Impact of leader-follower behavior on evacuation performance

An exploratory modeling approach

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by

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https://www.teamworkandleadership.com/2018/02/do-this-one-thing-to-be-a-more-charismatic-leader.html

Preface

This thesis investigates the influence of leader-follower behavior on evacuation performance. It was written to receive a Master of Science in Complex System Engineering and Management. The idea of the thesis was already developed in the Research challenge course in the first year of my master's, where I had to conduct a literature review in this field under the supervision of Dr. Natalie van der Wal. Thus, we further developed the idea for this thesis during meetings in November and December. Without the help of my supervisors, finishing this thesis would not be possible as they supported me during the process, reminded me about the essential aspects, and found the proper scope for the limited time.

In particular, I want to thank my first supervisor Dr. Natalie van der Wal for the possibility to write my thesis about this topic. Your enthusiasm for your research and this field led me to choose this subject, and your supportive words helped to motivate me every day. Furthermore, I want to thank Dr. Willem Auping and Dr. Dorine Duives for your valuable feedback, the possibility of continually asking questions, and for supporting me on short notice. This always helped me to learn a lot during this time and increase the quality of the work. Moreover, I want to thank Dr. Milad Haghani from the University of New South Wales for providing me with the data of their experiment in order to validate my model.

In addition, I thank my friends and my girlfriend, who have always given me new ideas and brought me different thoughts during that time. Sharing the time with you made the process easier and more enjoyable. Finally, I want to thank my family for supporting me, giving me valuable feedback, and providing me the possibility to pursue my master's at the TU Delft.

Jakob Irnich
Delft, August 2022

Abstract

Leadership may be seen as one of the most influential group decision-making structures during an evacuation. Therefore, understanding this behavior is essential in order to implement it properly in evacuation models that are utilized to explore the optimal strategies to prepare buildings for emergencies. Different leader-follower behaviors may be observed in models and empirical studies, such as group gathering, backtracking, and group flexibility. However, a comparison of these behaviors resulting in possible substantially different estimates of optimal evacuation procedures is lacking. Hence, first, a framework for leader-follower behavior was developed, which may aid researchers in modeling leader-follower behavior in evacuation models. Then, three different leader-follower behaviors were chosen whose influence on the evacuation and response time as well as on the intragroup distance was investigated in more detail with the help of an agent-based model combined with exploratory modeling. In particular, backtracking, group gathering, and the possibility for followers to change the leader were selected as these behaviors may be encountered in distinct evacuation phases and apply to different group structures.

First, an uncertainty analysis was performed for the base model to investigate how uncertainties influence the core leader-follower behavior. Then, a base ensemble was utilized to examine the impact of the three chosen behaviors to increase the result's robustness. The base ensemble was created with the help of a Latin hypercube sampling over the uncertainty space. Finally, multi-variant behavior testing was executed. It encompasses the testing of all different combinations with a base ensemble.

The literature review indicated four different structures that must be determined to model leader-follower behavior in evacuation models. In addition, the framework showed how certain decisions provide the possibility to include or exclude specific leader-follower behaviors. The uncertainty analysis demonstrated that the evacuation time of the core leader-follower behavior is influenced by the familiarity, population, and the chosen distribution of the recognition time, while the response time is influenced by the group distribution. Finally, the separation at the beginning of the evacuation influences the intragroup distance.

The investigation of the three leader-follower behaviors showed that backtracking and flexibility of the group increase the evacuation time. In turn, group gathering only influences the response time. The intragroup distance may increase with backtracking and flexibility of the group, while group gathering does not affect the mean total intragroup distance. However, all behaviors lead to a lower intragroup distance for smaller groups. Finally, the multi-variant behavior testing demonstrated that the combination with the group's flexibility and backtracking show the most significant impact on the key performance indicator and the highest increase in the evacuation time. In comparison, only combinations with group gathering affect the response time. Further research needs to validate these results in empirical studies. Furthermore, the influence of additional leader-follower behaviors needs to be investigated.

Contents

Nomenclature

Abbreviations

Abbreviation	Definition
KPI	Key performance indicator
ODD	Overview, design concepts, and detail
ASET	Available safe egress time
PRIM	Patient rule induction method
CART	Classification and regression tree

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1 Introduction

Fire accidents, environmental disasters, or terror attacks are critical situations where people might need to evacuate a building or a location in order to safeguard their lives. For example, evacuations were needed in the terror attack on the World Trade Center, which resulted in over 2000 fatalities (Centers for Disease Control and Prevention (CDC), 2002) and the Station nightclub fire in Rhode Island in 2003 in which one hundred people lost their lives (Grosshandler et al., 2005). In order to prevent high mortality rates, it is necessary to prepare buildings and events to expedite evacuation from large crowds. Fire safety engineers may utilize evacuation models to test the required evacuation time in advance to facilitate effective evacuations and prevent fatalities. Thus, these models need to be as accurate as possible to learn valuable insights about the location. In order to achieve an optimal representation of real-life evacuation, it is essential to integrate human behavior into these models (E. D. Kuligowski & Gwynne, 2010).

Human behavior in fire investigates human response to critical situations (E. D. Kuligowski, 2016). It includes "people's awareness, beliefs, attitudes, motivations, decisions, behaviors, and coping strategies in exposure to fire and other similar emergencies in buildings" (E. D. Kuligowski, 2016, p. 2070). Observations of real-life emergency evacuations have displayed different behaviors of individuals. For example, people tend to choose a familiar exit or replicate the behavior of other individuals in the crowd (Kinateder et al., 2018). Though not only individual behaviors may be observed, also group behaviors must be considered. Groups develop inside the crowd or already exist before and may grow (Quarantelli, 1995). Examples of group behaviors are leader-follower behavior or the knowledge transfer inside the group (Aguirre et al., 2011). In addition, various behaviors could be observed regarding group decision-making, such as consensus, conformity, or leadership (Haghani et al., 2019). Furthermore, the social composition of groups influences evacuation behavior. For instance, family members, dating partners, and a trusted leader in a group can positively impact the evacuation time of groups (Aguirre et al., 2011).

In general, leadership can be seen as a core attribute of social groups (Hogg et al., 2012). The leaders motivate the group members to reach a shared goal (Wills, 1994). In behavioral theory, the leader drives the group's movement, and thus guides the "followers" in their decisions towards the exit (Moussaïd et al., 2010). Empirical studies discovered that leadership was one of the most influencing decision-making processes during an evacuation (Haghani et al., 2019). In addition, real-life observations of these critical situations revealed that leaders play an essential role in the evacuation process (Jones & Hewitt, 1986).

Various researchers have already explored leader-follower behavior with the help of empirical studies (Bernardini et al., 2021; Cuesta et al., 2016; Ding and Sun, 2020). For instance, Jones and Hewitt (1986) observed different behaviors of leaders and followers in an office building fire in Canada. In particular, they realized that a leader might be imposed through hierarchical structures or emerge spontaneously. In addition, the group may split in case of different opinions about the decisions, leading to a new group with another leader. Moreover, Xie, Lee, Cheng, et al. (2020) realized in an experiment that the leader is always moving in the forefront, and thus, vertical movement of the group appears.

