three different evacuation scenarios, in which the total evacuation time has been plotted. If we look only at the clearance time, scenario C seems the most effective one, while one might indicate that scenario A or B are more efficient in evacuating most of the evacuees. Therefore, the times at which 50% or 75% of the evacuees have been evacuated can also create valuable insights, as is used by Franzese and L. Han (2002). In addition, Urbanik (2000) argues that using the standard deviation of the evacuation time also provides more insight than the total evacuation time alone.

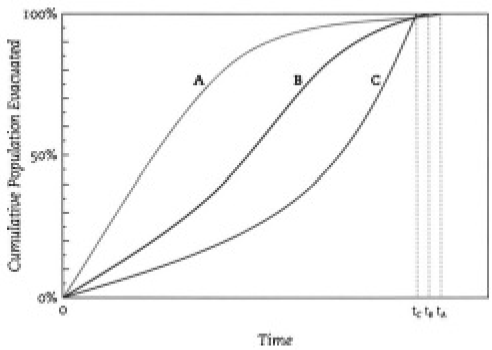

Figure 2.1: Evacuation time for different evacuation scenarios

Another commonly used time-based MOE is the delay experienced by an individual evacuee, which goes hand-in-hand with the individual travel time and the (individual) exposure time (L. D. Han *et al.*, 2007; Z. Fang, Q. Li, Q. Li, L. D. Han, and D. Wang, 2011; Z. Fang, Q. Li, Q. Li, L. D. Han, and Shaw, 2013). The individual delay and travel time can indicate whether bottlenecks are still present, how an individual perceives the evacuation, and where there is room to improve (S. P. Hoogendoorn and Daamen, 2005). However, the individual travel time should not be used as a measurement to evaluate the complete evacuation. Evacuees might not follow evacuation instructions and use other routes instead, which makes the MOE dependent on the compliance of the evacuees (L. D. Han *et al.*, 2007). Therefore, this MOE is only of assistance in assessing where to improve the evacuation strategy and optimally should be used in a sensitivity analysis to indicate uncertainties. Furthermore, the individual delay and travel time also correlates with the (individual) exposure time (e.g., to airborne toxins and radiation) (L. D. Han *et al.*, 2007; H. Zheng *et al.*, 2010; Freire *et al.*, 2013). Nevertheless, the exposure time will not be used in this study since the emergency is not simulated in the form of hazardous matter.

Besides time-based MOEs, space-based MOEs can generate performance insights as well. The density at congestion points and bottlenecks (e.g., stairs, entrances, exits, small corridors and elevators) and the average speed of evacuees are the most commonly used (S. P. Hoogendoorn and Daamen, 2005; J. Zhou *et al.*, 2019; Aleksandrov *et al.*, 2019; Vermuyten *et al.*, 2016b). On one hand, these MOEs create value for the evaluation of the evacuation, by indicating the most crowded bottlenecks and possible improvements. On the other hand, these MOEs do not depict the performance of the evacuation itself. For example, the density distribution among bottlenecks might not be optimal, but the evacuation strategy can be the most optimal one. Therefore, space-based MOEs should be used to calibrate the evacuation strategy rather than evaluating the performance.

2.2. Evacuation modeling

Evacuation modeling aims to understand the evacuation processes by means of a model, a model "helps us to simulate, visualize, manipulate and gain additional information about the process being represented and, therefore, improve life safety" (Cuesta *et al.*, 2015). Simulation modeling and experiments are the main methods applied to evaluate and improve evacuations (B. Liu *et al.*, 2018). In most models, "individuals are treated as autonomous agents, and these individuals can perceive information and decide independently based on their own behavior rules" (B. Liu *et al.*, 2018).

2.2.1. Overview of different approaches

Evacuation models can be divided into two categories: microscopic models and macroscopic models (Ding *et al.*, 2017; B. Liu *et al.*, 2018; Yao *et al.*, 2019). Microscopic models treat evacuees as individual entities, whose behaviour is determined by physical and social law (Twarogowska *et al.*, 2014). Macroscopic models treat the crowd as a whole and are described by averages such as the density, speed and location (Hughes, 2003; Treuille *et al.*, 2006). Throughout the years, researchers used multiple methodological approaches for evacuation modelling. X. Zheng, Zhong, *et al.* (2009) indicate seven different methodological approaches for evacuation modeling: cellular automata (microscopic), lattice gas (microscopic), social force (microscopic), fluid dynamics (macroscopic), agent-based (microscopic), game theory (macroscopic) and experiments with animals (microscopic). As can be seen, the macroscopic models are outnumbered. According to Goatin *et al.* (2009), articles in which macroscopic models are used are fewer than microscopic models. An important argument for this phenomenon is that we are able to handle computationally expensive models better and better, which shifted the majority of the used models towards microscopic (Wagner and Agrawal, 2014). Microscopic models are computationally more expensive since they can simulate low-level phenomenon of evacuees and are used for numerical simulations and experiments (Hamacher and Tjandra, 2001; X. Zheng, Zhong, *et al.*, 2009; Ronchi, Corbetta, *et al.*, 2017). In regards to this study, microscopic models are also able to make use of external input data and are often used to simulate smaller areas, such as buildings and events.

Next to the different methodological approaches of evacuation modeling, the general framework for describing human behaviour and movement in evacuation modeling can be assigned to a three-layered approach (S. P. Hoogendoorn, 2001; Haghani and Sarvi, 2018; Kurdi *et al.*, 2018; Haghani, Sarvi, Shahhoseini, and Boltes, 2019). This framework represents the decision-making process during evacuation for modeling purposes in three layers: (1) a strategic layer, (2) a tactical layer, and (3) an operational layer. The strategic layer describes "what-to-do" and can be modelled by three behavioural states according to Reneke and Reneke (2013): normal, investigating and evacuation state. The tactical layer describes "where-to-go" and can be modelled by the Protective Active Decision Model by Lindell and Perry (2012), Belief Desire Intention framework (Lee, Son, *et al.*, 2010; Okaya and Takahashi, 2011) and a route calculation algorithm, such as Dijkstra or A*. The operational layer describes "how-to-get-there" and can be modelled by a locomotion model, such as social force or optimal step (Kleinmeier *et al.*, 2019). An important assumption within the framework is that humans act rationally and are not physically or mentally disabled. This three-layered framework has been recognised by many authors and is widely used to describe/simulate/model human behaviour in crowds and during evacuations (Wagoum, 2013; Haghani and Sarvi, 2018; Haghani, Sarvi, Shahhoseini, and Boltes, 2019; Vermuyten *et al.*, 2016b).

2.2.2. DATA-DRIVEN MODELING

The aforementioned methodological approaches are currently the main approaches used for evacuation modeling. These approaches provide the fundamental framework for simulating evacuation (B. Liu *et al.*, 2018). A limitation for these methods is the lack of quantitative data on evacuation situations (Gu *et al.*, 2016). The lack of data might result in incorrect parameter inputs and behaviour rules of agents and can skew simulation results (B. Liu *et al.*, 2018).Therefore, data to supplement evacuation models introduces a new way of evacuation modeling: data-driven evacuation modeling. Based on gathered, or retrieved, data, the evacuation model can better reproduce real-life behaviour as is done in multiple studies (Purser and Bensilum, 2001; Z. Fang, W. Song, *et al.*, 2010; Z.-M. Fang *et al.*, 2012; Gu *et al.*, 2016; B. Liu *et al.*, 2018; Yao *et al.*, 2019).

Data to supplement evacuation models is usually used to enhance the visual realism of evacuation simulations (Yao *et al.*, 2019) and can be in multiple forms, such as video, network traces or questionnaires. For example, Yao *et al.* (2019), Lee, S. Jain, *et al.* (2021) and Wal, Robinson, *et al.* (2021) use video footage to evaluate and observe how humans move in buildings during evacuation, and use this as an input for the evacuation model to better reproduce real-life behaviour. Lerner *et al.* (2007), B. Liu *et al.* (2018), Xu *et al.* (2019) and Tian *et al.* (2020) use video footage to evaluate the path and exit choice of evacuees. Wal, Robinson, *et al.* (2021) used video footage to analyse risk behaviors during evacuation to create emergency communication strategies that might reduce these risks. Wachtel *et al.* (2021) used bluetooth sensor data in order to identify different types of evacuee movements. Martın *et al.* (2020) used Twitter and survey data to investigate whether evacuation behavior differs by race to use this in future models. Wagner and Agrawal (2014) employed medical data to assess the health condition of evacuees. Van der Wal (2019) interviewed several experts to retrieve data about risk behaviors, which can be used as an input to an evacuation model. Arnold *et al.* (1982) used a questionnaire answered by occupants in a building to gather data about people's behavior. Unlike interviews and questionnaires, videos and network traces can explicitly evaluate real human behaviour, and therefore are more valid as an input data source to base the model on.

Despite the fact that data-driven modeling improves the usability and validity of the evacuation model, the scene adaptability decreases as the input data mainly focuses "on training models for specific scenarios and apply them to the same scenario" (Yao *et al.*, 2020). Especially for interviews, questionnaires and to a lesser extent video footage, this might have implications if the data is used to enhance the evacuation. Ibrahim *et al.* (2016) argue that uncertainties of evacuation scenarios, may worsen the crowd calamity circumstances, which aligns with the lack of scene adaptability of several input data sources. Therefore, network traces or video footage that capture several scenarios seem more promising to evaluate and enhance evacuation strategies.

2.2.3. WIFI DATA AND USER PROFILES

As mentioned in 2.2.2 network traces are a promising application to evaluate and enhance evacuation strategies. Network traces, such as radio frequency, Bluetooth and WiFi, are able to track the movement of connected users. All of these technologies have their own advantages and limitations. Radio frequencies are very accurate and do not introduce any privacy concerns, as it is based on the reflections of the signals directed to humans (Adib and Katabi, 2013). Despite these advantages, radio frequencies do not perform well in crowded areas due to inability to distinguish individuals (Santana *et al.*, 2020). Bluetooth traces are also very accurate and devices are often equipped with a Bluetooth functionality, however Bluetooth requires a dense infrastructure as the Bluetooth signal only reaches a limited distance (Opoku, 2012; Santana *et al.*, 2020). On the other hand, WiFi has greater reach, is able to handle crowded areas better and can be used by the increasing pool of IoT-devices that are based on WiFi signals (Zafari *et al.*, 2019; Mohottige *et al.*, 2020). In this regards, WiFi traces seem to be the most promising application to evaluate building occupants and one of the most studied movement tracing technology in literature (Woo *et al.*, 2011; Kumar *et al.*, 2014; Depatla and Mostofi, 2018).

WiFi traces can have multiple use cases. For example, Orsini *et al.* (2019) used WiFi traces to train neural networks to predict airport passenger behavior, Woo *et al.* (2011) employed WiFi traces to position coworkers and vehicles, Depatla and Mostofi (2018) use WiFi traces to count the number of occupants in a building, Ruiz-Ruiz *et al.* (2014) derived user roles out of WiFi traces to inform building facility planning, Calabrese *et al.* (2009) retrieved common usage characteristics of buildings out of WiFi traces. These examples can be categorized by tracking or user profiling, as are the main categories of WiFi studies reviewed by Redondi and Cesana (2018). Concerning evacuation, it is to say that evacuation studies that use WiFi data are only present in the tracking domain: Mohottige *et al.* (2020) successfully detect the event of evacuation based on WiFi data. Moreover, they state their study is "the first work to show that building evacuations can be evaluated systematically and accurately at scale using WiFi data". This poses new possibilities for evacuation studies. Particularly user profiling can generate insights about how, when and where people move, which can be valuable for evacuation studies.

A user profile is a virtual representation of a user, in which information about preferences, behaviours and interests are captured (Schiaffino and Amandi, 2009; Tang *et al.*, 2010; Cufoglu, 2014; Kanoje *et al.*, 2015). Based on gathered data of the user, patterns and characteristics can be extracted, which are often used to personalize content, advertisements and social approaches (Cufoglu, 2014; Trusov *et al.*, 2016; Liang, 2018; S. Zhao *et al.*, 2019). In regards to WiFi data, user profiling can be used to create a profile in which routes, entrance/exit choices, occupation times and visit frequencies can be captured (Qin *et al.*, 2013; Ruiz-Ruiz *et al.*, 2014; Kalogianni *et al.*, 2015; Mohottige *et al.*, 2020). For example, based on WiFi data Ruiz-Ruiz *et al.* (2014), Abedi *et al.* (2014) and Kalogianni *et al.* (2015) classify users into user roles, such as employee, one-time visitor or frequent-visitor, and usage patterns, such as frequency, duration and utilization peaks. These extracted roles and usage patterns are promising to evaluate and enhance evacuation, as they create insights in potential bottlenecks, route choices and the initialisation of evacuation variables, such as compliance and familiarity with environment.

3

USER PROFILING

This chapter focuses on the knowledge discovery of WiFi data. First, the chosen method to extract knowledge out of WiFi data will be elaborated on. After, a WiFi traces data set of the TU Delft is acquired to derive knowledge for the input of the evacuation model.

3.1. METHODOLOGY

To extract knowledge out of WiFi data, data mining techniques will be used. Data mining, also known as knowledge discovery, can be described as "the discovery of structures and patterns in large and complex data sets" (Hand and Adams, 2014). Data mining methods can be categorized as predictive or descriptive (Elkan, 2013; N. Jain and Srivastava, 2013; Slimani and Lazzez, 2014; Garcıa *et al.*, 2015). Predictive methods aim at retrieving future values of data using existing data (Jovanovic *et al.*, 2002; Jonas and Harper, 2006; Soni *et al.*, 2011), while descriptive methods identifies interesting regularities, patterns and relationships (Siraj and Abdoulha, 2007; Peng *et al.*, 2008). As this study aims to retrieve user roles and usage patterns in the TU Delft building based on existing data, instead of predicting user roles of new occupants, descriptive methods will be used.

Peng *et al.* (2008), Siraj and Abdoulha (2007) and N. Jain and Srivastava (2013) distinct three different methods for descriptive knowledge discovery: summarization, clustering and association ruling. Summarization, or exploration, is used to explore the data set and map the data into subsets (Dunham, 2006). Statistics such as mean, variance, correlation and frequencies are derived to characterize the general properties of the data set (Remondino and Correndo, 2005; Siraj and Abdoulha, 2007; N. Jain and Srivastava, 2013). Clustering partitions the set into classes which are similar based on characteristics or behavior (Remondino and Correndo, 2005; Siraj and Abdoulha, 2007). Association ruling aims to find patterns that describe categorical data based on if-then structures (Siraj and Abdoulha, 2007; Slimani and Lazzez, 2014), i.e. 80% of people who used A to enter the building, also used A to exit the building.

In this study the goal of descriptive data mining is to retrieve temporal and spatial features, and user roles out of the data set. To retrieve individual (per user) and general (per population) temporal and spatial features - such as number of visits, visit durations, used entrances and exits, occupancy rates and usage rates - the summarization method will be used. The categorization of users into user roles will be done by the clustering method. To do so, a rule-based classification mechanism that classifies user roles based on the temporal and spatial features is used. These methods will be elaborated further in their sections respectively.

3.1.1. DATA COLLECTION

In collaboration with the TU Delft's “Data Platform for Researchers” a representative data set was collected. This data consists of WiFi traces from all of the buildings that are present on the TU Delft campus. The TU Delft uses the ‘eduroam’ wireless network infrastructure, which makes use of linked authentication servers which can be used across the whole campus (Eduroam, n.d.). As the network infrastructure is linked, building occupants can be tracked across buildings and its floors.

WiFi traces are collected through sensors, such as WiFi Access Points (APs), deployed across the campus. These APs record detections and connections of WiFi devices, extract its MAC address and log the trace accordingly (Chilipirea *et al.*, 2018). The following elements are logged within one trace:

- MAC Address
- Timestamp of the detection of the device by the AP
- Name of the AP

By following multiple traces of the same MAC Address their movement and visiting sessions can be replicated. As the location of the APs is known (e.g., on which floor and next to which entrance, exit, stairs or elevator) it can be derived how long the user is in the building and which exit or entrance he or she takes. For example, WiFi data is able to provide how a building occupant moves through the building: the user enters through the main entrance, takes the stairs to the first floor and sits there for 90 minutes, after which he takes the stairs back to the first floor and exits through the main entrance.

For this study ethical approval was granted by the ethics committee of the TU Delft, as an important concern for the collection of WiFi data is privacy. All data one collects about a user should be compliant with the GDPR. The GDPR (GDPR, n.d.) indicates two categories of compliance: data protection and data privacy. Data protection is about keeping the data safe, whereas data privacy is about empowering users to make their own decisions about the application of their data (GDPR, n.d.). To comply with the GDPR in this study, a Data Management Plan (DMP) was created and submitted to the TU Delft's data steward and ethics committee. A DMP is a "document that describes how you will treat your data during a project and what happens with the data after the project ends" (Michener, 2015). According to the data steward and the ethics committee, the DMP should consider a privacy-aware solution for the collection of MAC Addresses, as MAC Addresses can be re-associated to a specific device. To do so, the TU Delft's Data Platform for Researchers automatically hashes MAC Addresses of devices, which has also been done in other studies in regards to WiFi traces (Ruiz-Ruiz *et al.*, 2014; Redondi and Cesana, 2018; Mohottige *et al.*, 2020).

3.1.2. DATA CLEANING

In order to derive results out of the WiFi data data, a representative data set should be used. The process from raw data to usable data is called data cleaning. As the data is predefined in the documentation of the *Data Platform by Researchers*, the only cleaning that needs to be done is selecting the meaningful variables and translating the timestamps to actual time. In addition, the data will be checked for duplicate devices, i.e. a person has a connected smartphone and laptop at the same WiFi network, as this might skew the results. Table 3.1 represents how the cleaned data set looks like.