In line with observations in empirical studies, researchers also implemented leader-follower behavior in models. For instance, J. Li et al. (2021) developed a social force model, including leader-follower behavior. They modeled that the leader is slowing down if the group's distance increases. Other authors, such as J. Wang et al. (2015), did not include this behavior. However, they incorporated that the group is gathering before the evacuation. Leader-follower behavior implemented in evacuation models differs substantially, such as Mao et al. (2019), Qin et al. (2018), Fachri et al. (2017), Pan et al. (2021), Lu et al. (2017). These differences in model implementation potentially result in substantially different estimates of the optimal evacuation procedure. Unfortunately, a comparison of these behaviors of optimal evacuation procedures is lacking. A thorough comparison of different model implementations is essential to better understand the impact of leader-follower behaviour models on the evacuation performance.

The implementation of leader-follower behavior in evacuation models comes with various challenges that need to be considered. Already the different observations about leaders in one fire evacuation from Jones and Hewitt (1986) show that uncertainty is predominant in evacuations. It is comprehended that the group may split, and a new leader may emerge. However, some groups with an imposed leader may stay together during the whole evacuation. It is unclear when and how often each behavior may be observed in a real-life evacuation. In addition, the group structure may differ between buildings and time points. This may only demonstrate a few uncertainties in evacuation models. Nevertheless, models need to cope with this behavioral and parameter uncertainty. Exploratory modeling may be used to investigate how the model reacts under uncertainty and in a complex environment (J. Kwakkel, 2018). Therefore, this modeling approach is employed in order to answer the following research question:

How do different leader-follower behaviors in groups (backtracking, group gathering and flexibility of the group) influence the evacuation and response time as well as the intragroup distance inside buildings?

The following sub-questions lead to answering the main research question:

- SQ1: Which leader-follower behaviors are currently modeled in evacuation models?
- SQ2: Which (evacuation) model structures influence the leader-follower behavior?
- SQ3: Which leader-follower behavior are observed in empirical evacuation studies?
- SQ4: How can different leader-follower behavior be implemented in evacuation models using an exploratory agent-based modeling approach
- SQ5: How do the identified behaviors and structures influence the evacuation and response time as well as intragroup distance inside buildings?

Therefore, first, a systematic literature review of leader-follower behavior during evacuation is conducted. This results in a modeling framework for leader-follower behavior, see Chapter 2. Secondly, different approaches and uncertainties in evacuation models are explained in more detail as well in Chapter 2. In Chapter 3, the methodology, including the setup of validation and verification of the model, is discussed. Chapter 4 introduces an innovative agent-based model and provides the verification and validation of this model. After the model presentation, the results are shown in Chapter 5. Finally, the thesis ends with a discussion and conclusion in Chapter 6.

2

Literature study

First, it is necessary to receive an overview of current research regarding leader-follower behavior and define a common understanding of uncertainty. Therefore, the first part investigates leader-follower behavior in models and empirical studies. Then, the focus shifts towards evacuation research and uncertainty.

2.1. Leader-follower behavior

In order to gain a deeper understanding of leader-follower behavior in group evacuation, a systematic literature review was conducted. In particular, the focus was laid on how specific modelers implemented leader-follower evacuation behavior and how empirical studies observed this behavior. This thesis, first, debates the leader-follower behavior found in models, in order to receive an overview of the state of the art. Then the focus shifts to empirical studies to increase the knowledge about this behavior in real-life. Finally, both findings were combined in a framework for leader-follower behavior in evacuation models, that can be used by evacuation modelers in general and will also be used in designing the evacuation model for this study.

2.1.1. Method for literature survey

In order to receive valuable literature, the following method was used. The search was conducted with Scopus and limited to the English language. The following search terms were utilized:

- **Group or collaboration** as the leader-follower behavior is restricted to group behavior.
- **Behaviour or behavior** as the focus is on the behavior of persons
- **Evacuation** to constrain the search to evacuation models
- **Leader** to receive only models which implemented the leader-follower behavior

In addition, the search terms were only applied to the title, abstract, and keywords of the papers to restrict the hits and to obtain the core articles. An exception was made for the last keyword “leader”. This search terms was searched in all fields to find all models, which implemented leadership in their model without mentioning it in the abstract. This search resulted in 111 articles. Figure 2.1 provides a flow diagram of the literature search. These articles were initially screened for evacuation models and empirical studies, limiting the hits to 50 as not all papers described models or empirical studies for evacuation research. Then the focus was on the implementation of the leader/follower behavior in groups. Again, in only 34 articles of 50 articles, this behavior was found. Finally, one more article was found by forward snowballing.

2.1.2. Leader-Follower behavior in models

The literature review shows that **leader-follower behavior** is essential for evacuation models. However, its implementation varies. Nearly all models contained that the leader explores the path and moves towards the entrance, while the group members follow the leader. This can be seen as a core definition of leader-follower behavior. Some authors only included this core behavior in their model (H.

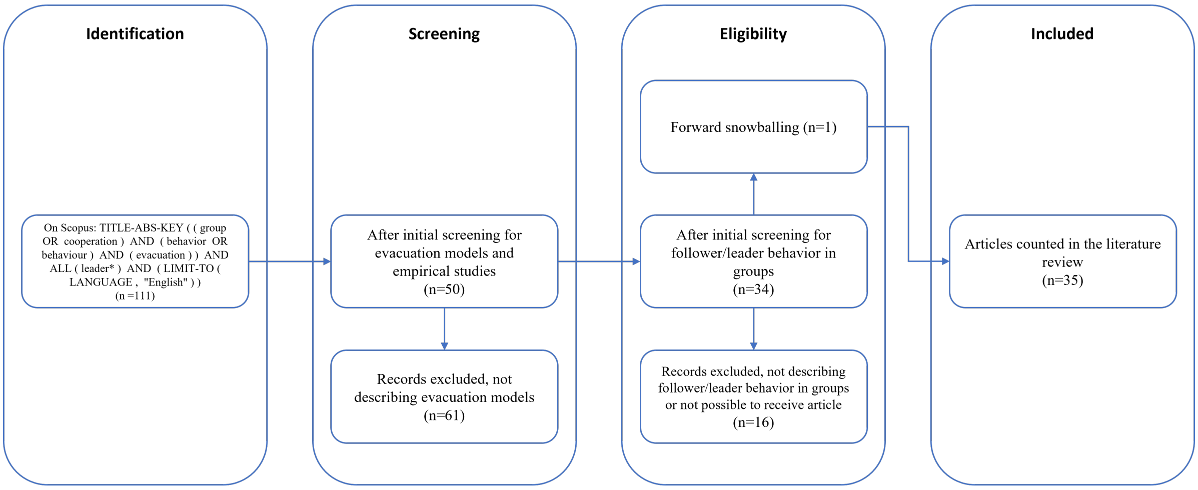


Figure 2.1: Flow chart of core article selection

Zhang et al., 2018; Qin et al., 2018; K. Li et al., 2018; Wei et al., 2014; B. Liu et al., 2018; Cho et al., 2016). Nevertheless, various researchers included additional actions or characteristics of leaders and followers. For instance, Lu et al. (2017), Pan et al. (2021) and J. Li et al. (2021) implemented back-tracking of the leader towards the center of the group in case a member departed or lost the connection from the group. In some models, the group is gathering before the leader searches the path (J. Wang et al., 2015) or the yearning of followers depends on an external variable or training levels (Xie, Wai, et al., 2020; Mao et al., 2019). Furthermore, two modelers designed different types of groups, where only one contains a leader (J. Li et al., 2021; El-Tawil et al., 2017). Xie et al. (2022) focused on the emergence of leader-follower groups in a crowd, whereby the leader occurs as the agent in the group with the closest distance from the exit.