MacAddress	Time	First Time	Device	Location	AP Name
A4067638	Thursday, July 01, 2021 01:31:11	Monday, May 17, 2021 08:36:35	Intel-Device	TUDelft >30-IKC_ISD-FMVG >FMVG-1e Verdieping	A-30-0-019
45F5E733	Monday, July 05, 2021 08:43:58	Monday, May 17, 2021 08:36:35	Unclassified	TUDelft >30-IKC_ISD-FMVG >IKC_ISD	A-30-0-013
BBE31442	Monday, July 05, 2021 02:46:30	Monday, May 17, 2021 08:36:35	Intel-Device	TUDelft >30-IKC_ISD-FMVG >FMVG-1e Verdieping	A-30-0-014
FD0A9AA	Wednesday, June 30, 2021 02:07:32	Monday, May 17, 2021 09:01:44	iPhone11,2	TUDelft >30-IKC_ISD-FMVG >FMVG-1e Verdieping	A-58-0-037
B9AB9513	Wednesday, June 30, 2021 01:47:23	Monday, May 17, 2021 09:06:46	iPhone11,2	TUDelft >30-IKC_ISD-FMVG >FMVG-1e Verdieping	A-58-0-037

Table 3.1: A snippet of the cleaned data set

Furthermore, while collecting the traces, a built-in function was created to only collect the traces of the TPM faculty building. This function also prohibited duplicate traces from being added, as the collection was done real-time but could not prevent older traces from being retrieved multiple times.

3.2. RESULTS

The results have been derived out of the cleaned data set, which consists of 3956 traces of the TPM Faculty building of the TU Delft. The traces date from July 07 to July 14. The results can be found in table 3.2.

Outcome	Value
People observed	834
People entering through main entrance	100%
Mean people per day	104
People visited >1 day	122
People visited >2 days	0
People visited >3 days	0
People visited >4 days	0
Familiarity over a week	14,62%

Table 3.2: Overview of outcomes derived out of the available WiFi data

According to the results, only 122 people visited the TPM faculty more than once during the week of July 07 to July 14. Especially in regards to the visiting policy of buildings at the TU Delft during COVID-19, which state that visits to the campus should be minimized and only when necessary, this number seems feasible. When looking at the familiarity, the assumption was made that if a person visits more than once during a week, the person is familiar with the building. However, in regards to COVID-19, only people that work at the TPM faculty are allowed to visit. In other words, the familiarity of the people should realistically be close to a 100%.

It is to say that a lot more knowledge out of WiFi data can be derived. However, in regards to the scope of this study and the generation of the WiFi traces during COVID-19, these results have been chosen to present. These results can be implemented in the form of the evacuee familiarity of the building and population size. In regards to the population size, familiarity and COVID-19, the derived population size of the WiFi data is considered to be 15-20% of the normal occupancy and the familiarity is considered as invalid, as is argued for above. The experiment conducted with this data can be found in section 5.1. The implications and usefulness of WiFi data will be discussed in section 6.

4

Agent-based model

This chapter presents the agent-based model (ABM) that is developed to evaluate the effectiveness of evacuation strategies and the evuacation strategies that will be tested. First, the substantiation of the chosen modeling method will be presented. After, the model will be explained according to the ODD protocol (Grimm, Berger, Bastiansen, *et al.*, 2006; Grimm, Berger, DeAngelis, *et al.*, 2010), which evaluates the model in terms of purpose, elements, processes and assumptions. Next, the evacuation strategies that will be tested will be introduced and elaborated on. Lastly, the model verification and validation is presented.

4.1. Methodology

For this project, seven different methodological approaches for evacuation modeling have been considered, as derived by X. Zheng, Zhong, *et al.* (2009): cellular automata, lattice gas, social force, fluid dynamics, agent-based, game theory and experiments with animals. While all of these approaches successfully describe evacuation behaviour, only one is fit for purpose for this particular research. Within the proposed model, agents should be decomposed into different types of individuals (user profiles) that are rational and can interact with each other and their environment. Furthermore, emerging behaviour within the model should be captured and analysed in order to calibrate the evacuation strategies. Therefore, based on these requirements, the modelling approach Agent-based modelling has been chosen and will be elaborated on in the following paragraph.

According to Cuesta *et al.* (2015) evacuation modelling has transitioned from pure equation-based models towards agent-based models. To complement this statement, Wagner and Agrawal (2014) reviewed more than 50 papers that used agent-based modelling as an approach to simulate evacuation behaviour. Agent-based modelling (ABM) decomposes a complex system as a collection of autonomous decision-making units called agents (Bonabeau, 2002; X. Chen and Zhan, 2014). With ABM, each agent will be able to follow certain rules and to interact with other agents and its environment during the evacuation, and therefore, fits the purpose of the research. Furthermore, the power of ABM is "its ability to capture the collective behaviour of all agents in a complex system" (X. Chen and Zhan, 2014). Hence, ABM will capture the emerging behaviour during evacuations and is able to use this to calibrate evacuation strategies. Also, in light of the user profiles, each agent can be modelled based on the derived user profiles accordingly.

4.2. Model representation

The model representation follows the ODD (Overview, Design concepts, Details) protocol by Grimm, Berger, Bastiansen, *et al.* (2006) and Grimm, Berger, DeAngelis, *et al.* (2010). The ODD protocol is used to standardize agent-based model descriptions and to increase the replicability. The model will be described in the following order: purpose of the model, model elements, processes, concepts and initialization. The software used to implement the model is called NetLogo.

4.2.1. Purpose of the model

The purpose of the model is to evaluate the effectiveness of several evacuation strategies by comparing them to the base case, i.e. traditional evacuation behaviour without any intervention, in different scenarios. This is done in two ways: (1) exploring the uncertainty space to see under which circumstances an evacuation strategy is effective and robust, and (2) evaluating the effectiveness of evacuation strategies in which the input parameters are derived out of WiFi data. With the results of these two experiments, the question if WiFi data can be used to determine effective education strategies can be answered. The model will be used for simulation in which numerous scenarios can be tested, in this way uncertainties can be differentiated and a robust conclusion can be drawn.

The model will simulate an evacuation in the TPM faculty building of the TU Delft. The first two floors have been chosen to implement in the model. Furthermore, the model will focus on physical and environmental interactions, e.g. walking speed because of density, following instructions and lining up in queue. These types of interactions are sufficient to determine the effectiveness of several evacuation strategies, this demarcation is used in multiple studies (Wagner and Agrawal, 2014; Kurdi *et al.*, 2018; J. Zhou *et al.*, 2019; Aleksandrov *et al.*, 2019). However, this does pose the possible limitations of this study, as psychological influences are left out.

4.2.2. MODEL ELEMENTS

The model contains three hierarchical levels: individual, spatial and environment. First, an overview of the used map will be presented. Secondly, the individual level will be elaborated on. Thirdly, the environment level will be explained and lastly the temporal and spatial scales will be presented.

MAP

As stated in subsection 4.2.1, the model represents the first two floors of the TPM faculty building of the TU Delft. The image of the model is created by simplifying the original map of the building, this has been done by:

- Omitting all floors higher than the first - Stairs and Exit choice are important aspects in evacuation modeling (Z. Fang, W. Song, *et al.*, 2010; Kurdi *et al.*, 2018; J. Zhou *et al.*, 2019) and as evacuees are assumed to stay on the same stairs all the way to the first floor, the stairs choice behaviour on the upper floors will be the same. This choice has also been made with the increasing complexity and computational capacity in mind.
- Omitting the elevator - The elevator present at the TPM faculty building is relatively small (approximately 6m2) and can only transport 6 people at the same time: this relatively small number is assumed to not influence the outcome of the simulation. Also, traditional evacuation plans exclude elevators, as elevators are prone to losing power due to emergency circumstances (Zu-Ming *et al.*, 2011)
- Omitting rooms and other obstacles - Additional walls and obstacles might increase bottlenecks at positions that are not relevant. These unforeseen bottlenecks may spread the arrival of evacuees at critical bottlenecks (e.g., stairs, exits and intersection points), which can skew the results of the model. Moreover, other studies also use a more simplistic version of the map they are simulating, such as Wagner and Agrawal (2014) and Wal, Formolo, and Bosse (2017).
- Making all of the edges straight - NetLogo uses a grid in which sloping edges are not displayed well unless they are at a 45 degree angle.

Figure 4.1: Actual map versus simplified map of the modelled TPM faculty

Figure 4.1 shows the complete image of the model. Exits and stairs are displayed by means of blue and yellow blocks respectively. The exits and stair in the middle are considered to be the main components of the building, i.e. the components which are always known to the evacuee. The other exits are emergency exits, which are closed under normal circumstances.

INDIVIDUAL LEVEL

The individual level consists of entities called 'evacuees', who are assumed to be homogeneous in demographic data, e.g. gender, age, height and weight. Each individual consists of the following states: familiar, compliant, got-help, phased-decision, walking-speed, reaction-timer, queue-timer, current-floor, destination and staff-member. A possible sub-type of an evacuee is defined in the state 'staff-member?'. This state indicates whether an evacuee transforms into a trained staff member in a particular evacuation scenario. A complete overview of all variables, states and its values related to the 'evacuee' entity can be found in table 4.1. How these states and variables are used in processes of the model will be elaborated on in section 4.2.3

Variable name	**Value(s)**	**Purpose and references**
State	Investigating, evacuating, queueing and waiting	States of an evacuee to base their behaviour
Walking speed	See section 4.2.3	Values are based on (Ibrahim *et al.*, 2016)
Reaction-timer	Uniform random 30	S. Gwynne *et al.* (2009)
Familiar?	true, false	Indicates whether an evacuee is familiar with the building
Compliant?	true, false	Indicates whether an evacuee will be compliant with provided guidance
Got-help?	true, false	Indicates if an evacuee has already listened to guidance
Current floor	0, 1	Indicates the current floor the evacuee is on
Destination	Exit or stairs	The destination the evacuee is moving towards
Staff-member?	true, false	Indicates whether an evacuee serves as an evacuee staff member during the evacuation

Table 4.1: Variables the evacuee is based on

SPATIAL LEVEL

The spatial level consists of static elements which are interacted with by 'evacuees'. In this model these elements are stairs, walls, exits and queues. Each element has been elaborated on its purpose, variables and values underneath.

Stairs

In this model stairs are the only means to travel floors. An evacuee is assumed to always travel downstairs, i.e. an evacuee will not travel up stairs during an emergency. The stairs in the TPM faculty are stairs with a mid-landing area. Mid-landing area stairs are characterised by dividing the stair into two components with a horizontal plane between it (figure 4.2).

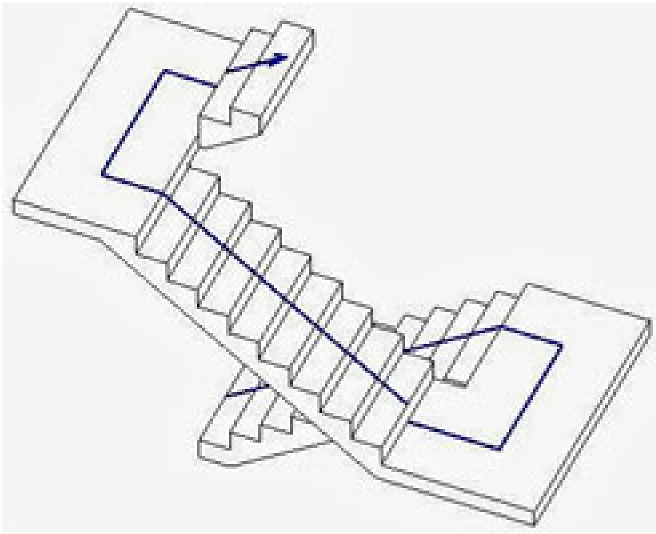

Figure 4.2: An example of mid-landing stairs

The dimensions of the stairs have been rounded, as our model consists of cells of 1x1m (see 4.2.2). By calculating the diagonal plane of the stairs, the time needed to travel downstairs can be calculated. Multiple studies evaluated the speed on mid-landing area types of stairs (Z.-M. Fang *et al.*, 2012; Norén *et al.*, 2014; Huo *et al.*, 2016; Ding *et al.*, 2017; Zeng *et al.*, 2017) and while these studies do not conclude the exact same speed, the mean of these studies will be used as 'walking-speed' on stairs (0.8m/s). The throughput of entering the stairs has been determined by taking the width of the stairs and the assumption that only 1 person per meter can enter the stairs, by doing so the speed on the stairs can also be assumed to be constant, i.e. the capacity of the stairs is fixed and therefore the time one 'evacuee' takes to travel downstairs can be handled as a constant. In addition, because of the fixed throughput, queues may emerge as the number of 'evacuees' wanting to enter the stairs can be greater than the capacity of the throughput (this phenomenon is elaborated on later in this section). All of these values and related variables are shown in table 4.2.

Variable	**Value**	**Explanation**
Stair width	3 m	Rounded and assumed that all stairs are the same width
Diagonal plane	9 m	Rounded and calculated
Mid landing plane	2 m	Rounded and measured
Length stairs	11 m	Calculated (diagonal plane plus mid landing plane)
Walking speed on stairs	0.8 m/s	Norén *et al.* (2014)
Duration on stairs	14 seconds	Calculated (length stairs / speed on stairs)
Capacity of stairs	3 evacuees/second	Assumption based on NetLogo grid

Table 4.2: Variables and values regarding the component 'stairs'

Exits

In this model exits are used to leave the building and consider the 'evacuee' as safe. We distinguish two types of exits: main and emergency exits. Both of these exits are translated to flat doors and rounded in terms of width. The throughput of these exits is also determined by a flow of 1 person per meter. In this case this translates to 3 persons per second for the main exits and 1 persons per second for the emergency exits. If the number of 'evacuees' exceeds the maximum flow throughput, a queue will emerge. The values and related variables of exits are presented in table 4.3.

Variable	Value	Explanation
Main exit width	3 m	Rounded and assumed that all main exits are the same width
Emergency exit width	1 m	Rounded and assumed that all emergency exits are te same width
Throughput exits	1 evacuee/meter/second	Assumption based on NetLogo grid

Table 4.3: Variables and values regarding the component 'exits'

Queues

In this model queues have been predefined around exits and stairs to recreate the so-called 'zipper' or 'clogging' effect in queues. This effect consists of multiple independent staggered queues that are formed in front of bottleneck - i.e., exit or stairs (Wu *et al.*, 2018). The behaviour of this phenomenon has been extensively examined in literature (Okazaki and Matsushita, 1993; Schantz and Ehtamo, 2015; Wu *et al.*, 2018) , and states that people are trying to come as close to the destination as possible exerting forces on the people in front of them, filling in gaps in the queue, hence creating a half-circle like queue in front of the bottleneck (figure 4.3). By predefining these queues in the model, the behaviour in such clogging effects can be recreated as is explained in section 4.2.3.

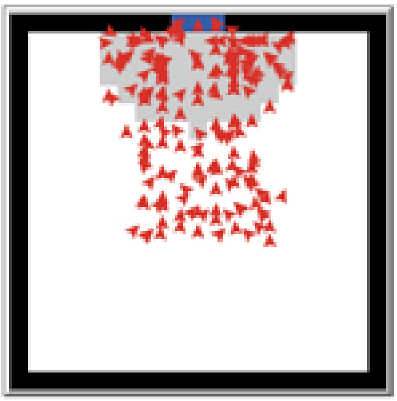

Figure 4.3: An example of a queue in the model

ENVIRONMENT LEVEL

The environment level consists of high-level variables that are used and can not be influenced by other elements. These variables include forces that drive the behaviour used by processes and entities (Grimm, Berger, DeAngelis, *et al.*, 2010). In the model, only variables used to calculate the nearest destination and shortest paths were used to drive the behaviour. Other variables, such as states are elaborated on in the individual level.

Scales

Netlogo makes use of a grid. Each grid cell is called a patch and is based on coordinates. To make calculations easier, each patch is 1x1 meter. A downside to this decision is that we can not make use of float lengths, as widths and heights can only represent integers. However, as we know this limitation beforehand, all elements are created with the same proportion.

In regards to the time, NetLogo makes use of ticks in which actions are performed individually and discretely. In this model one tick represents one second. By doing so, the movement of 'evacuees' can be easily calculated, e.g. an 'evacuee' walks one meter/second, which represents one patch per tick. In this manner, the total evacuation time can be calculated by indicating how many ticks have passed until the last 'evacuee' has exited the model.

4.2.3. PROCESS OVERVIEW AND SCHEDULING

This section elaborates on all the processes undertaken by 'evacuees' and interactions with other elements. Each tick these processes will take place and are calculated by the model. The following subsections indicate the name of the process, the literature or assumptions behind them and a flow chart in which the order of the actions take place.

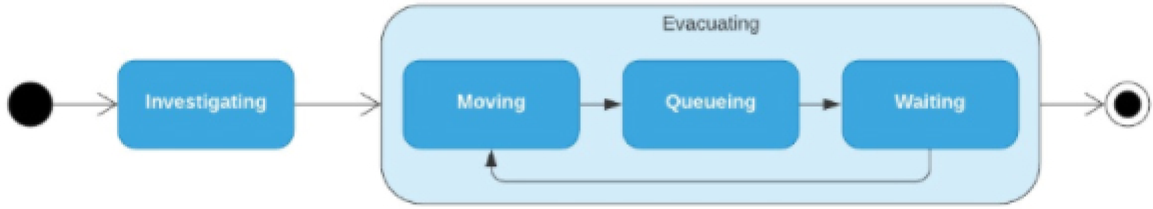

Figure 4.4: State diagram of an evacuee

The processes are driven by the states of the 'evacuees', the states consist of: investigating, evacuating, queueing and waiting (figure 4.4). These states are built up on the three states derived by Reneke and Reneke (2013): normal, investigating and evacuating. In our model the normal state can be omitted, as the emergency happens when the simulation starts. The evacuation state consists of sub-states moving, queuing and waiting, as these states are essential in creating the clogging effect during the evacuation, therefore these states are approached independently in the model. It is important to notice that an 'evacuee' can loop twice through the evacuating state as an 'evacuee' might travel from the first floor towards the exit.

Investigating

At the start of the simulation the time for an 'evacuee' to react is calculated. This is called the investigating state and is determined by the pre-evacuation time, i.e. the time it takes one to start evacuating. In this state, one decides whether he should evacuate, gathers his belongings and decides his evacuation path Reneke and Reneke (2013). To model this phenomenon a database of pre-evacuation time by Lovreglio, E. Kuligowski, *et al.* (2019) was used. Lovreglio, E. Kuligowski, *et al.* (2019) reviewed over 103 evacuations and categorised them by the mean pre-evacuation time. For this study the mean pre-evacuation time of S. Gwynne *et al.* (2009) has been used which holds approximately 15 seconds. To replicate this time, at the beginning of the emergency the pre-evacuation time of each 'evacuee' is calculated by a random uniform distribution of 30 seconds, as the study of S. Gwynne *et al.* (2009) does not present the standard deviation of the mean. It is to say that this pre-evacuation time is smaller compared to other studies. However, we argue that by reducing the pre-evacuation time, other factors that influence the total evacuation time will be more evident. Therefore, the pre-evacuation time is considered as a less important factor within our model. After the predefined pre-evacuation time of the evacuee has passed, the evacuee decides his destination and calculates the path towards it. Algorithm 1 represents the pseudo-code of the process.

```
Data: set reaction-timer random 30
while investigating do
    if reaction-timer < 0 then
        start evacuating;
    else
        set reaction-timer - 1
    end
end
```

Algorithm 1: Investigating reaction-timer procedure

Evacuating

In the evacuating state all processes take place for an evacuee to evacuate successfully. Figure 4.5 represents the processes an evacuee undertakes towards exiting. Each of these processes will be elaborated on in the following sub-paragraphs.

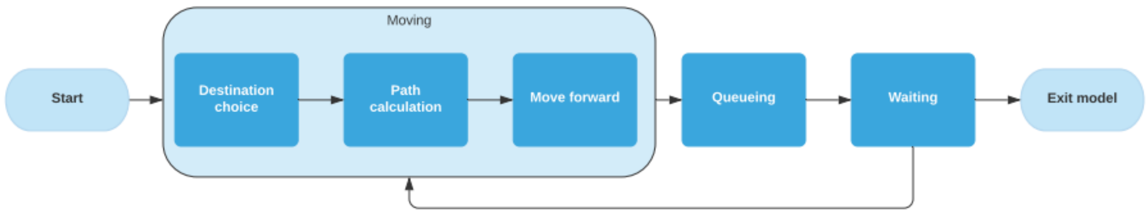

Figure 4.5: Process diagram of an evacuee in the 'evacuating' state

Destination choice
The destination choice takes place when the evacuee transitions from the investigating to the evacuating state. In this model, the choice of the destination - i.e. stairs or an exit - is determined by whether the evacuee is familiar with the building (see figure 4.6). It is assumed that only evacuees that are familiar with the building take the nearest stairs or exit, i.e. 'evacuees' that are not familiar with the building will always take the main stairs or exit. This assumption is widely used in the study of evacuation (Benthorn and Frantzich, 1999; Grosshandler *et al.*, 2005; Nilsson, Frantzich, *et al.*, 2008; Kinateder *et al.*, 2018). Especially in this model this assumption relates, as the exits beside the main exit are emergency exits, which are not particularly visible within the building.

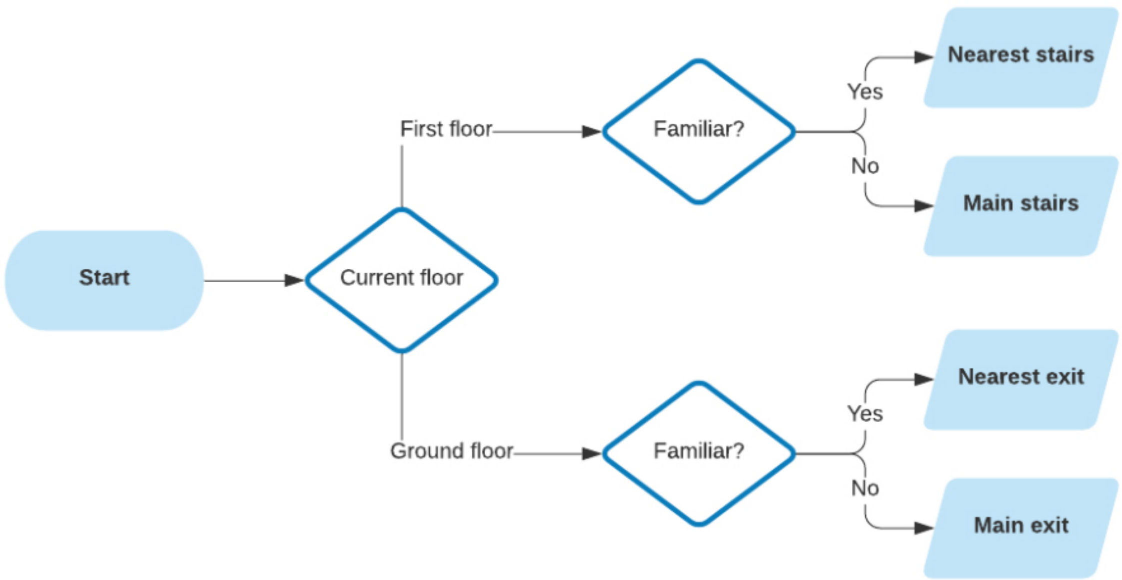

Figure 4.6: Flow diagram of destination choice

Path calculation
If the destination has been chosen by the evacuee, the evacuee should decide its path towards it. In this model, the shortest-path calculation algorithm A* will be used (see figure **??**). The A* path calculation algorithm is widely known and can be considered as the best shortest path algorithm because of its lower computational power compared to e.g. Dijkstra (Cui *et al.*, 2012). By using this algorithm, the model uses the assumption that every evacuee knows the shortest path towards his destination.

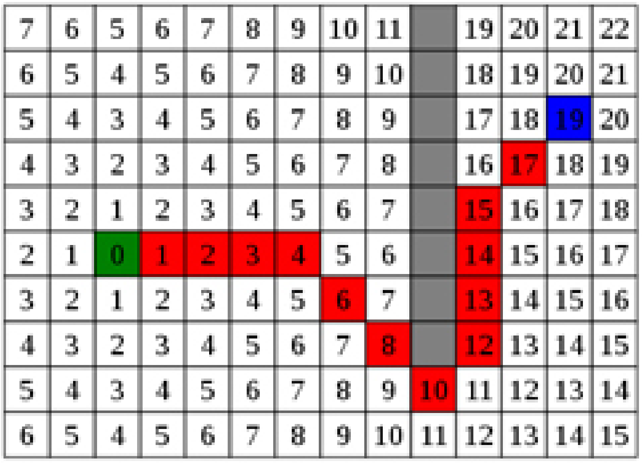

Figure 4.7: Visual representation of the A* Algorithm. The green and blue color indicates the starting and end point respectively. The red point is the path with the least cost, and therefore is considered as the optimal path.

Moving

In the moving process the evacuee is told how to get to his destination and at what speed. The locomotion behavior of the evacuee has been modelled by a heuristics function of the social force model, which calculates the walking speed accordingly. The social force model states that "the walking motivation of pedestrians is expressed in the form of force, and the speed of pedestrians can be changed continuously with the surrounding walking environment" (Yuan *et al.*, 2018). In the heuristics function the force of other evacuees near the actual evacuee is translated to density, which is used as an input for the table of Ibrahim *et al.* (2016). Table 4.4 represents the walking speed of a person under the provided density circumstances, which are used in the model to calculate the walking speed of each evacuee. By using this heuristics function, the walking speed decreases as the density increases, which is a real life phenomenon and described in multiple studies of evacuation (Ibrahim *et al.*, 2016; B. Liu *et al.*, 2018; Wu *et al.*, 2018; J. Zhou *et al.*, 2019).

Density (in persons)	Walking speed (m/s)
< 2	0.8
2	0.7
2 - 5	0.55
5 - 7	0.35
> 7	< 0.1

Table 4.4: Walking speed in the model, derived from (Ibrahim *et al.*, 2016)

While moving, the evacuee can be influenced by strategies if the strategies are visible to the evacuee, which defines the new destination based on the evacuation strategy consequently.

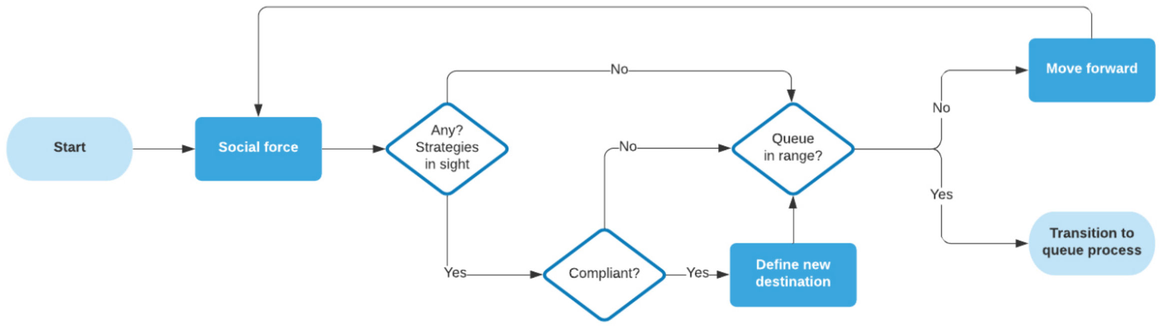

Figure 4.8: Flow diagram of the moving process of an evacuee

Queueing and waiting
The queueing process represents the clogging effect which has been elaborated on in subsection 4.2.3. When entering the queue for a stairs or exit, an evacuee wants to come as close to the destination as possible. If there are more than three evacuees in front of him, the evacuee tries to move left or right in order to find a more optimal spot in the queue. The number three has been chosen as the walking speed is influenced heavily from this number.

If the evacuee reaches the destination and is able to take the stairs or exit the model, a 'first-in-first-out' queue is applied. For example, if 6 evacuees reach the exit simultaneously, only 3 can enter the destination (see subsection for elaboration on the number 3). The first three are able to enter the destination and the other three are put in the queue. The next 'tick' - i.e. second - the three that were put in the queue are released and the queue is filled with other evacuees that are now ready to enter the destination.

4

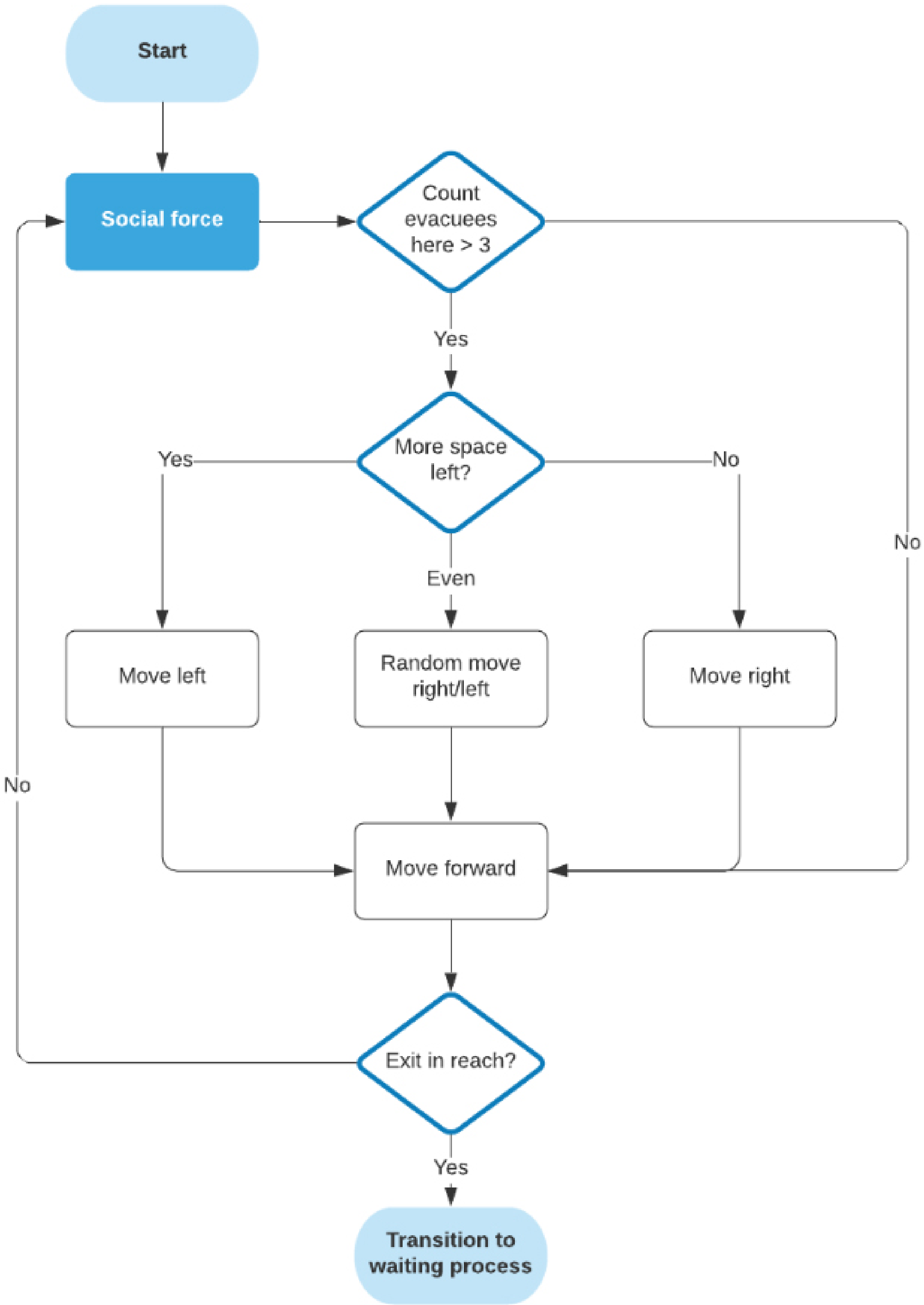

Figure 4.9: Flow diagram of the queueing process of an evacuee

4.2.4. DESIGN CONCEPTS

This subsection indicates which concepts, theories, hypotheses and modeling approaches were used to design the model. This will be done by elaborating on the following concepts: basic principles, emergence, adaptation, objectives, prediction, interactions, stochasticity and observations.

Basic principles. Basic principles such as walking and seeing are modelled under the assumption that evacuees can move in any direction (360 degrees) and can see any object or agent up to 6 meters in front of them.

Emergence. Emergent behaviour in the model is mainly represented by adjusting the walking speed of evacuees to the density accordingly. This will differ for every scenario and therefore produces emergent behaviour. Furthermore, the queues derive emergent behaviour as well, as for every run the arrival times at queues will differ.

Adaptation. Evacuees are adaptive to guiding elements, such as signs or other people. If an evacuee is able to see such an element, the evacuee can decide to change its path. However, the assumption is made that only compliant evacuees will follow these guiding elements. Objectives. The objectives are the criteria that makes an evacuee change his mind. In this case, the objective of adaptation is to take a nearer exit, to eventually decrease the total evacuation time.

Prediction. Prediction indicates how evacuees react to future conditions. In this case, the behaviour in queues apply. Evacuees are assumed to fill the whole queue by looking every tick for a more optimal spot to reach the destination as soon as possible, i.e. the clogging effect. This prediction is based on comparing the number of evacuees in front, left and right of him. Based on these observations, the evacuee predicts what the optimal step for him will be.

Interactions. The model focuses on physical and environmental interactions only. The physical interactions are represented by the social force model; a model that suggests that the motion of pedestrian is driven by forces of others (Helbing and Molnar, 1995). The environmental interactions are based on vision and seeing things that influences the behaviour of the evacuee, such as signs and other people. Psychological influences are left out in the model.

Stochasticity. Parameters that are based on a probability or a mean value, such as pre-evacuation time, familiarity and where the next optimal step will be in a even-crowded queue, are determined by a uniform distribution.

Observations. Observations indicate the outputs of the model. In this model, the key performance indicators evacuation time, mean density, mean waiting time and mean walking speed are calculated and returned after every run. With these KPIs, the effect of an evacuation strategy can be evaluated.

4.2.5. INITIALIZATION

This subsection provides an overview of the starting point of the simulation, i.e. the initial state of the model. The initialization of the model is based on four parameters: population size, distribution of evacuees familiar with the building, distribution of evacuees compliant with guiding elements and the strategy switches. The distributions are initialized by determining a stochastic value between 0 and 1 (e.g. 0.8) and if that value is lower than the value of the familiarity in the model (e.g. 0.9), the evacuee obtains the state familiar. Furthermore, by the initialization, subsets of valid patches, i.e. patches on which evacuees can move, exits, stairs and queues are defined. By subsetting these elements, calculations will be easier to computationally process. Lastly, the position of the evacuees are randomly generated as well; this has been done by selecting a valid patch of the subset and placing the evacuee on it accordingly.

4.3. EVACUATION STRATEGIES

To evaluate evacuation behaviour and test it accordingly, several evacuation strategies will be implemented and tested. These strategies include both structural changes to the model as parametrical changes to e.g. capacity, speed, width and decision-making. Section 2.1.1 elaborated on the several types of existing evacuation strategies to increase the evacuation efficiency. This section detailed three categories as introduced by Vermuyten *et al.* (2016b): (1) architectural design and infrastructure adjustment, (2) mathematical programming and optimisation of path/departure-schedule planning, and (3) behavioural modification, training and active instructions. To explore the effectiveness of these categories, evacuation strategies out of each category are chosen. An overview of all the evacuation strategies that will be tested in the experiments can be found in Table 4.5.