In addition, the knowledge of followers and leaders varies. For example, in most models, the leader and followers know where the exit is located. However, various authors limit the information to the leader, whereas followers are only influenced by the position of the leader (P. Li et al., 2020; J. Wang et al., 2015; H. Liu et al., 2018; Datta and Behzadan, 2019; Pan et al., 2021; Fachri et al., 2017; Xie et al., 2022). Moreover, the properties of followers may diverge. For instance, Y. Li et al. (2021) included children as followers which reduces the group's speed. In turn, Fachri et al. (2017) focused on elderly people. In two models followers reduced their velocity after reaching a certain distance to the leader (Lv et al., 2018; Fachri et al., 2017). Sirakoulis (2014) implemented that followers always chase after the agent in the group with the lowest distance to the entrance. At this, the leader may change over the evacuation period. Emotions played a role in two articles. The emotions of other individuals may influence the leader, or group members are affected by the leader's emotion (Mao et al., 2020). A loss of leadership may even appear if too many emotions are shown (Mao et al., 2019).

Not only the core behavior differs, but also the **determination of the leader** in the models is changing. Most of the authors randomly selected the leader before the start of the evacuation. Nevertheless, one author chose the person in the middle of the group as a leader (H. Zhang et al., 2018), while others selected the agent with the lowest distance to the exit (Qin et al., 2018). Finally, some authors defined the leader based on the highest knowledge or social bond (B. Liu et al., 2018).

In addition, the **flexibility of the group** can be distinguished in the models. Some authors lock the number of agents in one group (Qin et al., 2018; Fachri et al., 2017), while others allow evacuees to change groups (Mao et al., 2020; Sirakoulis, 2014). Furthermore, the **crowd compilation** varies. In a few models, every evacuee is assigned to a group (Mao et al., 2019; Sirakoulis, 2014). In contrast, other authors included individuals as well (Qin et al., 2018; El-Tawil et al., 2017).

All models used different **methodologies**. Nevertheless, social force models account for the largest share. Moreover, cellular automata, velocity-based egress models or agent-based models are used. Finally, the area of the **evacuation** diverges. Most of the models play in a squared room with one exit to investigate the influence of certain variables. However, public building and outside areas are also explored. Some modelers even studied specific places, such as concert halls or passenger ships. Table 2.1 summarizes the identified behavior implemented in each model. In addition, the different structures of the models found are shown in Table 2.2.

	Social force model												Cellular automata				Agent-based model			Velocity-based egress model		
	H. Zhang et al. (2018)	Qin et al. (2018)	K. Li et al. (2018)	Mao et al., (2020)	Wang et al. (2015)	Mao et al. (2019)	J. Li et al. (2021)	Xie, Wai, et al. (2020)	B. Liu et al. (2018)	H. Liu et al. (2018)	Xie et al. (2022)	Lv et al. (2018)	Y. Li et al. (2021)	Lu et al. (2017)	Wei et al. (2014)	Sirakoulis (2014)	Fachri et al. (2017)	El-Tawil et al. (2017)	Pan et al. (2021)	Datta & Behzadan, (2019)	P. Li et al. (2020)	Cho et al., (2016)
Leader searches the path/Move towards entrance	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Group member move towards leader	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Backtracking of the leader							✓							✓					✓			
Leader is influenced by emotion of other individuals				✓		✓																
Group gathering before the evacuation					✓																	
Intra-group emotion contagion: Leaders have greater impact on group members				✓																		
Who knows, where the exit is	Follower, Leader	Follower, Leader	Follower, Leader	Follower, Leader	Leader	Follower, Leader	Follower, Leader	Follower, Leader	Follower, Leader	Leader	Leader	Follower, Leader	Follower, Leader	Follower, Leader	Follower, Leader	Follower, Leader	Leader	Follower, Leader	Leader	Leader	Leader	Follower, Leader
Acceptance of the leader relies on trainings level						✓																
Leaders may lose leadership due to too panicky emotion/ change to a new leader						✓																
Desire to follow the leader depends on a random variable								✓			✓											
Different types of groups, where only one has a leader							✓											✓				
Followers are children													✓									
Followers are elderlies																	✓					
External individuals (not in a group) influence the leader or other followers				✓																		
The velocity of followers change with the distance of leader to catch-up												✓					✓					
Follower avoids leaders path in order to create a free movement of leader																	✓					
Leader may change, due to a change of position (always the leader closest to the exit is the leader)																✓						
Leader/follower group emerges spontaneously in the crowd during the movement. Whereby the leader is always the one in front											✓											
The leader must be in the vision of the follower											✓											
Follower may change to another leader if another leader has more influence											✓											

Table 2.1: Follower-leader behavior in models

		Zhang et al. (2018)	Qin et al. (2018)	K. Li et al. (2018)	Mao et al. (2020)	Wang et al. (2015)	Mao et al. (2019)	J. Li et al. (2021)	Xie et al. (2020)	B. Liu et al. (2018)	H. Liu et al. (2018)	Xie et al. (2022)	Lv et al., (2018)	Y. Li et al. (2021)	Lu et al. (2017)	Wei et al. (2014)	Sirakoulis (2014)	Fachri et al. (2017)	El-Tawil et al.(2017)	Pan et al. (2021)	Datta & Behzadan (2019)	P. Li et al. (2020)	Cho et al. (2016)
Determination of the leader	Center of the group	✓																					
	Closest to the exit (distance)		✓	✓					✓			✓	✓			✓	✓			✓	✓		
	Closest to the exit (time, calculated before)										✓												
	Largest sum of relationship values among the pedestrians									✓													
	Leaders are evacuees with highest knowledge																	✓					
	The leaders were identified based on interviews about a previous evacuation to reproduce the event																		✓				
	Random				✓	✓	✓	✓						✓	✓							✓	✓
Variability of group size	Fixed group		✓	✓		✓			✓	✓	✓		✓	✓		✓		✓	✓	✓	✓	✓	✓
	Possibility to change the group/ switch between groups	✓			✓		✓	✓				✓			✓		✓		✓				
Crowd compilation	Only groups						✓		✓		✓				✓	✓		✓		✓			
	Groups and separate individuals	✓	✓	✓	✓	✓		✓		✓		✓	✓	✓			✓		✓	✓	✓	✓	✓
Evacuation area	Outside area (Urban bock)		✓																			✓	
	Public buildings (office, school, shopping mall; hospital)	✓			✓		✓				✓			✓	✓			✓	✓		✓		
	Squared room			✓		✓		✓	✓	✓	✓	✓	✓		✓	✓	✓						
	Concert						✓																
	Passenger ship																						✓
	Train station																			✓			