For the first category "architectural design and infrastructure adjustment", four evacuation strategies to

Category	Name	Influences	Studies
1	Wider exits	Flow throughput, clogging effect	Haghani, Sarvi, and Shahhoseini (2019), Kretz *et al.* (2006)
	Wider stairs	Flow throughput, clogging effect	Haghani, Sarvi, and Shahhoseini (2019), Kretz *et al.* (2006)
	Wider both	Flow throughput, clogging effect	Haghani, Sarvi, and Shahhoseini (2019), Kretz *et al.* (2006)
	Obstacles	Flow throughput, clogging effect	Helbing, Farkas, *et al.* (2000), Shi *et al.* (2019)
2	Dynamic signs	Decision making, locations of congestions	Xie *et al.* (2012), E. R. Galea *et al.* (2014)
	Phased evacuation	Pre-evacuation time, locations of congestions, flow throughput	Cepolina (2009), Z. Fang, Q. Li, Q. Li, L. D. Han, and D. Wang (2011)
2,3	Evacuation staff	Decision making, locations of congestions	Formolo *et al.* (2018), Wal, Formolo, Robinson, *et al.* (2021)
3	One-way traffic	Decision making, locations of congestions, flow throughput	Wolshon (2001) and Theodoulou and Wolshon (2004)

Table 4.5: Overview of evacuation strategies used in the experimental set-up

experiment with have been determined. The evacuation strategies "wider exits", "wider stairs" and "wider both" consist of architectural adjustments to the width of the exits and stairs in the model. These strategies have been chosen over the spatial placement of exits, as replacing a whole exit or even stairs is assumed to be less feasible compared to only adjusting existing ones. In regards to the feasibility, obstacles have been chosen as the fourth and last architectural strategy, as obstacles do not require architectural adjustments but rather architectural additions. These architectural strategies are focused on increasing the flow throughput of exits and stairs, which will influence the extent of the clogging effect. The hypothesis is that these strategies improve the evacuation efficiency, especially when queues for these types of bottlenecks occur.

The second category "mathematical programming and optimisation of path/departure-schedule planning consists of two evacuation strategies that will be evaluated in the experiment: dynamic signs and phased evacuation. Other evacuation strategies in this category consist of complete information availability, i.e. smart evacuation systems. In regards to the aforementioned feasibility, these strategies are disregarded. The dynamic signs strategy consist of 12 placed nearest-exit signs in the building. These signs are assumed to be visible to anyone who passes it and directs the evacuee to the nearest-destination at that given point. It is up to the evacuee to follow the sign or not (see elaboration of compliance in section 2.1.1). The dynamic signs strategy influences the destination decision-making of the evacuee (see section 4.2.3), and therefore reduces the congestion at the main destinations of the building. The phased evacuation strategy is derived by Z. Fang, Q. Li, Q. Li, L. D. Han, and D. Wang (2011) and constitutes of a distributed waiting-time strategy to spread the start of the evacuation among evacuees. The waiting-time is distributed horizontally, this implies that the evacuation phases are considered per area (Koo *et al.*, 2013). The phased evacuation strategy influences the pre-evacuation time, as the evacuees depart differently the congestion is assumed to decrease. However, it remains unknown if the increased pre-evacuation time makes up for the decreased congestion at bottlenecks. Also in literature, the effectiveness of these types of strategies remains contradictory (Koo *et al.*, 2013; Gravit *et al.*, 2018; L. Yang *et al.*, 2021).

The third category "behavioural modification, training and active instructions" contains two evacuation strategies: evacuation staff and one-way traffic. The evacuation staff consists of trained employees who guide evacuees towards their nearest destination and inform them about the emergency accordingly (J. Wang *et al.*, 2015; X. Song *et al.*, 2017; Formolo *et al.*, 2018; Wal, Formolo, Robinson, *et al.*, 2021). Six employees have been assigned to take place at intersection points: if the emergency starts the evacuee staff members are asked to take in their positions and guide the evacuees to safety. A downside compared to dynamic signs is that evacuation staff members are not always visible to the evacuee, they might be surrounded by other people or are not wearing any notable clothing. The evacuee staff members influence the destination decision-making of the evacuee, and therefore reduces the congestion at the main destinations of the building. The one-way traffic strategy consists of one-way paths implemented in the building. This strategy is derived from 'traffic evacuation' and is evidently helpful in evacuating networks (Hobeika and C. Kim, 1998; Urbanik, 2000; Wolshon, 2001; Theodoulou and Wolshon, 2004). In buildings this strategy has not yet been evaluated, therefore it is unknown what the effect will be. This strategy influences the flow throughput in the building, as evacuees can not 'cross' each other but only walk after each other. Both of these strategies are also dependent on the compliance of the evacuees, i.e. the evacuees decide whether to follow the guidance or not.

4.4. MODEL VERIFICATION AND VALIDATION

A model will never be a fully accurate representation of reality. However, it can be used to gain valuable insights into the workings and behavior of a system. This process of verification and validation allows a model to be tested on its usability and outcomes for the purpose it has been designed for (Martis, 2006). Model verification can be described as testing whether the model is coded correctly, units are consistent and if there are any numerical errors (Pruyt, 2013). Whereas model validation tests whether the model generates plausible behaviour and meets the objectives of the study (Pruyt, 2013). To do so, several tests proposed by Pruyt (2013) and Ronchi, E. D. Kuligowski, *et al.* (2013) are used, which are elaborated on in each of the following sections.

4.4.1. VERIFICATION

To verify the model, quantitative (hypothetical) tests were performed proposed by Ronchi, E. D. Kuligowski, *et al.* (2013). These tests analyse the human behaviour in the main core components of evacuation models, namely 1) pre-evacuation time, 2) movement and navigation, 3) exit usage, 4) route availability and 5) flow constraints. The proposed procedures (table 4.6) test whether model results and behaviour are representative and accordant compared to current behavioural theories (Ronchi, E. D. Kuligowski, *et al.*, 2013). Each of the elements were tested based on conditions proposed by Ronchi, E. D. Kuligowski, *et al.* (2013) accordingly. All of these tests were passed, therefore the model can be concluded as verified.

4.4.2. VALIDATION

For the validation, the correspondence between the model outcomes and real-world phenomena are assessed qualitatively and quantitatively. Two tests were performed to determine the validity of the model: (1) direct-structure test, and (2) structure-oriented behaviour test (Senge and Forrester, 1980). The latter also includes the evacuation model validation proposed by Ronchi, E. D. Kuligowski, *et al.* (2013), which is a validation method designed for evacuation models in buildings. However, despite the valid boundaries and the ability to replicate real behaviour, there will always be not-modelled factors that influence the outcomes of the system. Also, certain key factors may be an oversimplified representation of the actual system. Therefore, the outcomes of the model can only be used in the context of this study.

The direct-structure tests show that the boundaries and structure of the model are in accordance with reality and the research. In this study two goals are central: (1) the evaluation of the evacuation efficiency of several evacuation strategies, and (2) if an effective application of these evacuation strategies in a building can be determined based on WiFi data. These goals have been translated to an agent-based model in which the substantiation can be found in section 4.2. Out of these goals and outcomes of the model, it can be concluded that the model and its boundaries reproduce valid behaviour to ensure the research goals of this study. It is to say that the boundaries of the model are set to the goals accordingly, other influences on evacuation behaviour such as groups or social influence are disregarded.

Out of the structure-oriented behaviour tests it can be concluded that the behaviour produced in the model is valid. This conclusion is based on the evaluation of two tests: direct extreme conditions test, and face validation and quantitative replicability tests proposed by Ronchi, E. D. Kuligowski, *et al.* (2013). The direct extreme conditions test the limits of the model and whether structures hold under extreme conditions (Pruyt, 2013). The face validation and quantitative replicability tests extend the verification tests executed in section 4.4.1, by comparing the outcomes of the core elements of the model to human behaviour data of evacuation experiments (Ronchi, E. D. Kuligowski, *et al.*, 2013).

The direct extreme conditions test has been applied to the input variables population, familiarity and compliance. As these input variables are so-called ‘sliders’, the values can not represent invalid inputs, i.e. percentages can not become negative or larger than one. By modelling the inputs this way, the model will not explode. Therefore, the model can be concluded as robust and valid.

Core component	Element	Variable	Experimental study	Type
1	Pre-evacuation time	reaction-timer	Lovreglio, E. Kuligowski, *et al.* (2019) & S. Gwynne *et al.* (2009)	Data
2,5	Social force heuristics	walking speed	Ibrahim *et al.* (2016) & Yuan *et al.* (2018)	Data
2,5	Queueing	walking speed, direction, evacuation time	seyfried2009new, daamen2010capacity, von2015spatial, wu2018estimation	Data
3	Destination choice	destination	Benthorn and Frantzich (1999), Grosshandler *et al.* (2005), Nilsson, Frantzich, *et al.* (2008), and Kinateder *et al.* (2018)	Face
3, 5	Flow throughput	walking speed, evacuation time	Haghani, Sarvi, and Shahhoseini (2019)	Data
2, 4, 5	Obstacles	direction, evacuation time	Helbing, Farkas, *et al.* (2000), Jiang *et al.* (2014), and Shi *et al.* (2019)	Data
2, 3	Decisions	destination, reaction-timer	Face validation	Face

Table 4.6: Validation tests, inspired by Ronchi, E. D. Kuligowski, *et al.* (2013)

Table 4.6 shows the face validation and quantitative replicability tests. These tests consist of comparing data of evacuation experiment studies with the main core elements of the evacuation model. By validating each element individually, confidence in the validity of the whole model can be increased. It can be concluded that based on this test, the model is valid compared to experimental evacuation studies. A complete elaboration on each of these elements can be found in the following subsections.

4.4.3. PRE-EVACUATION TIME

The pre-evacuation time is modelled based on the mean pre-evacuation time observed by S. Gwynne *et al.* (2009) in their experimental study. This value holds a mean pre-evacuation time of 15 seconds. An elaboration of how this phenomenon is modelled can be found in section 4.2. To validate this value of the pre-evacuation time, a submodel is used. This submodel contains a small area in which evacuees randomly spawn to evacuate. By running the simulation 600 times and evaluating the mean pre-evacuation time (figure 4.10), it can be concluded that the mean pre-evacuation time used in the model is valid to the observed pre-evacuation time in S. Gwynne *et al.* (2009).

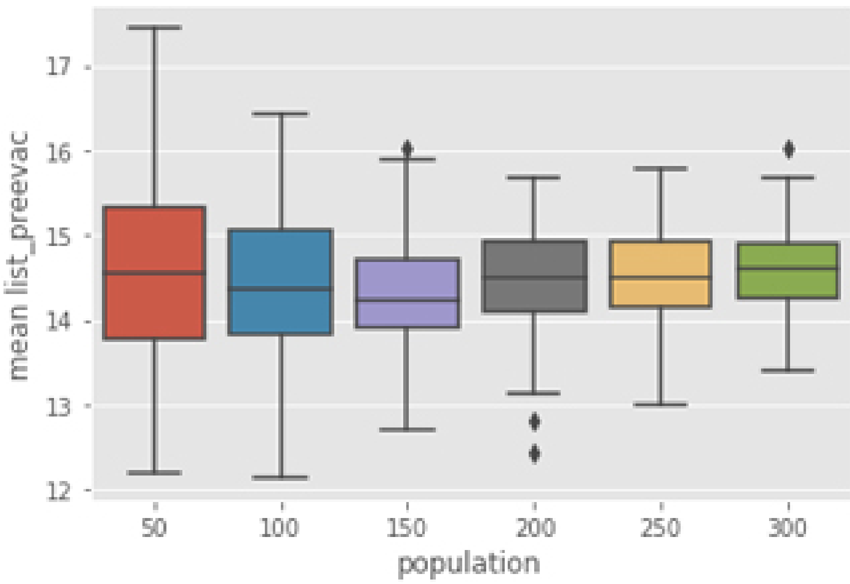

Figure 4.10: Boxplot of the mean pre-evacuation time observed in the validity experiment

4.4.4. SOCIAL FORCE HEURISTICS FUNCTION

The social force heuristics function changes the walking speed according to the density at the location of the evacuee. For a complete elaboration of the social force heuristics function see section 4.2. This social force heuristics function will be validated in a submodel (figure 4.11) with a length of 30 meters. This submodel starts with randomly placed evacuees in the main room (bottom) of the map. To validate if the social force heuristics function works as intended the total evacuation time will be tested as the population size increases. If the population increases, the density increases with it and should decrease the total evacuation time. The ratios will be compared to the data of Ibrahim *et al.* (2016).

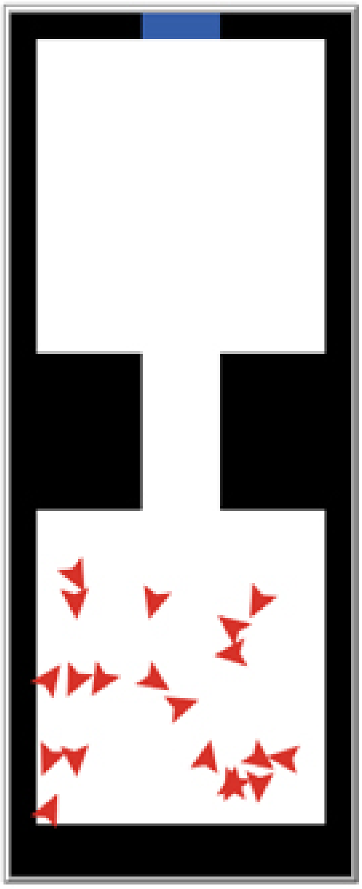

Figure 4.11: Boxplot of the mean pre-evacuation time observed in the validity experiment

To start off, a population size of 1 has been simulated. With this size, the evacuation time should be approximately 30 seconds, as the walking speed is set to 1m/s if there is no decreased density. The results of the experiment can be found in table 4.7.

Population	Evacuation time
1	30
5	35
10	40
20	47
50	64
100	89
200	136

Table 4.7: The evacuation time compared to the population

From the results it becomes apparent that the evacuation time increases as the population increases. Based on this it can be concluded that the density within the building is negatively correlated with the walking speed. The exact same data can not be replicated, however as the relationship between density and walking speed is proven the conclusion that the social force heuristics function is valid can be drawn. A limitation of this function can be that the walking speed is not completely accordant other studies, however this will only decrease or increase the speed of the evacuation; the correlation remains.

4.4.5. QUEUE

The behavior of evacuees in a queue is modelled according to the clogging and zipper effect (Seyfried *et al.*, 2009; Daamen and S. Hoogendoorn, 2010; Schantz and Ehtamo, 2015; Wu *et al.*, 2018). These effects state that people are trying to come as close to the destination as possible, exerting forces on the people in front of them.

A complete elaboration of this phenomenon can be found in section 4.2.3. To validate this phenomenon the process of building up the queue has been visually compared to clogging effects in experimental studies. The top left picture of figure 4.12 shows the emergence of a queue in the model, while the remaining three pictures show the effect in experimental studies.

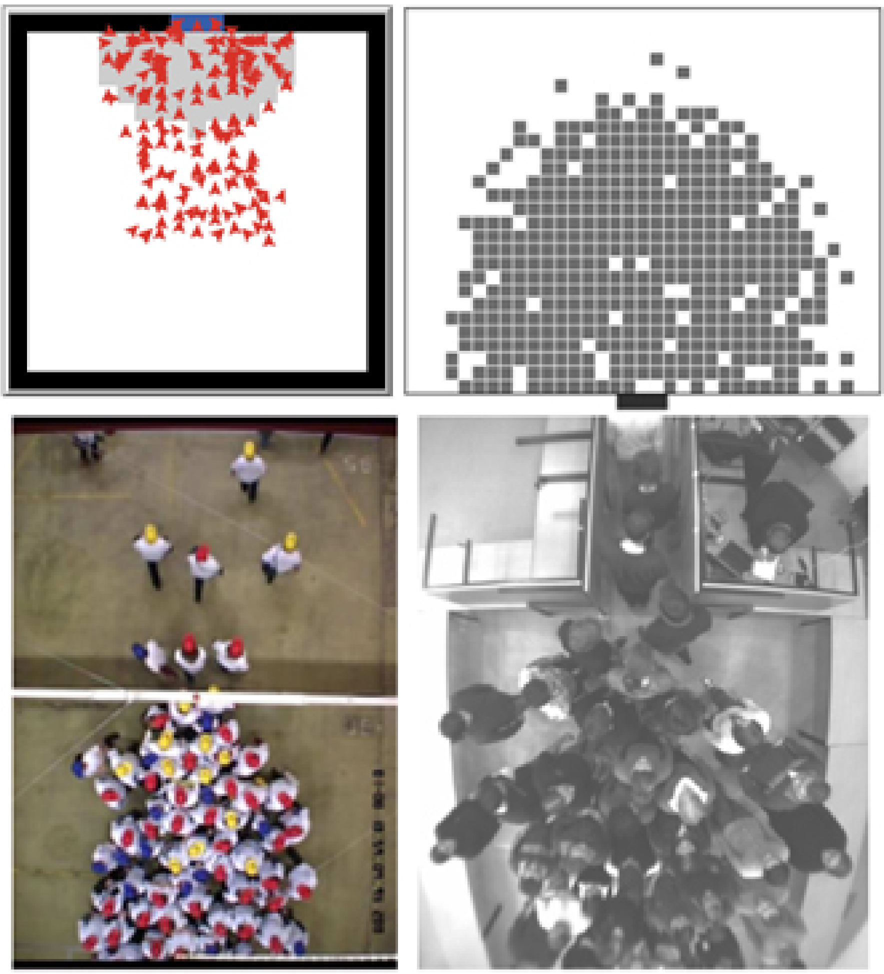

Figure 4.12: Observed clogging effect in this study compared with Seyfried *et al.* (2009), Daamen and S. Hoogendoorn (2010), Schantz and Ehtamo (2015), and Wu *et al.* (2018)

By visually comparing the effects it can be concluded that the modelled queue is valid according to the observed experimental studies. Numerical validity on this comparison is lacking, and therefore might skew the validity of this process. However, it is argued that the structure of the emergence of a queue can be validated, which replicates the behaviour and occurring delay of the evacuees.

4.4.6. DESTINATION CHOICE

The destination choice of an evacuee is based on its familiarity with the building. This assumption is widely used in studies, such as benthorn1999fire, grosshandler2005report, nilsson2008influencing, kinateder2018exit. In the complete model, the main exit and stairs are the one located in the top center. To validate this phenomenon a face validation test will be executed. A population of 10 evacuees will be spawned randomly, if they are familiar they are coloured blue and if they are not red. By looking at the destinations of these evacuees, the phenomenon within the model can be validated. Figure 4.13 shows that the blue evacuees take the nearest stairs, whereas the red evacuee is on its way to the main stairs, while he was closer to another stairway. It can be concluded based on this face validation test that the destination choice is valid.

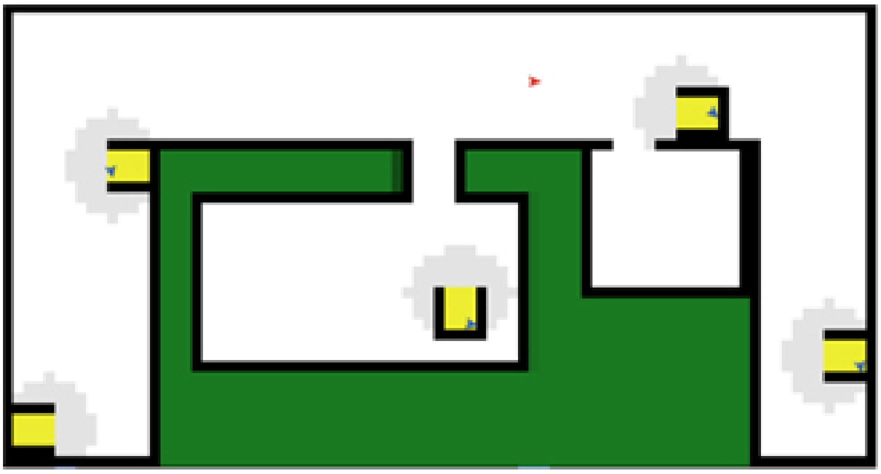

Figure 4.13: Face validation of destination choice of familiar evacuees

4.4.7. THROUGHPUT OF DESTINATIONS

The flow throughput of destinations is an essential element in creating queues. For a complete elaboration of this phenomenon see section 4.2.3. To validate the flow throughput of destinations, i.e. the width of the stairs or exit, a study of Haghani, Sarvi, and Shahhoseini (2019) will be used. This study states that if the width of the exit increases (60cm, 90cm, 120cm), the flow throughput increases, hence reduces the total evacuation time. To validate this phenomenon, the same map as experiment A.3 will be used. To validate the flow throughput compared to the study of Haghani, Sarvi, and Shahhoseini (2019), different widths of the exit will be experimented with. As the NetLogo software makes use of grid cells, the width of the exit can only be assigned to whole numbers. Therefore, an exit width of 1, 2 and 3 meters will be evaluated. For the population a sample size of 200 has been used.

Exit width	Evacuation time
1	213
2	117
3	88

Table 4.8: The evacuation time compared against the width of an exit

From table 4.8 it can be derived that the experiments reproduce the same results as Haghani, Sarvi, and Shahhoseini (2019): as the exit width increases, the flow throughput increases, hence reducing the total evacuation time. Based on this outcome, it can be concluded that this sub model is valid given the boundaries of this study.

4.4.8. OBSTACLES

According to multiple studies (Helbing, Farkas, *et al.*, 2000; Jiang *et al.*, 2014; Shi *et al.*, 2019), obstacle placement in front of a bottleneck, i.e. exit or stairs, can increase the flow throughput of the bottleneck accordingly. To test this phenomenon an experiment is performed. Helbing, Farkas, *et al.* (2000) and Jiang *et al.* (2014) observed that placing an obstacle asymmetrical in front of the exit, increases the flow throughput of the exit. Therefore, 2 obstacles (1 meter by 1 meter) are placed in front of the exit. Eventually the total evacuation time with obstacles will be compared to the total evacuation time without obstacles.

The results presented in table 4.9 indicate that for every population size, an asymmetrical obstacle placement in front of the exit improves the total evacuation time. It can be concluded that this process is valid according to previous studies.

Obstacles	**Population**	**Evacuation time**
False	200	70
True		68
False	400	112
True		104
False	600	154
True		146
False	800	196
True		191
False	1000	239
True		231

Table 4.9: The evacuation time compared obstacle placement under different population sizes

5
Results

This chapter explores the ABM evacuation model by performing simulation experiments under different scenarios. The results and implications of the experiments will be detailed and assessed. The first section consists of elaborating on the design of the experimental set up, i.e. which methods, input parameters and policies will be used. The second section will present the derived results of these experiments.

5.1. Experimental set-up

As mentioned, this study aims to determine (1) effective evacuation strategies under different circumstances and (2) effective evacuation strategies in a case study, in which data is derived out of WiFi data. To address these study aims, experiments that represent various evacuation strategies will be performed and compared with a scenario in which no evacuation strategy is implemented. To do so, the Exploratory Modeling and Analysis (EMA) Workbench created by Kwakkel (2017) will be used. EMA is a research methodology that analyses complex systems by performing computational experiments to improve the decision making under deep uncertainty (Bankes, 1993; Kwakkel, 2017). The EMA workbench is a software package library that allows a user to connect his model and access various exploratory modeling and experiment techniques using Python. For the EMA workbench to produce results, the uncertainties, policies and outcomes of the model should be defined. By predefining a range of values in which uncertainty parameters can occur, different scenarios can be explored. This increases the robustness of the outcomes in regards to the effectiveness of the evacuation strategies.

5.1.1. Parametrization

This subsection details the outcomes and inputs of the experiments. Three experiments will be performed. The first experiment consists of extensively exploring the base case by evaluating all possible scenarios within the model boundaries. The second experiment consists of evaluating the evacuation strategies and comparing them to the base case. The last experiment will use the derived results out of WiFi data (see section 3.2) as an input for the model.

Key performance indicators

Variable	Explanation	Units
evac100	The time at which all of the evacuees have been evacuated	Seconds
evac95	The time at which 95% of all evacuees have been evacuated	Seconds
evac75	The time at which 75% of all evacuees have been evacuated	Seconds
evac50	The time at which 50% of all evacuees have been evacuated	Seconds
mean density	The density calculated per destination (exit or stairs) over the duration of the evacuation	Evacuees/m2
mean delay	The delay of each evacuee in seconds over the duration of the evacuation	Seconds
mean walking speed	The walking speed of each evacuee in m/s over the duration of the evacuation	m/s

Table 5.1: The key performance indicators used in the experiments

Table 5.1 shows the key performance indicators (KPIs) of interest that are assessed in the experiments. The used KPIs are derived out of the literature study about measuring the effectiveness of evacuation (see section 2.1.2). The KPIs will only be calculated at the end of the simulation, unless specified otherwise. As the goal of the experiments is to determine if, how and why evacuation strategies positively influence the evacuation efficiency, the total evacuation time is leading. However, other evacuation times are specified as well to evaluate whether unusual behaviour occurs during the evacuation.

Repetitions

To average out the stochasticity of the model, a sufficient number of repetitions for the experiment should be determined. To do so, a convergence test has been performed. This test consists of a sample of runs based on 9 combinations of input values for population size and familiarity. Figure 5.1 shows the total evacuation time, averaged over the repetitions. It can derived that convergence occurs more or less at 50 repetitions, as the spread of the averaged total evacuation time becomes practically constant. Therefore, the experiments will use a number of 50 repetitions.

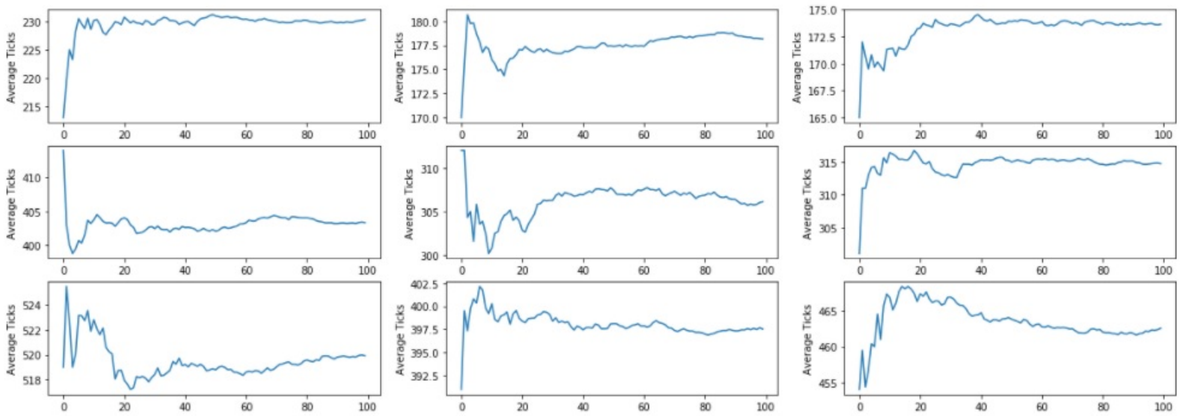

Figure 5.1: Convergence of outcomes to determine number of repetitions. Horizontally the ticks are shown and vertically the total evacuation time.

Base case experiment

The base case experiment acts as an exploratory experiment. The goal of this experiment is to evaluate the effect of the input parameters population size and familiarity on the KPIs. By doing so, the standard behaviour of the model can be produced and described. Table 5.2 shows the experimental set-up of the base case experiment. It was decided to run the model over 5000 scenarios to get an overview of the uncertainty space and how the model behaves.

Parameter	**Value**
Population	Random integer between 400 and 2200
Familiarity	Percentage between 0 and 100

Table 5.2: Input variables of the 'base case' experiment

Evacuation strategies experiment

The evacuation strategies experiment establishes the foundation on which the research question can be concluded. The goal of this research is to compare the different evacuation strategies with the base case under certain circumstances in order to determine if a set of input variables can determine an effective evacuation strategy inside a building. The evacuation strategies tested are detailed in section **??**. Table 5.3 shows the experimental set up of the evacuation strategies experiment. The experiment will run 100 times for each combination of input variables, this sums up to 40.500 scenarios (Crowd density 3 options * Familiarity 5 options * Compliance 3 options * Strategies 9 options * 100 experiments).

The categorical values of the input parameters have been determined based on the following assumptions:

- **Crowd density** - the values for the population represent a low, medium and high density occupancy rate of the building, these values constitute to a population of 700, 1400 and 2100 respectively. These values have been derived out of the results of the 'base case' experiment.

Parameter	Value
Crowd density	low - medium - high
Familiarity	0 - 0.25 - 0.50 - 0.75 - 1
Compliance	0.4 - 0.65 - 0.9
Strategies	Base Case, Wider Exit, Wider Stairs, Wider Both, Obstacles, Dynamic Signs, Phased, Evacuation staff, One-way traffic

Table 5.3: Input variables of the 'evacuation strategies' experiment

- **Familiarity** - the values for the familiarity are evenly distributed and can be assumed to represent to real-life examples of buildings occupant types: 0% (e.g., museum or hospital), 25% (e.g., city hall), 50% (e.g., university faculty), 75% (e.g., business premises) and 100% (e.g., high school).
- **Compliance** - the values of the compliance are represented by an evacuee that is willing to comply (90%) to an evacuee that hesitates to comply (45%). This way, the effect of the compliance can be evaluated as well among three evenly distributed values.

CASE STUDY EXPERIMENT

The case study experiment will test which evacuation strategies are effective given the circumstances derived out of the WiFi data. As discussed in section 3.2, the WiFi results are assumed to be invalid. However, we would like to compare the derived results with the assumed correct results to show that the results are different, hence underscribing the necessity of using data to improve evacuation strategies practically. The results showed that approximately 15% of the population is familiar with the building and that the average people visiting the building is about 5% of the normal occupancy compared to COVID-19 times, and therefore, the population size will be calculated to a 100%. For the assumed correct values, a familiarity close to 100% will be used. To cope with uncertainties in the data because of COVID-19, the experiments will be conducted with a predefined range of the population size and familiarity to ensure that the outcome of the effectiveness of the strategies is not limited to one specific combination of values. Table 5.4 presents both of the experiment parameters. The experiments will be run over 2000 scenarios.

Parameter	Values of derived outcomes	Values of assumed outcomes
Population	Random integer between 1300 and 1700	
Familiarity	Percentage between 5 and 25	Percentage between 80 and 100
Strategies	Base Case, Wider Exit, Wider Stairs, Wider Both, Obstacles, Dynamic Signs, Phased, Evacuation staff, One-way traffic	

Table 5.4: Input variables of the 'case study' experiment

5.2. RESULTS

In this section, the results from the experiments will be shown. As three experiments have been executed, the results consist of the analysis of the base case (section 5.2.1), the analysis of evacuation strategies compared to the base case (section 5.2.2 and the analysis of the evacuation strategies in the case study scenario (section 5.2.5).

5.2.1. BASE CASE

This subsection elaborates on the results from the 'base case experiment'. The results will first be explored and detailed, after which a scenario discovery will be performed.

EXPLORATION

By performing an open exploration of the data, it can be indicated how the KPIs perform in a large sample of the two uncertainties population and familiarity. An overview of the results of an experiment with 5000 different scenarios are shown in figure 5.2.

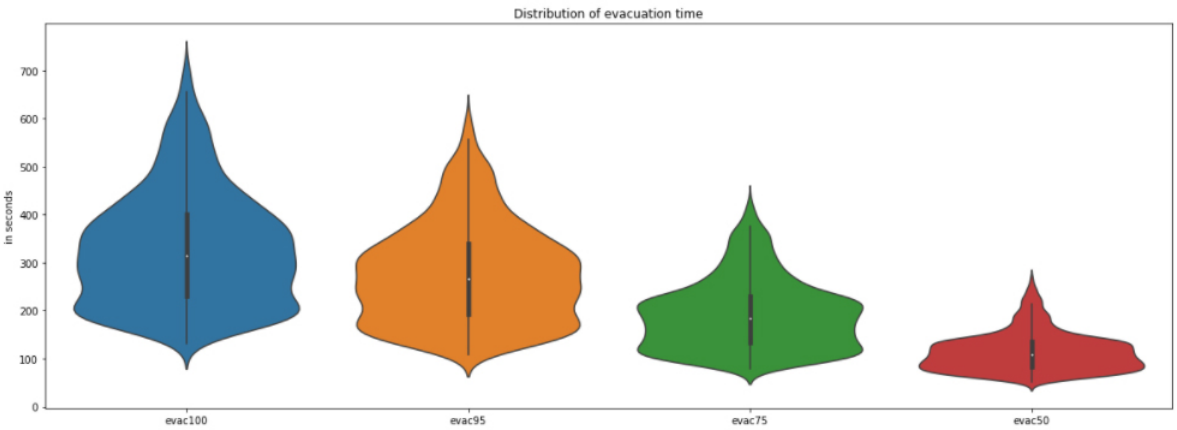

Figure 5.2: Exploration of the different evacuation throughputs

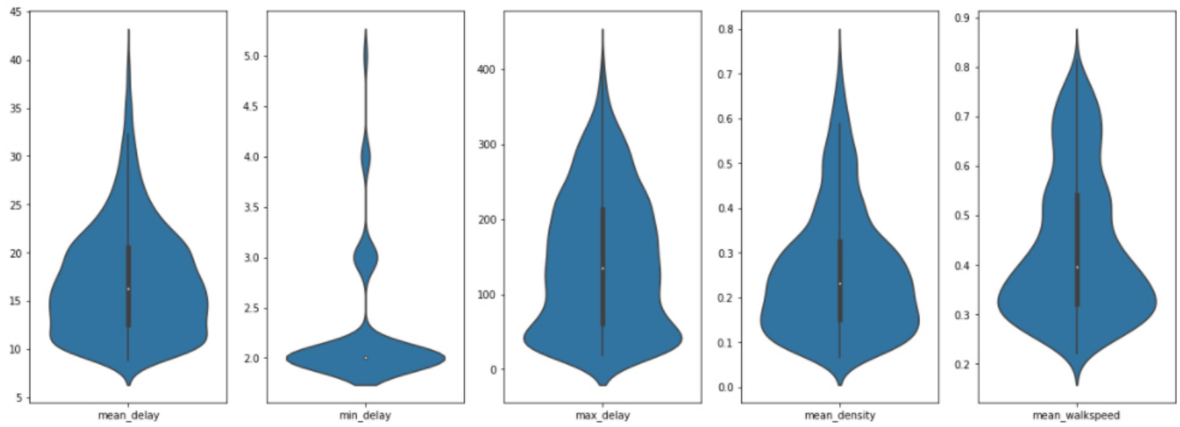

Figure 5.3: Exploration of the KPIs mean delay, minimum delay, maximum delay, mean density and mean walking speed

Figure 5.2 shows the distribution of the evacuation KPIs and a comparison with the density KPIs. As can be seen, the results are evenly distributed per KPI. This strengthens the validity of the experiment, since a great spectrum of different scenarios result in different outcomes. Another important indicator for the validity of the model is the correlation between the KPIs. Figure 5.3 shows that the evacuation time correlates with the walking speed, density and queue delay times, which is valid according to multiple studies (Guanquan and Jinhua, 2006; S. Liu *et al.*, 2009; Ronchi, Norén, *et al.*, 2015; H. Kim *et al.*, 2019; X. Wang *et al.*, 2021).