Table 2.2: Variables that influence the Follower-Leader behavior in models

2.1.3. Leader-Follower behavior in empirical studies

Leader-follower behavior may not only be observed in models, but it also may be perceived in empirical studies. Therefore, a literature study was conducted in order to investigate behaviors found in experiments to compare the respective outcome with results of the models summarized in the first literature study. The literature review shows that not only the behavior included in models differ, but also the behaviors found in experiments and real-life observations vary. Generally, the results may be divided into behavior during the evacuation process and overall results of leader-follower behavior. First, Xie, Lee, Cheng, et al. (2020) observed that groups with leaders demonstrate a vertical movement compared to groups without a leader. They also realized that leadership behavior weakened if the visibility got worst. Two authors confirmed that the leader searches the path whereby the leader moves at the forefront of the group and recognizes first the exit direction (Xie, Lee, Cheng, et al., 2020; P. Zhang et al., 2021). However, if the leader's speed increases, leadership efficiency declines due to difficulties following the leader (Cuesta et al., 2021; P. Zhang et al., 2021). Moreover, in two experiments a spontaneous leader emerges, who encourages other members to evacuate (Cuesta et al., 2016; Cuesta et al., 2021). Bernardini et al. (2021) investigated the behavior of elderlies and found that their desire to follow is higher compared to other age groups. In observations of real-life evacuations, Gershon et al. (2007), Gershon et al. (2012), and Jones and Hewitt (1986) noted that the ability to follow the leader depends on authority. Further, Gershon et al. (2007) observed that in the world trade center tragedy, people delayed their evacuation due to the believe that the manager won't approve the evacuation. More pre-movement activities were encountered by Jones and Hewitt (1986). They noted that the leader notify other colleagues about the fire and instructed them to collect personal belongings. The followers complied with these instructions. After finishing the tasks, some groups gathered before the evacuation, while the leader waited for the followers.

Different general results about leader-follower behavior were discovered in various experiments. The social relation was investigated in four experiments. Ma et al. (2017) found that social ties influence the effectiveness of leadership groups in crowds. Lovers may be more efficient as mother-daughter couples. Furthermore, one experiment showed that the crowd consists of leaders, followers and lonely evacuees (L. Li et al., 2020). With the help of a social network analysis, Xie, Lee, Cheng, et al. (2020) perceived that normal leaders with the highest trust score might also result in evacuation leaders. However, contradicting results were obtained in an experiment by Ding and Sun (2020). They observed that evacuees may not follow the opinion leader, and that other variables during the evacuation may have a greater influence. Other contradicting results were unearthed about the dominance of leadership. Haghani et al. (2019) state that leadership was the dominant driver in decision-making in their experiment in contrast to consensus or conform decision making. In comparison, Cuesta et al. (2021) measured that unanimity and majority are the leading decision-making methods. Leadership reached only the maximum of four percent of decision-making methods in all experiments. Finally, X. Wang et al. (2020) utilized questionnaires to investigate the behavior on a passenger ship. They concluded that passengers will most likely follow the leader.

As already described in chapter 2.1, further structures and variables may impact leaders, and followers, behavior in models. The first variable, which changes in all empirical studies, is the **determination of the leader**. Two different kinds of determination could be observed: no determination, which led to an emergent leader or an imposed leader. In six experiments, an emergent leader was witnessed. In contrast, three experiments chose a leader up front. Moreover, in observations both kinds of leaders could be identified whereby the imposed leader was established through a work hierarchy.

Another variable is the **crowd composition**. It varies between only groups, groups as well as individuals and no groups, resulting in only a crowd. Seven empirical studies focused on only groups without including individuals in the crowd. On the other hand, four authors involved external individuals in their investigation. In contrast, P. Zhang et al. (2021) investigated only leaders in a crowd without any groups.

Moreover, the **flexibility of the group** differs. In one observation, people may change to another leader or the group may split, whereby a new leader in the group emerges (Jones & Hewitt, 1986). All other empirical studies did not investigate the possibility of changing the group.

In addition, various authors included **social relations** of study participants in their investigations. It varied from determining the leader in the group (Xie, Lee, Cheng, et al., 2020) to creating groups due to real-life personal relations (Ma et al., 2017). In total, seven studies investigated or used social ties.

Finally, the **responsibility of the leader** changes. Some articles focused on leaders in a group, while others looked into leaders in crowds. In total, nine authors investigated group leaders. Which relates to the majority of the articles found. Three other authors studied leaders in crowds, while two of them included leader groups (Ding and Sun, 2020; Ma et al., 2017). All behavior and variables are summarized in Table 2.3 and Table 2.4.

		Experiments									Questionnaire	Observations		
		Ma et al. (2017)	Haghani et al. (2019)	Xie, Lee, Cheng, et al (2020)	Cuesta et al. (2016)	Ding & Sun, (2020)	L.Lie et al. (2020)	Cuesta et al. (2021)	P. Zhang et al. (2021)	Bernadini et al. (2021)	X. Wang et al. (2020)	Gershon et al. (2007)	Gershon et al. (2012)	Jones & Hewitt (1986
Determination of leader	No determination (emergent or random)	✓	✓	✓	✓			✓		✓		✓	✓	
	Imposed leader					✓	✓		✓			✓		✓
Crowd composition (investigated)	Only groups	✓	✓		✓			✓		✓		✓	✓	✓
	Groups and individuals			✓		✓	✓							✓
	No groups								✓					
Group flexibility	Possible to change group										Not mentioned			✓
	Fixed group	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	
Social relation	Social relation included	✓		✓		✓	✓					✓	✓	✓
	Random		✓		✓			✓	✓	✓				
Inter-group or intra- group		Inter-group (couple as leader)	intra-group	intra-group	intra-group	Inter-group (couple as leader)	intra-group	intra-group	Inter-group	intra-group		intra-group	intra-group	intra-group

Table 2.3: Variables that influence the leader-follower behavior

		Experiments									Questionnaire	Observations		
		Ma et al. (2017)	Haghani et al. (2019)	Xie, Lee, Cheng, et al (2020)	Cuesta et al. (2016)	Ding & Sun, (2020)	L. Lie et al. (2020)	Cuesta et al. (2021)	P. Zhang et al. (2021)	Bernadini et al. (2021)	X. Wang et al. (2020)	Gershon et al. (2007)	Gershon et al. (2012)	Jones & Hewitt (1986
Leader-Follower behavior	Groups with a leader demonstrated vertical movement in contrast to the horizontal movement of groups without a leader			✓										
	Leader searches the path			✓					✓					
	Leadership behavior weakened when visibility worsened			✓										
	Spontaneous leader emerges and encourages other participants to evacuate				✓			✓						
	Higher leader speed may reduce the leadership efficiency, due to difficulties to follow the leader							✓	✓					
	Elderly people have a higher likelihood to follow the leader									✓				
	Ability to follow a leader depends on authority											✓	✓	✓
	Inaction: Delayed evacuation due to belief that manager would disapprove of leaving the workplace											✓		
	Group gathered before the evacuation													✓
	The leader notifies others and tells the followers to collect personal belongings													✓
	The follower collects personal belongings													✓
	Groups may split due to different opinion, which leads to new emergent leaders													✓
	Groups may increase →new followers are following the leader													✓
Results	It can be found that most of the emergency leaders obtained the highest trust score. This indicates that the emergency and normal leaders are likely to be the same person.			✓										
	Leadership as the lowest decision-making process							✓						
	Leadership as the most dominant decision-making process		✓											
	The effectiveness of groups as leaders in crowds depends on the social tie. Lovers may be more efficient as a mother-daughter couple.	✓												
	Passengers most likely follow the leader										✓			
	Opinion leaders in social relationships may not be evacuation leaders.					✓								
	Social network analysis shows that there are followers, leaders and lonely evacuees in crowds						✓							

Table 2.4: Follower-leader behavior in empirical studies

2.1.4. A modelling framework for leader-follower behavior

The literature review about leader-follower behavior in models and empirical studies exemplified different behaviors of leaders and followers. In addition, it illustrates that the leader-follower behavior may vary depending on the evacuation situation. For instance, only in offices or at work a leader may be imposed through hierarchical statuses (Jones & Hewitt, 1986). Therefore, in order to include leader-follower behavior through hierarchical structures, a modeler needs to investigate if this model choice is suitable for the location of interest. In order to aid modelers in modeling leader-follower behavior, a framework was developed, which contains four model structures with the different leader-follower behavior.

The ”determination of the leader” is not the only varying model structure observed in the literature study. In addition, three other model structures were witnessed: crowd compilation, group compilation, and group size variability. All may include or exclude unique leader-follower behaviors.

First, for the model structure ”determination of the leader” seven options could be observed in models and empirical studies, such as random distribution, the group member closest to the entrance defined by time or distance, social structures, highest knowledge, emergent leader or imposed leadership through hierarchy. This choice may influence the range of options for a leader and the follower pre-movement behavior. Only if the hierarchical structures are present, delayed evacuation may emerge due to the belief of disallowance by the manager (Gershon et al., 2007).

After the leader's determination, the crowd compilation needs to be determined. The crowd may consist of groups and individuals or only groups. Only if individuals are present, they may influence the leaders and followers or increase the group. The third structure is the group compilation. Four unique possibilities were revealed in the literature study: the inclusion of elderlies or children, different types of groups whereby just one included a leader or a random group compilation with no specification. Only if elderlies are represented in the group, they may be more likely to follow the leader (Bernardini et al., 2021). Finally, the variability of the group is an essential model structure. If groups are flexible, a follower may change to another leader with more influence, or leaders may lose leadership. Furthermore, groups may split due to different opinions, or incoming individuals may increase the group. These flexible groups may represent emergent groups in evacuations (Fang et al., 2016). Controversially, fixed groups may be seen as social groups with a close social relation (Köster et al., 2014). In addition to the different structures of the model, various pre-movement actions may be observed by leaders and followers, such as group gathering before the evacuation, notification of the leader to collect personal belongings and followers pursuing his advice or inaction because they do not believe in consent to leave.

Finally, the leader-follower behavior needs to be defined. The behavior may be divided into physiological and psychological behavior. The core behavior of leaders and followers is composed of the follower moving towards the leader and the leader searching the path. However, supplementary behaviors may be added, such as backtracking or the leadership weakening of when visibility worsens. All possible behaviors and the framework can be found in figure 2.2. The framework is limited to the knowledge observed in the literature study and may be improved in the future. However, the framework aids evacuation researchers in modeling leader-follower behavior in evacuation models.

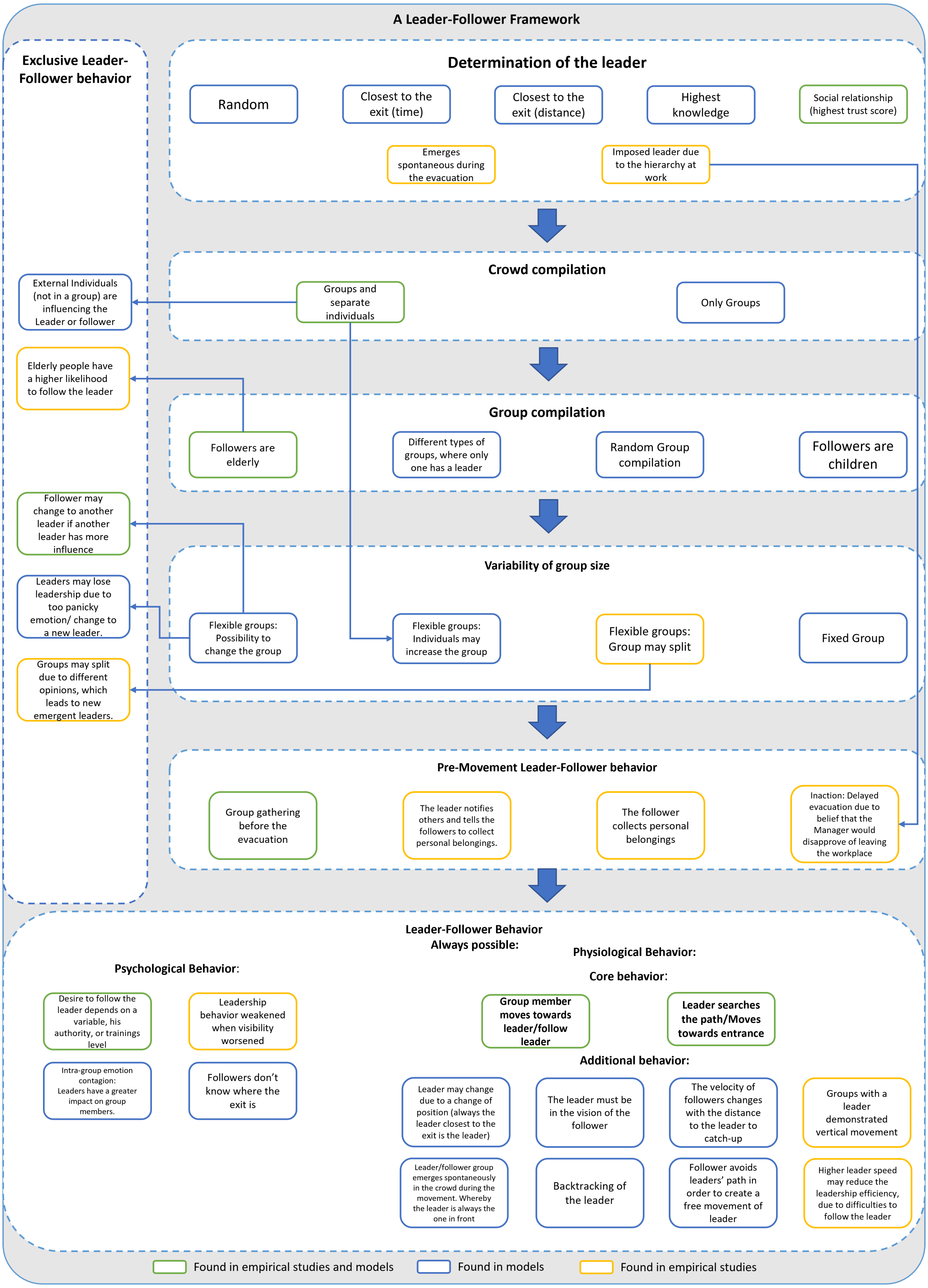


Figure 2.2: A leader-follower framework

2.1.5. Three unique leader-follower behaviors in the model

The literature study provided an overview of various leader-follower behaviors in evacuation research. However, in the model only three unique leader-follower behaviors are investigated to gain knowledge about their influence on various Key performance indicators (KPIs) due to the time limitations of this research. The reason for choosing ”backtracking”, ”group gathering”, and ”flexibility of the group” are observations in empirical studies and previous models of these behaviors in different group structures and individual phases of the evacuation process. Backtracking and group gathering may be found in social groups (Köster et al., 2014) whereby the flexibility of the group may relate to emergent groups in evacuation (Fang et al., 2016). In addition, the behavior phase differs for these three behaviors. Backtracking and flexibility of the group may appear during the group's movement whereby group gathering may be seen as a pre-movement action (Forssberg et al., 2019). All reasons for choosing the three behaviors are summarized in Table 2.5. A detailed description of each behavior may be found in Chapter 4.1.7.