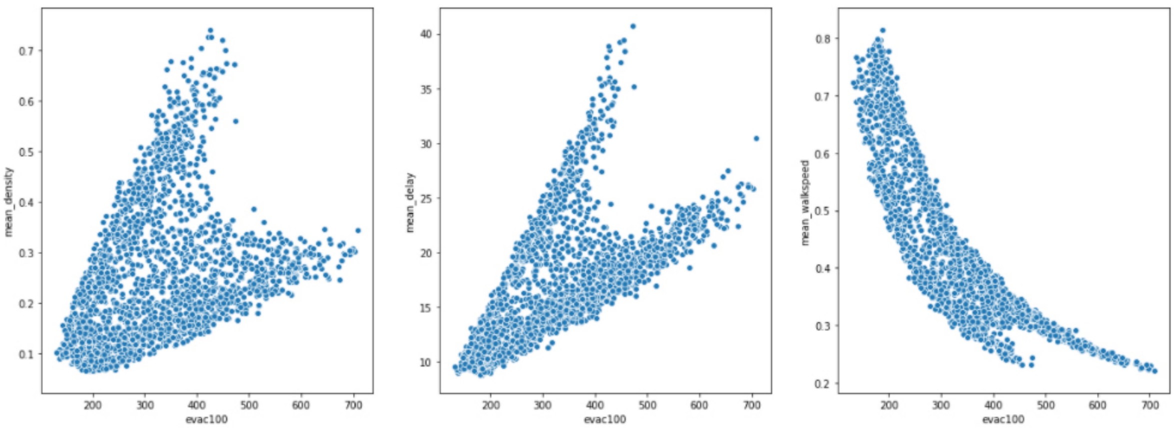

Figure 5.4: The evacuation time plotted against density, delay and walking speed

POPULATION

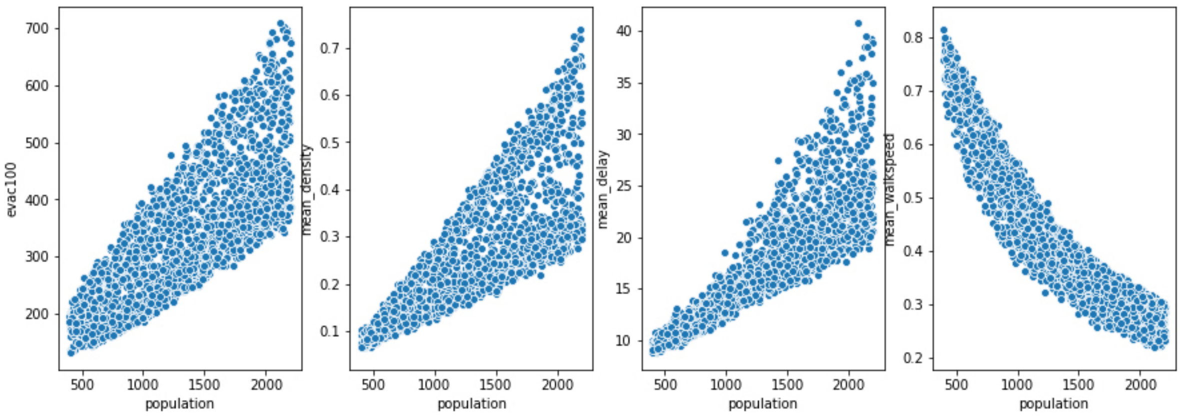

Figure 5.5: The evacuation time plotted per population size

Figure 5.5 shows the effect of the number of evacuees on the KPIs. The results indicate a linear effect of the size of the population on the outcomes of the simulations. This also applies for the confidence intervals: as the size of the population increases the outcomes become less confident, i.e. are more spread. These phenomena seem correct. As the size of the population increases, the density within the building increases with it: resulting in higher densities at bottlenecks which decreases the flow throughput (walking-speed) of the evacuees to eventually increase the total evacuation time of the building. The decrease of the confidence interval can be attributed to the familiarity of the building, as the outcomes are averaged over the familiarity values. Especially for large sizes of the population, the stairs and exit choice - which is based on the familiarity - becomes more and more of an influence as these choices can increase the queues for the bottlenecks.

FAMILIARITY

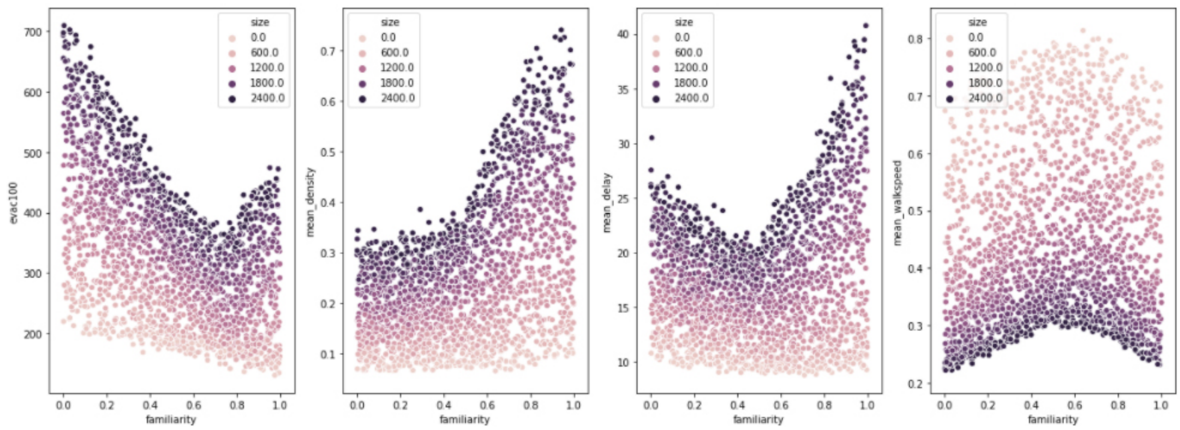

Figure 5.6: The evacuation time plotted per familiarity value

The effect of familiarity with the building on the KPIs has been plotted in figure 5.6. The population values are indicated by color, i.e. the darker the color the higher the population size. The results indicate that as the familiarity increases the evacuation time decreases, which is in line with the phenomenon that familiar evacuees take the shortest exit instead of the main exit, hence avoiding congestion. An interesting result is derived from the influence of the familiarity on the mean density: as the familiarity increases the mean density increases as well. However, this can be attributed to the calculation of the KPI: since the mean density is calculated over all stairs and exits, a higher mean density specifies a more distributed density. Furthermore, the mean delay - i.e., the time an evacuee is in queue - seems not to be very influenced by the familiarity but rather by the population size: as the population increases, congestions increase which leads to a higher delay time. Lastly, the walking speed seems to be parabolically influenced by familiarity. As the familiarity is low, most of the evacuees will gather at the main exit, which leads to one big congestion and lower walking speed respectively. On the contrary, as the familiarity increases to 1, every evacuee is very decisive in reaching their destinations, which leads to a scenario of every evacuee reaching the bottlenecks as soon as possible, accumulating the congestions respectively. However, if the familiarity is average, a part of the evacuees are reaching the destinations as soon as possible, creating more space for the others to travel to the main entrance. whereas the others are still walking around.

Concluding from this section so far, the population size has a positive correlation and the familiarity a negative correlation with the total evacuation time. To increase the validity of this conclusion, the Patient Rule Induction Method (PRIM) was used to find the scenarios that are classified as 'the worst'. Originally designed by Friedman Fisher (1999), PRIM is a technique that iteratively narrows down the uncertainty space until boxes are found that form a good trade-off between coverage (what fraction of the total outcomes of interest are in the box) and density (what fraction of all cases in the box are actually of interest). In this case, 'the worst' was defined as scenarios that are simultaneously in the worst 33.3% outcomes of the total evacuation time. Figure 5.7 shows the results of the PRIM analysis. These results indicate that the worst scenarios are produced by the highest values of population (in this case 1500 and higher) and low values of familiarity (in this case 0 to 0.43). Based on these results, 89% of the 'worst' results can be predicted with a precision of 81%.

5

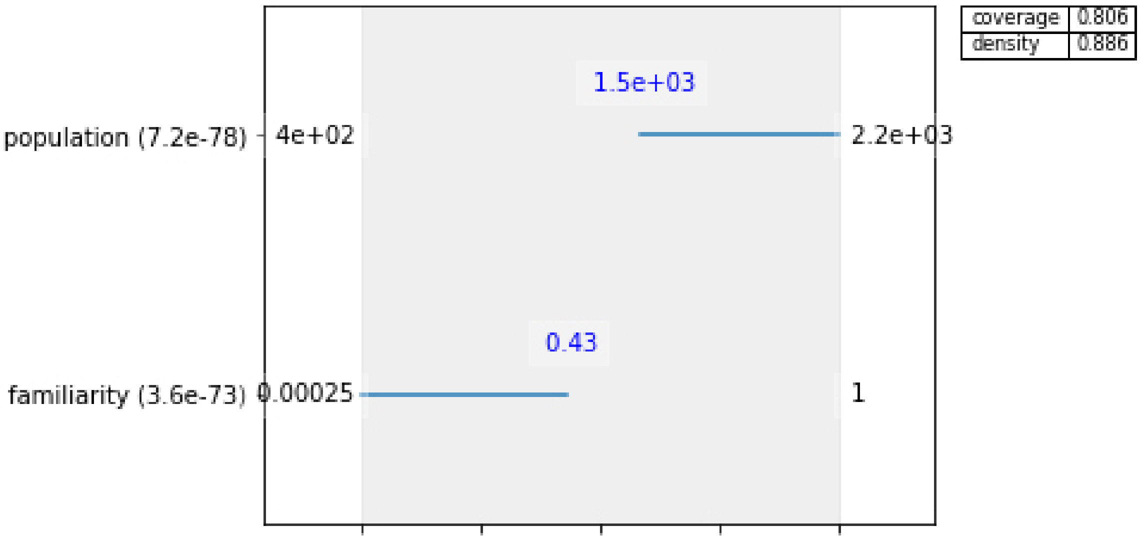

Figure 5.7: Outcomes of PRIM in regards to worst case scenarios

5.2.2. EVACUATION STRATEGIES

In this subsection the results of the evacuation strategies will be shown, the conducted experiments can be found in section **??**. First, an overview of all the evacuation strategies compared to the base case is presented. Secondly, the results of each evacuation strategy are individually discussed and interpreted. Lastly, the variables population, familiarity and compliance are evaluated.

OVERALL EFFECT

Figure 5.8 shows an overview of the total evacuation time per evacuation strategy, summed over all of the scenarios. It becomes apparent that summed over all scenarios the evacuation strategies increase the evacuation efficiency positively compared to the base case.

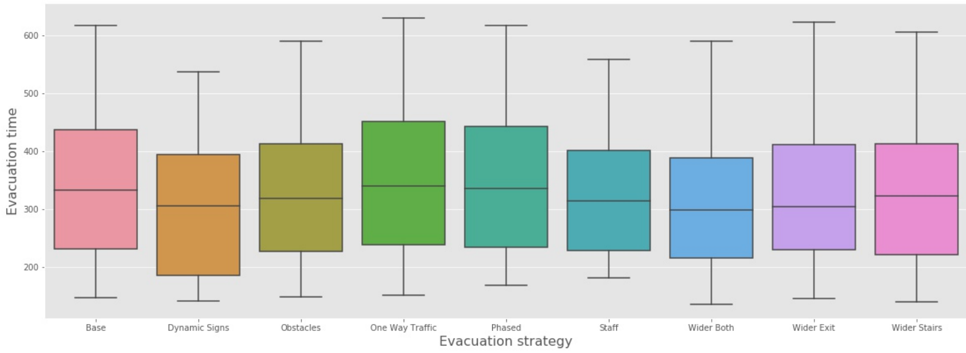

Figure 5.8: Overview of all strategies

Table 5.5 gives a numerical overview of the mean, minimum, maximum and standard deviation of the total evacuation time to strengthen the previous observation. An important observation out of table 5.5 is that the standard deviation is lower for almost every policy compared to the base case. This indicates that the outcomes of the experiments are closer to each other, which concludes that in these policies the expected evacuation time can be predicted more confidentially. Especially in regards to the possibility of casualties during evacuations, increased confidence in the outcomes of the total evacuation time is critical in ensuring crowd safety.

	Mean	**Min**	**Max**	**Std**
Base	340	147	618	125
Dynamic signs	305	142	537	110
Obstacles	328	148	591	118
One way traffic	349	151	631	129
Phased	348	168	618	119
Evacuation staff	323	181	559	97
Wider exits	306	136	591	113
Wider stairs	320	146	623	120
Wider both	326	140	607	117

Table 5.5: Overview of mean, min, max and std of the total evacuation time of evacuation strategies

CROWD DENSITY

The total evacuation time per policy per categorical value of the population has been plotted in figure 5.9. It appears that most of the evacuation strategies perform better than the base case in regards to the evacuation time for each crowd density category. Especially for higher crowd densities the relative effect of the evacuation strategy is of more influence. An explanation for this phenomenon is that as the crowd density in a building increases (the number of people in the building), larger congestions and slow flow throughput at bottlenecks may occur. By implementing evacuation strategies that spread and optimise these congestions or increase the flow throughput at bottlenecks, the evacuation efficiency can be enhanced.

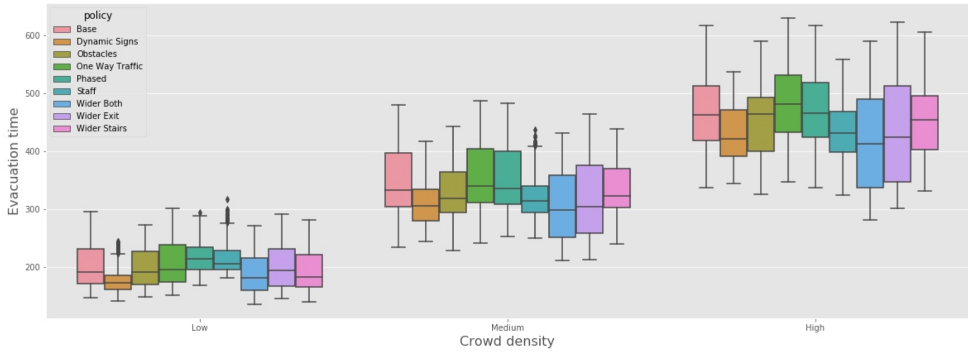

Figure 5.9: Overview of all strategies per population size

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FAMILIARITY

Figure 5.10 shows the total evacuation time plotted per familiarity category and evacuation strategy. For each of the familiarity values, except for 75% familiarity, each evacuation strategy seems to decrease the total evacuation time.

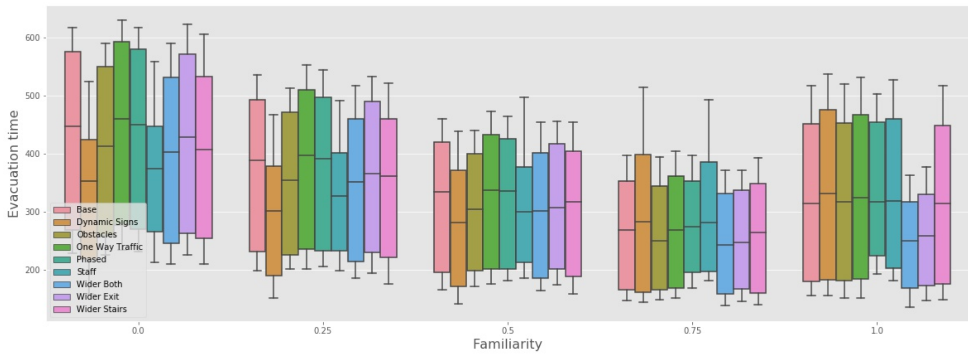

Figure 5.10: Overview of all strategies per familiarity categorical value

It becomes apparent that evacuation strategies that guide people towards the nearest exit are the most effective when the familiarity is lower. This result is in line with the made assumption that unfamiliar evacuees take the main stairs and exit. In these scenarios of low familiarity most of the evacuees will take the main destinations, hence creating large congestions and limiting the flow throughput of these bottlenecks. Evacuation strategies, such as dynamic signs and staff members, guide evacuees to their nearest destination, spreading the congestion and increasing the flow throughput. On the contrary, evacuation strategies that are the most effective when the familiarity increases are the strategies that increase the flow throughput at bottlenecks, such as wider exits and stairs, or obstacle placement at bottlenecks. As familiar evacuees move directly to the nearest destination, congestions mainly occur at destinations. Therefore, evacuation strategies that increase the flow throughput at these destinations are more beneficial for familiar evacuees. Another explanation of this phenomenon can be found in figure 5.11. Figure 5.11 shows the distribution of taken exits. As the emergency exits (exit 1, 2, 3 and 5) become more and more crowded as the familiarity increases, and are narrower compared to the main exit, strategies that influence the flow throughput of these emergency exits benefit the total evacuation time.