Behavior	Definition of the behavior	Reason for choosing this behavior	Group structure	Behavior phase
Backtracking	Leaders slow down and wait for the follower to catch up.	Backtracking was found in various models and is therefore used. Moreover, backtracking may be found, in particular, in social groups.	Social groups	Movement
Group gathering before the evacuation	The group is gathering near the leader before they follow the leader.	The behavior was found in empirical data and models. In addition, it relates to the pre-movement of the group.	Social groups	Pre-movement
Flexibility of the group: A follower may change to another leader if the other leader has more influence.	Every follower may change the leader, if another leader is closer.	The behavior was found in empirical data and models. Furthermore, it may be observed in emergent groups.	Emergent groups	Movement

Table 2.5: Reasons for choosing the three leader-follower behaviors for the final model

2.2. Evacuation models

After the elaborate description of leader-follower behaviors, the focus shifts to evacuation research. The goal is to understand which methodologies are currently utilized in evacuation research and how uncertainty is dominant in these models.

2.2.1. Overall approaches in evacuation research

Evacuation research may be divided into experiments, field methods, or modeling. Depending on the goal of the research, the approach may differ. First, experiments try to gather large numbers of individuals in experimental environments to simulate critical situations in order to receive valuable new insights into how people behave (Haghani & Sarvi, 2018). Overall, experiments may be divided into animal and social insect crowd experiments, laboratory experiments with social crowds, virtual/augmented reality crowd experiments, hypothetical choice surveys and evacuation drill experiments (Haghani and Sarvi, 2018; Haghani, 2020). Experiments provide researchers with control over variation as well as responses of people (when and what decisions to make), and they can be replicated (Haghani & Sarvi, 2018). However, a real evacuation may never be simulated due to ethical considerations (Haghani, 2020).

In contrast to experiments, in which an evacuation is simulated, field methods investigate real-life evacuations in more detail. This is especially useful to achieve a high environmental and conceptual realism of crowds (Haghani & Sarvi, 2018). However, variations of different structures and the investigation of specific aspects are impossible, as these situations have already passed. Haghani (2020) divides field methods into a post-incidents analysis of real-emergencies and crowd incidents, field observations in natural settings as well as qualitative interviews.

Finally, modeling may be utilized to simulate emergency situations. Already in the literature review at the beginning of the chapter, different methodologies were observed. In total, seven methodologies of modeling exist, which may be exploited to investigate the behavior in crowds, such as cellular automata, lattice gas, social force, fluid dynamics, agent-based, game theory, and experiments with animals (Zheng et al., 2009). All can be classified as either macroscopic or microscopic (Zheng et al., 2009). Macroscopic models focus on crowd movement as a whole, while microscopic models include different particles or agents with changing rules or equations (Y. Li et al., 2019). Microscopic models may further be classified as force-based (e.g. social-force), grid-based (e.g., cellular automata) and velocity-based models (Y. Li et al., 2019). In addition, models differ regarding space and time. Models may either be discrete or continuous (Zheng et al., 2009).

2.2.2. Uncertainties in evacuation models

First, it is essential to comprehend the concept of uncertainty to build a shared understanding. Depending on the field, the definition of uncertainty may differ, leading to different methods to tackle uncertainty (Thissen & Walker, 2013). Uncertainty may not be constrained only to the ”limited knowledge about future, past or current events” (Thissen & Walker, 2013, p. 220). More knowledge does not necessarily lead to a reduction of uncertainty. It can also result in a deeper understanding of the increasing complexity, which causes more uncertainty. Therefore, a more accurate definition is the one by Walker et al. (2003). He defines uncertainty as “any departure from the (unachievable) ideal of complete determination” (Walker et al., 2003, p. 5). In other words, an event is uncertain if the probability of the event is neither 0 nor 1 (Thissen & Walker, 2013). Hence, this definition is employed to understand uncertainty in evacuation models.

In evacuation models, uncertainty is predominant. Models implement certain data from experiments or observations of real-life evacuations in order to prepare buildings for critical situations. However, data about model inputs are limited (Averill et al., 2008). In addition, further limitations can be found in the quality of the available data. Averill et al. (2008) divides these limitations into temporal, contextual, and realistic nature. Temporal limitations refer to the changing physiological profile of the population or the influence of major accidents on considered theories, such as the World Trade Center towers. The contextual factors are related to the missing implementation of the backgrounds in experiments. For instance, office workers may perform differently than shoppers in a mall. Finally, the question arises if observations and data from fire drills or experimental data may represent a real-life evacuation. For instance, fire drills at the World Trade Center indicated a faster evacuation than the evacuation that was seen during the terror attack.

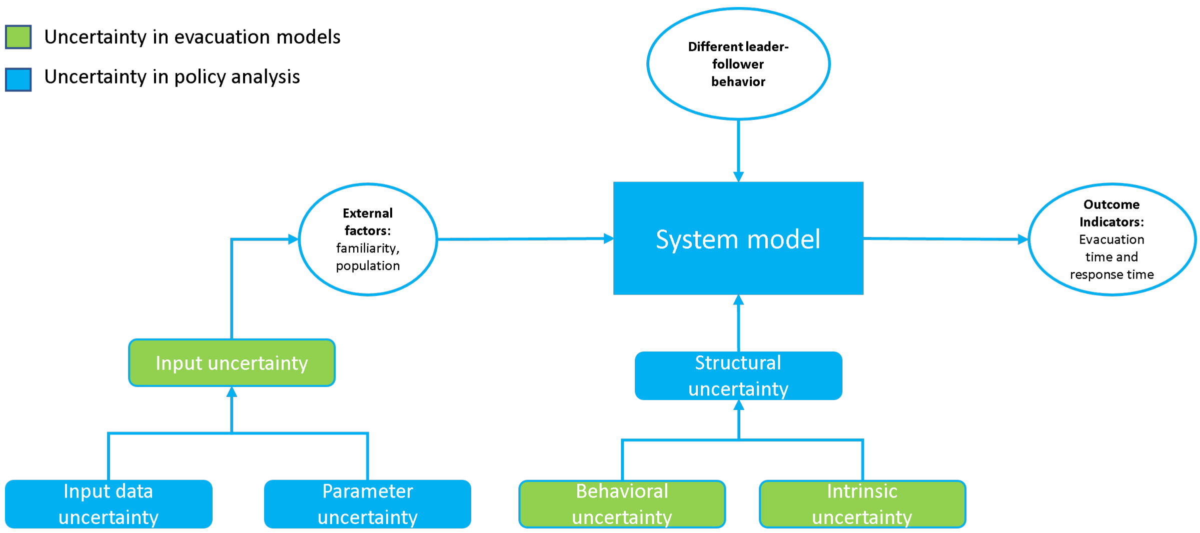


Figure 2.3: Uncertainty in evacuation models

J. H. Kwakkel et al. (2010) generally distinguish between different locations of uncertainty. Possibilities are system boundary, conceptual model, the computer model including its model structure as well as model parameters, input data, model implementation, and process output data. For evacuation models, these locations of uncertainty may differ. In evacuation models and fire safety engineering, four different uncertainties may be found (Lovreglio, Ronchi, and Borri, 2014; Ronchi et al., 2014):

1. Model input uncertainty: related to the parameters that are acquired from empirical studies and included in the model
2. Measurement uncertainty: related to the experimental measurement
3. Intrinsic uncertainty: related to mathematical assumptions and methods inherent in the model formulation
4. Behavioral uncertainty: related to human behavior during evacuation situations

Measurement uncertainty is more related to evacuation experiments which are outside the scope of this research. However, the three remaining uncertainties must be considered in the modeling process. Intrinsic and behavioral uncertainty relates to structural uncertainty for policy analysis as both describe the "lack of sufficient understanding about the system" (Walker et al., 2003). In addition, the model input uncertainty first described by Ronchi et al. (2014) does not differentiate between parameters utilized in the model. Therefore, it incorporates parameter uncertainty as well as input data uncertainty as defined by J. H. Kwakkel et al. (2010). Parameter uncertainty may further be divided into "parameters inside the model" and "input parameter to the model" (J. H. Kwakkel et al., 2010). The different locations of the uncertainties in the framework for model-based policy analysis are displayed in Figure 2.3. The definition and the relationship are summarized in Table 2.6

<table>
<tr><th>Location of uncertainty in policy analysis</th><th>Definition</th><th>Location of uncertainty by Ronchi et al. (2014) in evacuation research</th><th>Definition</th></tr>
<tr><td rowspan="2">Structural uncertainty</td><td rowspan="2">"Uncertainty about the structure of the system that we are trying to model implies that any one of several model formulations might be a plausible representation of the system, or that none of the proposed system models is an adequate representation of the real system" (Thissen et al., 2013, p. 226)</td><td>Intrinsic uncertainty</td><td>uncertainty related to mathematical assumptions and methods inherent in the model formulation</td></tr>
<tr><td>Behavioral uncertainty</td><td>It is the uncertainty about human behavior in evacuation situations</td></tr>
<tr><td>Parameter uncertainty</td><td>"Input is associated primarily with data that describe the reference (base case) system and the external driving forces that have an influence on the system and its performance." (Walker et al. 2003, p.10)</td><td rowspan="2">Input uncertainty</td><td rowspan="2">related to the parameters that are acquired from empirical studies and included in the model</td></tr>
<tr><td>Input data uncertainty</td><td>"Associated with determining the value for the different parameters both inside the model and as inputs to the model" Kwakkel et al. (2010)</td></tr>
</table>

Table 2.6: Summary of uncertainties in evacuation models

3

Research Methods

After the state of the art was presented in more detail. This chapter focuses on the research methods to answer the research question. Various approaches may be possible. First, the overall methodology and the reason for choosing these approaches are explained. Then, the methods for verification and validation of the model are described.

3.1. Methodologies

In order to answer the research question of how different leader-follower behaviors in groups (backtracking, group gathering, and flexibility of the group) influence the evacuation and response time as well as intragroup distance inside buildings, two methodologies are utilized. The reason behind choosing an agent-based model in combination with exploratory modeling is outlined in the following chapter.

3.1.1. The modeling approach

Different research approaches could be used to investigate the impact of leader-follower behaviors in groups on evacuations. First, evacuation research may be divided into experiments, field methods, or modeling as already explained in Chapter 2.2.1. Experiments have the advantage that the behavior of real individuals may be explored. However, a real-life critical situation may never be simulated for ethical reasons (Haghani, 2020). Therefore, individuals may behave differently if no danger is present (Poulos et al., 2018). In addition, human and material resources are needed, which may be prohibitively expensive (Poulos et al., 2018; MacAl and North, 2010). Field methods may solve these problems, as a real-life evacuation is studied in more detail. Nevertheless, as these situations already occurred, various behaviors for the same situation cannot be tested (Haghani & Sarvi, 2018). Hence, the influence of several behaviors cannot be compared. In contrast, modeling provides this opportunity. Here, parameters and behaviors may be varied, and the influence on the evacuation time may be studied. Moreover, different locations and events can be investigated (Poulos et al., 2018). The modeling approach may be seen as the only opportunity to conduct ethical studies about this behavior in these critical situations (El-Tawil et al., 2017). Therefore, the modeling approach is the most appropriate concept for answering the research question. Also, this approach may come with various limitations that need to be considered. For instance, only if the right level of detail is chosen, the model may aid in answering the research question (Couclelis, 2000). In addition, it may be challenging to include the complex behavior of systems in the model (Castle & Crooks, 2006). However, the modeling approach provides valuable insights into leader-follower behavior. Table 3.1 summarizes the advantages and disadvantage of different approaches.

This thesis describes the development of a novel model as currently there are no evacuation models available that explore the influence of different behaviors and the impact of uncertainty on leader-follower groups. Every model needs to be developed for its specific purpose (Edmonds et al., 2019). As the purpose of the new model presented here is to illuminate core uncertainties, discover new insights and provide a better understanding of leader-follower behavior, a new model needed to be created.

	Experiments	Field studies	Modeling
Advantages	- the behavior of real individuals may be explored	- shows real-time behavior of individuals	▪ **parameters and behaviors may be varied, and the influence on the evacuation time may be studied** ▪ **different locations and events can be investigated** ▪ **The modeling approach may be seen as the only opportunity to conduct ethical studies about this behavior in these critical situations**
Disadvantages	▪ a real-life critical situation may never be simulated due to ethical reasons → individuals may behave differently if no danger is represented ▪ Human and Material resources are needed	▪ various behaviors for the same situation cannot be tested → the influence of several behaviors cannot be compared	▪ May not represent a real-life scenario → Model need to be validated ▪ Scope of the model is restricted due to the limiting amount of time and computing power

Table 3.1: The comparison of different approaches and the selected modeling approach

3.1.2. Agent-based model

As already explained in chapter 2.2.1, various methodologies exist to model evacuations, such as social force models, fluid dynamics, and agent-based modeling (Zheng et al., 2009). All demonstrate multiple advantages as well as disadvantages, and each methodology may be utilized for unique research goals. As this research investigates different behaviors and their influence on the emergent pattern in a complex environment, agent-based modeling is a suitable methodology for this study. In particular, the possibility of implementing individual agent rules without knowing the emergent global behavior is an advantage of agent-based modeling (Borshchev & Filippov, 2004). In pedestrian crowds, underlying rules form emergent patterns, which express a complex situation (Gershon et al., 2012). Due to its bottom-up approach and ability to incorporate flexible and autonomous actions of agents in an environment (Jennings, 2000), agent-based models enable the integration of evacuee relationships and building interactions during an evacuation. Especially these attributes lead to choosing an agent-based model in order to answer the research question. However, it is essential to bear in mind that a model may never represent a real-world situation and may simplify certain aspects (van Dam et al., 2013). Furthermore, agent-based models are computer and time-intensive, which limits the scope and experimentation of the model (A. Li et al., 2020). Nevertheless, it may aid in providing valuable information about leader-follower behavior and their influence on an evacuation. Assorted tools exist to create an agent-based model, such as Mesa, Mimosa, or Netlogo (Abar et al., 2017). However, Netlogo has the advantage of a low development effort of the model as well as the possibility to realize medium and large-scale models and, thus, is utilized for the implementation of the conceptual model in this research (Abar et al., 2017).