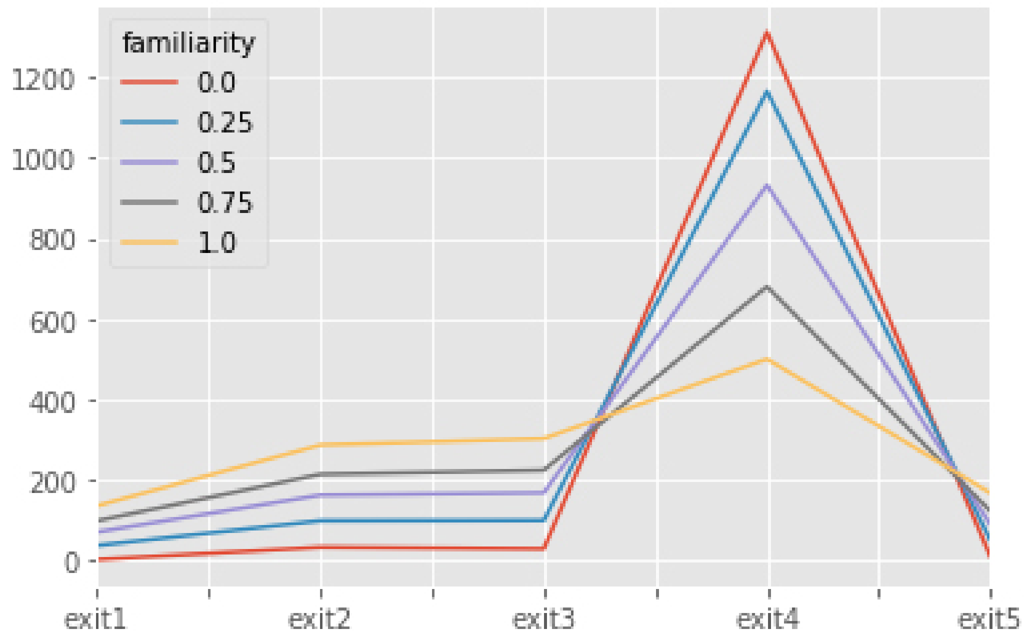

Figure 5.11: Distribution of taken exits per evacuation strategy

EVACUATION STRATEGIES

To determine the effect of the evacuation strategies in-depth, the evacuation strategies are evaluated separately. This is done by dividing the 8 evacuation strategies in two categories: guiding and bottleneck improvement strategies. The guiding category consists of the evacuation strategies in which the evacuee is guided to change his destination or path: dynamic signs, evacuation staff, one-way traffic and phased evacuation. Whether the evacuee follows the guidance or not is determined by the variable 'compliance'. The bottleneck improvement category consist of evacuation strategies that try to improve the flow throughput of bottlenecks: wider exit, wider stairs, wider both, obstacles

5.2.3. GUIDING EVACUATION STRATEGIES

Figure 5.9 showed that the guiding evacuation strategies "Dynamic Signs" and "Evacuee Staff Members" reduced the total evacuation time and increase the confidentiality of the outcome compared to the base case. However, the guiding evacuation strategies "One Way Traffic" and "Phased evacuation" did not positively influence the total evacuation time: the total evacuation times were more or less the same compared to the base case. This can be ascribed to the fact that for "Phased Evacuation" the pre-evacuation time increases, which can not be compared for, and for "One Way Traffic" evacuees tend to walk further to comply with the given instructions. Another observation is that as the crowd density increases (see figure 5.12), the relevant effectiveness of the strategies "Dynamic Signs" and "Evacuee Staff Members" compared to the base case increases accordingly. This phenomenon can be explained by the increasing building density: the building density increases, therefore guiding evacuees towards their nearest destination prevents congestion at the main entrances, which eventually decreases the total evacuation time .

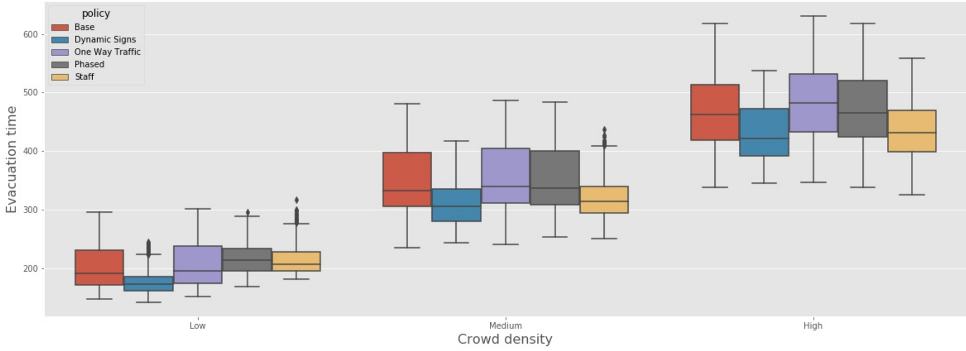

Figure 5.12: Overview of the total evacuation time per categorical value of crowd density for guiding evacuation strategies

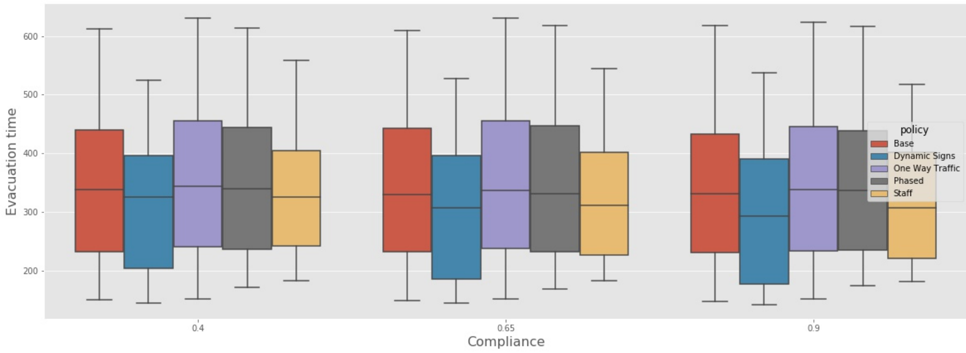

Figure 5.13: Overview of the total evacuation time per categorical value of compliance for guiding evacuation strategies

To further evaluate the effect of these strategies, its effect based on the familiarity and compliance is assessed. Figure 5.13 details the total evacuation time of the evacuation strategies based on the level of compliance. It becomes apparent that as the compliance increases, the effectiveness of the strategies "Dynamic Signs" and "Evacuee Staff Members" increases accordingly. This is not typical, as compliance indicates whether an evacuee complies to the given instructions. Figure 5.14 shows the effect of the guiding evacuation strategies based on the level of familiarity within the building. As stressed in section 5.2.2, the level of familiarity is of influence on the effectiveness of the guiding evacuation strategies. Familiar evacuees already take the nearest destination, hence decreasing the effect of the guiding evacuation strategies. Another observation is that as the familiarity increases from 75% to 100%, the total evacuation time increases. This phenomenon has been elaborated on in section 5.2.2. A last observation is that "Dynamic Signs" perform slightly better compared to the "Evacuation Staff Members". A possible explanation can be that staff members leave after all evacuees evacuated the building safely, resulting in a higher total evacuation time. Furthermore, evacuation staff members are less visible when the density around them is high, therefore less people are influenced by their guidance.

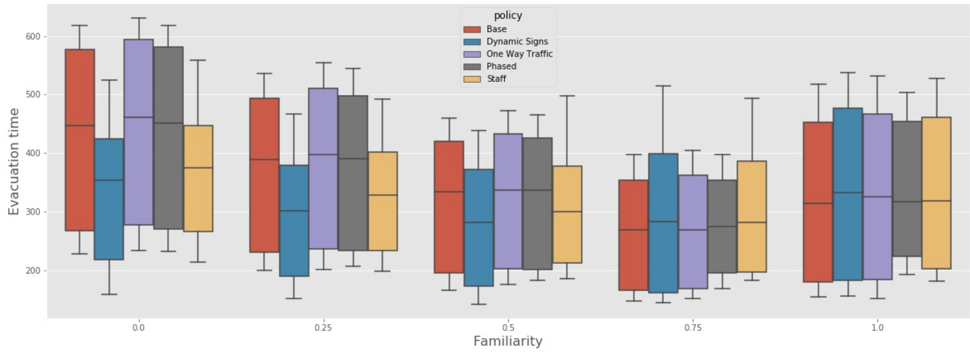

Figure 5.14: Overview of the total evacuation time per categorical value of familiarity for guiding evacuation strategies

5.2.4. BOTTLENECK EVACUATION STRATEGIES

The bottleneck improvement category consist of evacuation strategies that try to improve the flow throughput of bottlenecks: wider exits, wider stairs, wider both and obstacles. Figure 5.9 shows that for all of the crowd densities, bottleneck improvement strategies are improving the total evacuation time compared to the base case. Moreover, as the crowd density increases, the relative effectiveness of the strategy increases accordingly (see figure 5.15). When comparing the effectiveness of the bottleneck improvement strategies based on building familiarity (see figure 5.16). It appears that up to 75% of building familiarity holds the same effect, whereas the familiarity increases to 100% only strategies that improve the flow throughput of exits are effective. Section 5.2.2 elaborated on the fact that a population that is 100% familiar with the building increases the total evacuation time by increasing the size of queues at emergency exits. Therefore, the evacuation strategies that improves the flow throughput of these emergency exits are particularly effective for this scenario.

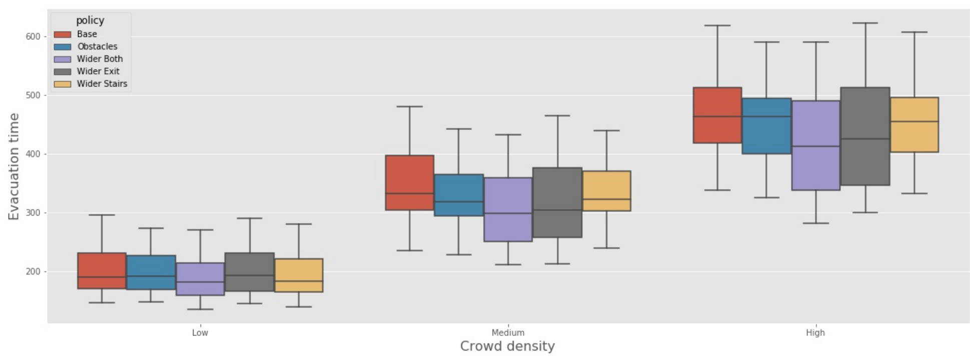

Figure 5.15: Overview of the total evacuation time per categorical value of crowd density for bottleneck improvement evacuation strategies

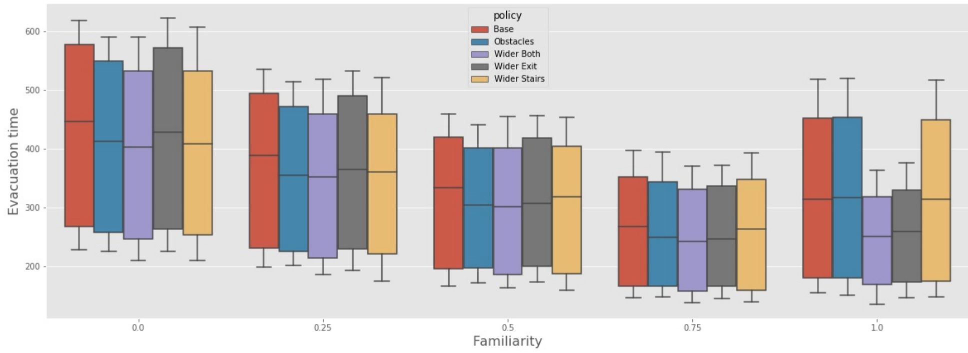

Figure 5.16: Overview of the total evacuation time per categorical value of familiarity for bottleneck improvement evacuation strategies

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5.2.5. CASE STUDY - TPM FACULTY OF THE TU DELFT

This section shows the results of the case study experiment, which is introduced in section 5.1.1. Two types of results will be shown: (1) the invalid familiarity outcomes of the WiFi traces and (2) the assumed correct familiarity outcomes of the TPM faculty building. By doing so, it becomes apparent that using other (invalid) values of familiarity influences the efficiency of evacuation strategies and underscribe the necessity of using data to determine efficient evacuation strategies for different scenarios.

WIFI DATA OUTCOMES

	Mean	Min	Max	Std
Base	434	373	509	28
Dynamic Signs	340	243	432	40
Obstacles	404	329	479	32
Phased	438	371	514	30
Staff	362	281	457	35
Wider exits and stairs	394	321	474	30

Table 5.6: Outcomes of the case study experiment with derived values

Table 5.6 shows the mean, minimum, maximum and standard deviation values of the case study experiment as was derived out of the available WiFi data of the TPM faculty building. As can be seen, all of the tested evacuation strategies are effective in decreasing the total evacuation time compared to the base case, given the population size and familiarity which were derived out of WiFi data. Averaged over both the population size and familiarity, guiding evacuation strategies, such as dynamic signs and evacuee staff members, seem to be the most effective strategies. However, before this conclusion can be drawn, the outcomes for the uncertainties individually will be analysed.

Figure 5.17 and 5.18 indicate the effectiveness of the evacuation strategies compared to the predefined range of the variables population size and familiarity. It becomes apparent that for all values of population size and familiarity, the guiding evacuation strategies 'dynamic signs' and 'evacuation staff members' are the most effective. This is line with the previous findings of section 5.2.2; as the familiarity and population size are not particularly high, the capacity of exits remains sufficient for these evacuation scenarios, and therefore guiding evacuation strategies perform best.

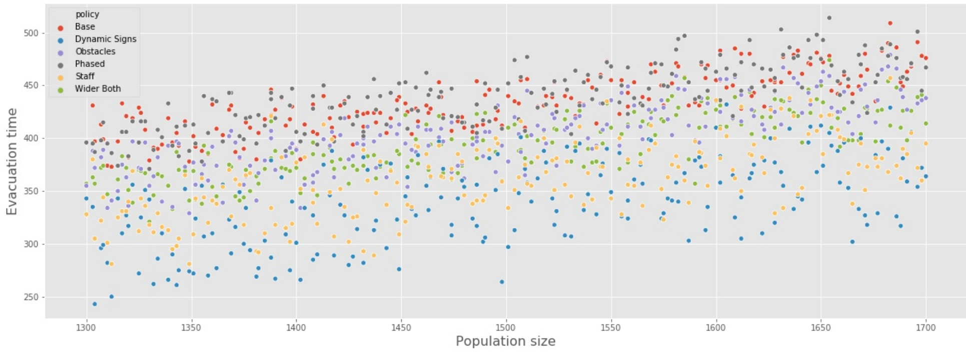

Figure 5.17: Overview of the total evacuation time per value of the population size and categorised per evacuation strategy

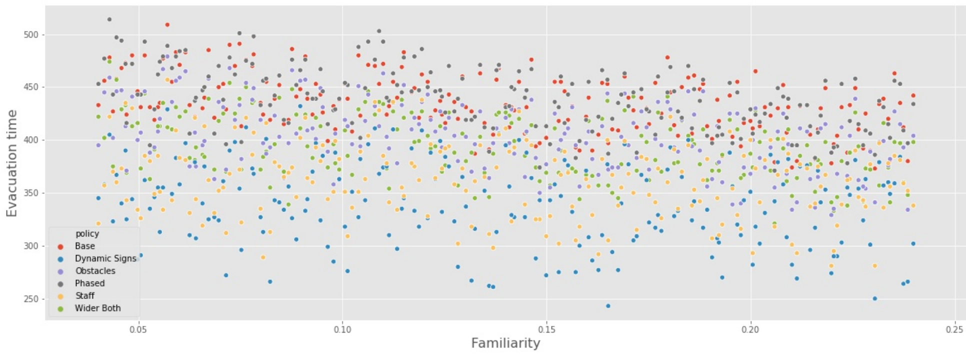

Figure 5.18: Overview of the total evacuation time per value of the familiarity and categorised per evacuation strategy

ASSUMED DATA OUTCOMES

	Mean	Min	Max	Std
Base	306	248	385	31
Dynamic Signs	333	267	400	31
Obstacles	305	239	385	34
Phased	312	251	387	30
Staff	325	257	402	32
Wider exits and stairs	248	207	298	20

Table 5.7: Outcomes of the case study experiment with assumed values

Table 5.7 shows the mean, minimum, maximum and standard deviation values of the case study experiment with the assumed to be correct values. As can be seen, in this case, only one of the tested evacuation strategies is effective in decreasing the total evacuation time compared to the base case. Averaged over both the population size and familiarity, making both the exit and stairs wider seem to be the most effective evacuation strategy. Out of Figure 5.19 and 5.20 it becomes apparent that indeed the bottleneck improvement strategy 'wider stairs and exit' is the most effective. Furthermore, it becomes evident that different outcomes of WiFi data derive different effective evacuation strategies, which stresses the necessity of using valid data for the experiments.

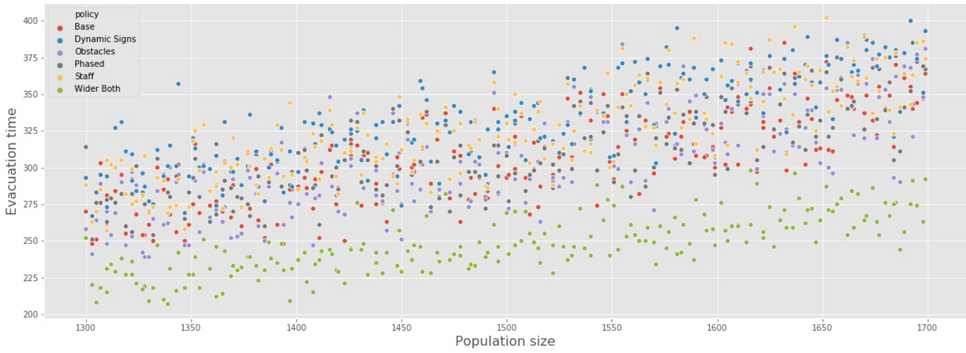

Figure 5.19: Overview of the total evacuation time per value of the population size and categorised per evacuation strategy for the assumed outcomes of WiFi data

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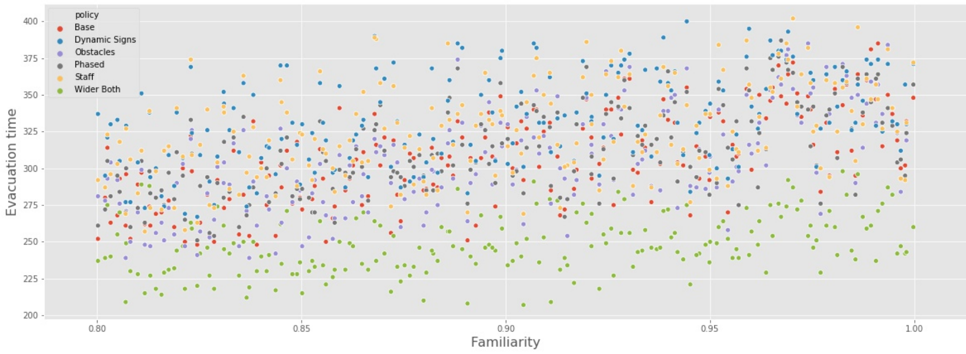

Figure 5.20: Overview of the total evacuation time per value of the familiarity and categorised per evacuation strategy for the assumed outcomes of WiFi data

6

Discussion and conclusions

Evacuation strategies are critical in preventing casualties during emergency evacuations in buildings (E. Galea, Sharp, *et al.*, 2008). As large-gatherings and higher crowd densities in buildings occur more often, the need for effective evacuation strategies in times of an emergency emerges (J. Zhou *et al.*, 2019). Therefore, this study answered the following research question: "How can effective evacuation strategies in a large building be determined based on WiFi data?". To do so, this study used: (1) an agent-based and exploratory modelling approach to test the effect of eight evacuation strategies on population size, familiarity and compliance, and (2) WiFi data to determine effective strategies in a practical case study of the TPM faculty building of the TU Delft. This chapter will elaborate and discuss the results, strengths, limitations and recommendations of this study.

6.1. Crowd density, familiarity and compliance

First we will discuss the influence of crowd density and familiarity on the total evacuation time. The crowd density and the percentage of familiar building occupants is of most influence on the total evacuation time. It was found that the crowd density has a positive correlation with the total evacuation time. This finding is rationally explainable; as the crowd density increases, congestions occur more often, hence increasing the total evacuation time. This phenomenon has been widely observed in multiple studies (Christensen *et al.*, 2013; X. Zhao *et al.*, 2017; Kinateder *et al.*, 2018).

Unlike crowd density, the effect of familiarity on the total evacuation time introduces a new finding. From a level of familiarity of medium-high (75%) and higher, the correlation with the total evacuation time becomes positive. This introduces a new factor, which has not been observed in literature before, namely the capacity of (emergency) exits and the emergence of unpredicted bottlenecks. As the familiarity increases, evacuees will take the nearest exit available. However, if one of those exits has a limited capacity, e.g. in this case multiple emergency exits with a width of one meter, large queues occur, which increases congestion and limits the outflow. Therefore, the evacuation should not only be evaluated on crowd density and familiarity, but also on the capacity of emergency exits and the emergence of other possible bottlenecks - which is underlooked. Studies that discuss the capacity of exits and corridors often assume complete knowledge, i.e. evacuees know which exit is the least crowded, such as Desmet and Gelenbe (2014) and L.-W. Chen *et al.* (2015). This knowledge can only be accomplished with the implementation of large intelligent systems, which are costly and prone to malfunction (Nguyen *et al.*, 2019; Santana *et al.*, 2020). Therefore, evaluating exit capacities and the emergence beforehand introduces a new way to improve evacuation.

In regards to the compliance variable, the compliance ensures the relative effect of evacuation strategies; as the compliance increases, the relative effect of these strategies increases accordingly. This finding was not unexpected, as the compliance indicates how many evacuee follow the provided evacuation strategy of a building. Moreover, this is in line with the findings of Pel *et al.* (2010) and Duarte *et al.* (2014) which state that the effectiveness of evacuation strategies is dependent on compliant behaviour.

6.2. Evacuation strategies

In regards to evacuation strategies, it can be concluded that the implementation of evacuation strategies does not directly lead to an increase in the evacuation efficiency and is very dependent on the evacuation circumstances, such as crowd density, familiarity and compliance, in which it takes place. This study differentiated and tested two types of evacuation strategies: guiding and bottleneck improvement strategies. Each of these types will be elaborated on individually in the next paragraphs.

An interesting finding is that the guiding evacuation strategies ‘dynamic signs’ and ‘evacuee staff members’ are most effective when the familiarity is low. However, due to the newly introduced exit capacity, the relative effect of guiding strategies decreases for high values of familiarity. This finding is contradictory with several studies that concluded that guiding evacuation strategies are helpful in complex and crowded scenarios. For example, E. R. Galea *et al.* (2014) and E. Galea, Xie, *et al.* (2015) argue that dynamic signs are an effective means to improve evacuation, and X. Song *et al.* (2017) and Formolo *et al.* (2018) derived a positive effect of using evacuation staff members on the evacuation time. All of these studies do not take the exit capacity into account, which generates different results. Furthermore, guiding evacuation strategies ‘phased evacuation’ and ‘one-way traffic’ were hardly effective or even increased the total evacuation time. For phased evacuation this finding corresponds with outcomes of Koo *et al.* (2013), Gravit *et al.* (2018), and L. Yang *et al.* (2021), which conclude that phased evacuation does not decrease the total evacuation time. However, this strategy does decrease the density at bottlenecks and the mean waiting time, which can be of value in case of a non-life threatening emergency, as the chance of casualties through trampling and tripping can be reduced. A last finding for guiding evacuation strategies is that ‘one-way traffic’ has no effect on the total evacuation time. It is to say that the implementation of such a strategy is completely new for buildings, however in urban evacuations this strategy is commonly implemented and evidently helpful (Urbanik, 2000; Theodoulou and Wolshon, 2004).

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A promising finding is that bottleneck improvement strategies, such as wider exits, wider stairs and placing obstacles in front of bottlenecks, are generally effective. Especially when the familiarity and crowd density is high, the effect of ‘wider exits’ and ‘wider stairs’ is optimal. This can be attributed to the limited capacity of exits and stairs, which are increased by bottleneck improvement strategies. These findings are in line with other studies: Seyfried *et al.* (2009) derived a linear growth of flow throughput with the width of a bottleneck, Garcimartın *et al.* (2016) found an increased exit flow as the exit size increases and Haghani, Sarvi, and Shahhoseini (2019) also indicated an increased exit flow if the exits’ width increases. Furthermore, the obstacle placement strategy findings are promising; compared to the base case, the total evacuation time was lower in every scenario if the strategy was applied. In the strategy, two asymmetrical obstacles were placed in front of the main exit and stairs, which increased the flow throughput at these destinations. This finding was particularly unexpected, as previous studies derived contradictory outcomes of the effectiveness with the implementation of this strategy. For example, Helbing, Farkas, *et al.* (2000) and Shi *et al.* (2019) observed a positive effect, while Q. Li, Gao, *et al.* (2019) and Zang *et al.* (2021) concluded a negative effect.

A last finding is that WiFi data can be essential in determining an effective evacuation strategy. However, in this study, WiFi data was not representative enough to draw valid conclusions because of collecting WiFi traces during COVID-19, which skewed data. It is to say that this study showed a proof of concept to use WiFi data, namely characteristics derived out of WiFi data are able to represent the conditions of an evacuation scenario. Therefore, based on possibly valid WiFi data, we are able to simulate several evacuation strategies for a specific scenario and determine the most effective one based on the total evacuation time. If WiFi data was lacking or not representative - as was the case in this study because of COVID-19, an evacuation manager might have chosen a strategy which seemed effective, while under the provided WiFi data conditions it was not (see section 5.2.5). For example, the most effective evacuation strategies based on the WiFi were guiding strategies, however these strategies were not effective at all when the assumed correct values were used. Hence, emphasizing the necessity of valid data and the usefulness of evaluating such data for the improvement of evacuation. To relate WiFi data to evacuation scenarios, characteristics that can be derived out of occupant WiFi data that is able to influence the behaviour of evacuees is evaluated. WiFi data is able to indicate how many occupants are present, which entrances and exits they take, and their frequency and duration of visits (see section 3.2). Out of this data, occupants’ influences on evacuation behaviour, such as familiarity with the environment, compliance with guidance and the population size present in the building are derived. Therefore, WiFi data - in general - can be used to calibrate and evaluate evacuation models by serving as an input for variables that influence evacuation behaviour, which is new to the body of evacuation literature.

6.3. Strengths, limitations and future research

To the best knowledge of the author, this study is the first to combine an evacuation model with an exploratory modeling approach, therefore this study presents a stepping stone of how exploratory modeling in combination with evacuation modeling can be used to generate insights in evacuation scenarios and evacuation efficiency. By doing so, the robustness of evacuation strategies can be determined, i.e. is a strategy efficient in every possible scenario. The ability of this study fills in the recommendation of Vermuyten *et al.* (2016b), which states that future research should identify possible and most effective areas of evacuation strategies.

One of the key strengths of this study is the prescriptive approach, rather than a descriptive approach. Prescriptive evacuation studies aim to recommend evacuation managers about evacuation strategies and improve these accordingly Vermuyten *et al.* (2016b). While efficient evacuation strategies are critical to mitigate casualties during an emergency (E. Galea, Sharp, *et al.*, 2008), prescriptive studies are underrepresented in the body of the literature Vermuyten *et al.* (2016a) and Vermuyten *et al.* (2016b). Therefore, this study introduces a complete approach to improve evacuation strategies, and therefore, increases the crowds' safety.

Another key strength of this study is the evaluation of multiple evacuation strategies in different evacuation scenarios, while other prescriptive studies often focus on one particular strategy and scenario, as has been stressed in section 2.1. By doing so, this study was able to conclude which evacuation strategies are effective under which conditions. Especially the new promising finding, which stresses the necessity of evaluating the exit capacity beforehand, poses practical recommendations for evacuation managers to increase the evacuation efficiency.

In regards to the used approach, this study presented a new methodological approach for evacuation modeling. This study used the Exploratory Modeling and Analysis (EMA) workbench to analyse the created agent-based evacuation model under deep uncertainty. As has been argued in the previous paragraph, this approach is able to evaluate the influence of different circumstances on evacuation behaviour and efficiency. The knowledge on possible uncertainties and sensitivities during evacuations is very relevant for both the prescriptive and descriptive domain,as it might bring new findings. Moreover, this approach handles the limitations of evacuation strategy studies as stressed by Ibrahim *et al.* (2016) and Vermuyten *et al.* (2016b). who indicates that uncertainties of evacuation scenarios may worsen crowd calamities and that the relative effectiveness and practicality of strategies are yet to be evaluated.

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In addition, this study showed that by using the above mentioned approach, practical case studies - i.e. buildings - can be evaluated based on WiFi data. This introduces new ways of determining effective evacuation strategies for practical applications. By using the derived knowledge out of the WiFi traces as an input for the evacuation and exploratory model, robust evacuation strategies can be determined. This strength also relates to the aforementioned limitations of current studies by Ibrahim *et al.* (2016) and Vermuyten *et al.* (2016b). However, the application of WiFi traces for this particularly case study was not representative at all, as the WiFi traces were collected during COVID-19 and derived skewed results, which will be elaborated on further in this section.

While the above mentioned strengths and findings are insightful and promising, this study also has some limitations. The limitations will be elaborated on based on the two objectives of the study: (1) to determine effective evacuation strategies in buildings under different circumstances and (2) to determine effective evacuation strategies given WiFi data as an input.

The first limitation involves the scope of the evacuation behaviour. In this study, the physical and environmental interactions are taken into account, while other elements that evidently influence evacuation behaviour have been left out, such as contagion, social influence, groups and leader/follower behaviour (E. Kuligowski, 2013; Aguirre *et al.*, 2015; Lovreglio, Ronchi, *et al.*, 2015; Xu *et al.*, 2019). However, it is to be said that an evacuation study that combines all of these influences is yet to be written. Also, the uncertainties that were used in this study for the evacuation scenario are limited.

Furthermore, the scope and application of the evacuation strategies is limited. In this study, seven evacuation strategies were derived. However, more evacuation strategies apply in buildings. For example, the strategies which include the spatial placement of exits, smart evacuation systems, speed on stairs or evacuation floors were not considered, while they might be effective strategies. Moreover, the application of the used evacuation strategies was implemented in one way, while other ways might derive different results. For example, in this study a horizontal phased strategy, i.e. area per area, was used. However, a vertical approach, i.e. floor per floor, or a different order of areas was not considered. Also, one placement of dynamic signs and evacuee staff was considered, while other placements derived other results. It is to say that the used implementations provide a good indication of how these strategies can be evaluated in different scenarios.

Another limitation can be found in the simplicity of individually modelled components, the interaction between them and the occurrence emergent behaviour. For example, in the model gender and age are left out, sight is not hindered by other people, an evacuee can only be influenced once per floor by a guiding evacuation strategy and people tend to walk near walls. Nevertheless, the model generates promising results which can be used as a starting point in further analysis.

A last limitation is the collection and application of WiFi data. In this study, WiFi traces have been collected during COVID-19, which generated skewed insights out of the data as the building had limited occupancy restrictions. Also the time span in which the WiFi traces were collected does not cover a complete cycle, e.g. a year, in which familiarity and (mean) population sizes can be determined with more certainty. Because of the data collection limitations and the possibility of skewed data, the application of the WiFi data in the model is limited as well. WiFi traces can generate many more insights than familiarity and population size alone. However, as these variables were the only valid variables possible - as movement behaviour was invalid due to prescribed paths and walking directions, the decision was made to only evaluate the familiarity and population size. However, it is to say that the used familiarity and population size were also not representative at all.

To cope with the above mentioned limitations, I will elaborate on several recommendations for future research. As the findings and strengths of this study emphasized the necessity of evaluating evacuation in a broader way, this study posed a stepping stone for future research to generate even more in-depth and robust findings to improve evacuation.

A first recommendation is to explore more factors that are of influence in evacuation. This study showed the importance of evaluating evacuation scenarios based on only three uncertainties and physical interactions only. However other factors apply as well, such as psychological interactions, demographic data and types of emergency. Therefore, future studies should aim at combining elements that influence evacuation behaviour and evaluate a larger sample of uncertainties.

Another recommendation for future studies is the evaluation of other evacuation strategies, or the optimization of tested ones. As has been stressed, this study only evaluated the implementation of 8 different evacuation strategies, while other evacuation strategies exist. Regardless of the fact that this study argued to have chosen the most likely feasible evacuation strategies, it recommends evaluating other strategies as well. Moreover, the implementation of these 8 evacuation strategies has not been optimised, as a specific evacuation strategy can also be individually improved. For example in this study, different placements of dynamic signs and obstacles could be tested, the phased evacuation could have taken place in another order, the one-way traffic was generally tested, and stairs and exits could have been individually tested in terms of width.

A last recommendation is in regards to WiFi data. This study showed that WiFi data can be used to evaluate a practical case study, i.e. a building, and inform evacuation managers of those buildings about possible effective evacuation strategies accordingly. As stressed in above mentioned limitations, the WiFi data was collected during COVID-19, and while the WiFi data was skewed, it derived a proof of concept and promising insights that are valuable for the extension of data-driven evacuation modeling. Therefore, future studies should aim at retrieving representative WiFi data, which is able to derive other patterns and knowledge that are useful for the evaluation of evacuation, such as frequent walking routes, occupancy rates and possible bottlenecks. To do so, the collection of WiFi traces should take place for a longer period to assume the data, such as familiarity and occupancy, is valid. For example, data should be collected during a year in which new students can be traced in September - the start of the academic year - or at open days. This data would lead to a different approach on how to handle evacuations in a particular building.

6.4. IMPLICATIONS

A first theoretical implication is the new finding this study implicated, namely evaluating the exit capacity of a building. While other studies laid the foundation for taking into account congestion, throughput, familiarity and crowd density, this study endorsed the effect of the exit capacity on the total evacuation time. By evaluating the exit capacity beforehand, it becomes apparent whether evacuation strategies are effective at all. For example, an evacuation strategy can be very efficient in guiding evacuees to the nearest emergency exit, but if this emergency exit has a limited capacity (as is the case in the TPM faculty building) larger congestions occur than what would happen at the main exit. Another theoretical implication is the use of WiFi data to supplement and enhance evacuation strategies. In this study, the collected WiFi traces were not representative, however it showed the proof of concept for using WiFi data as a basis to determine effective evacuation strategies. A last practical implication is that evacuation managers could use the approach of this study to derive insights about the effectiveness of evacuation strategies in their buildings. These insights pose benefits for the feasibility of the implementation of such strategies, as costs and efforts can be compared with the possible effects. For example, if for a specific strategy the total evacuation time is 5 seconds slower than the optimal evacuation strategy, but is more feasible in terms of costs and implementation, an evacuation manager can make a well-informed decision. This creates a tool for evacuation managers, which goes further than existing literature can provide.

6.5. CONCLUSION

The domain of research that tries to identify possible ways to improve evacuation, i.e. prescriptive domain, is under studied Vermuyten *et al.* (2016a) and Vermuyten *et al.* (2016b). Several studies successfully improve evacuation by optimizing existing evacuation scenarios in buildings. A shortcoming of these studies is that they often focus on one strategy and scenario in particular. Therefore, this study answered the following research question: "How can effective evacuation strategies in a large building be determined based on WiFi data?". To do so, an exploratory, data-driven and agent-based modelling approach was used. This approach is, to the knowledge of the author, new in the field of evacuation. The results show that with the exploratory approach, evacuation strategies can be evaluated based on their effectiveness in different scenarios, which indicates under which circumstances evacuation strategies perform well, or do not. Furthermore, the knowledge derived out of the exploration can be practically applied, as WiFi data is able represent the boundaries of an evacuation scenario. Therefore, in regards to the research question, effective evacuation strategies can be practically determined based on knowledge derived out of WiFi data. However, this study also has some limitations. For example, the evacuation behaviour was only based on physical interactions, the scope of the evacuation strategies was limited and the WiFi data used was collected during COVID-19, and therefore, could not be used. To cope with these limitations, future studies should explore other evacuation strategies, and other factors that are of influence on evacuation behaviour, such as contagion, social influence and group behaviour. Furthermore, even though the WiFi data could not be used, it presented a proof of concept for the use of WiFi data to determine practical effective evacuation strategies which can be used by evacuation managers of particular buildings. All in all, this study introduces a new approach to explore the improvement of evacuation strategies under different circumstances.

7

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