3.1.3. Exploratory modeling

The presence of uncertainty implies that more than one model may describe a system (Bankes, 1993). Each variation of parameters can be seen as another model of an evacuation. In an exploratory analysis different models in this parameter space will be chosen in order to investigate how the model behaves under the influence of uncertainties. Exploratory models do not predict or find precise answers to specific questions (Weaver et al., 2013). However, exploratory modeling may aid in gaining new insights about the model and help discover extreme behaviors of the model (Weaver et al., 2013). For instance, with the help of scenario discovery, scenarios may be identified that indicate policy-relevant regions in the uncertainty space of evacuation models. In addition, higher confidence in results, and thus a more robust solution may be achieved (J. H. Kwakkel, 2017). For leader-follower behaviors in evacuations, exploratory modeling may accomplish robust results about the influence on evacuations, independent from a selected situation. Hence, it increases the overall value for the evacuation research community. Therefore, exploratory modeling, in combination with agent-based modeling is employed to explore how specific leader-follower behaviors may influence the evacuation of buildings under uncertainty. Various tools for exploratory modeling exist, which are explained further.

Scenario discovery
Overall, scenario discovery may aid in finding policy-relevant scenarios in the uncertainty space. Scenario discovery utilizes data-mining algorithms such as the Patient Rule Induction Method (PRIM) or Classification and Regression Tree (CART) (Bryant & Lempert, 2010). PRIM provides the advantage of high interactivity and is, thus, applied in this work. In addition, it aids in finding the balance between the three measures for the quality of the scenario: coverage, density, and interpretability (Bryant & Lempert, 2010). Coverage is the percentage that satisfies the parameter ranges found in the scenario out of all cases that lead to a high evacuation time. In contrast, the density represents the percentage of cases with the identified parameter sets, resulting in a high evacuation time. A perfect set of scenarios includes a high value for all measurements. However, coverage and density compete, leading to difficulties in finding an ideal scenario. PRIM may aid in obtaining a high value for both of these measurements. In this research, scenario discovery is utilized to find different scenarios for changing available safe egress times (ASET) for the core leader-follower behavior. These scenarios may aid fire safety engineers and policy makers to find policies that help in achieving these ASET and reduce the evacuation time of the core leader-follower behavior. These results are beneficial for locations with a high distribution of leader-follower groups, such as offices or museums, where families and friends are present.

Feature scoring
Feature scoring helps to identify the relevance of uncertainties on KPIs. It may be seen as an alternative to a global sensitivity analysis, especially for computationally intensive simulation models such as evacuation models (Timmermans et al., 2020; Jaxa-Rozen and Kwakkel, 2018) as smaller sampling sizes may already lead to accurate results. Feature scoring estimates global sensitivity analysis measures with the help of a machine learning algorithm (Jaxa-Rozen & Kwakkel, 2018). Various algorithms exist. Nonetheless, the extra-trees algorithm developed by Geurts et al. (2006) may be the most accurate and is thus employed in this research.

Base ensemble
The difference between traditional and exploratory modeling is the absence of a base case, but the utilization of a base ensemble (Auping, 2018). A base ensemble represents a sample over the uncertainty space. Various sampling techniques exist to conduct an exploratory experiment, such as simple random, Latin hypercube, and Monte Carlo sampling (Thiele et al., 2014; van Dam et al., 2013). With the help of these sampling techniques, scenarios with different values for each uncertainty may be achieved, representing the base ensemble. These scenarios may then be utilized to compare the three behaviors' influence to the identical scenarios without these behaviors.

3.1.4. Overall methodology

Overall, this research may be separated into three different aspects. First, the goal was to understand leader-follower behavior with the help of literature, resulting in a leader-follower framework as it was already developed in Chapter 2. This framework may aid researchers in modeling this behavior. Secondly, explore the influence of uncertainties on leader-follower groups. This is needed to discover policy-relevant areas in the uncertainty space for locations with a high distribution of leader-follower groups, such as museums or offices. It is achieved with an open exploration of the model. Finally, the framework is utilized, and different leader-follower behaviors are compared to the core leader-follower behavior. The agent-based model aims to understand the underlying pattern and the influence of additional leader-follower behavior on the evacuation performance. Hence, the goal is not to predict the exact evacuation time of buildings. Instead, it strives to explain how and why additional leader-follower behavior influence evacuation performance. This provides new insights into leader-follower behavior and supports modelers and researchers in incorporating these behaviors in evacuation models due to their influence on the evacuation performance. The overall methodology is summarized in Figure 3.1.

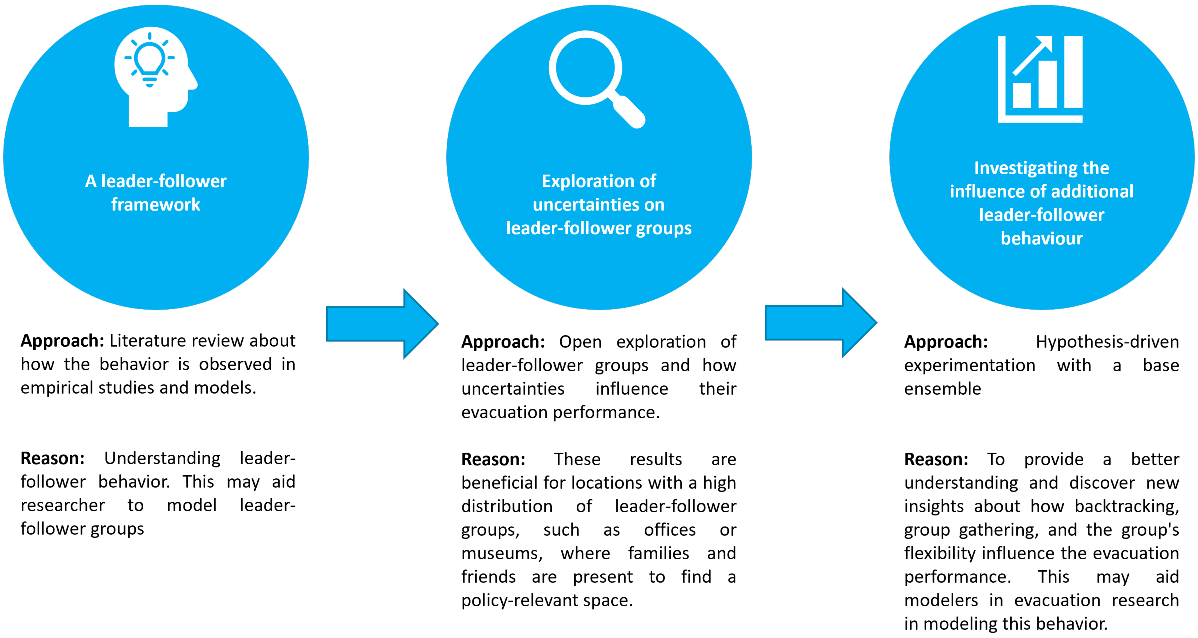


Figure 3.1: The overall methodology of this research

3.2. Set-up for verification

Verification answers the question if the model is built right (van Dam et al., 2013). The International Standards Organization (2008) defines verification as "the process of determining that a calculation method implemented accurately represents the developer's conceptual description of the calculation method and the solution to the calculation method". This definition is utilized in this research to verify the model. Ronchi et al. (2016) proposed various verification tests which may be used in order to verify the model. The tests are divided into different core components of an evacuation model. For each core component one test was selected and executed. The tests are summarized in Table 3.2. In addition, unit testing and recording of agent behavior are employed (van Dam et al., 2013).

Core component	Test
Pre-evacuation time	Pre-evacuation time distributions
Movement and navigation	- Movement around the corner - Group behavior
Exit usage	Exit route allocation
Route availability	-
Flow conditions	- Congestion - Flow rate

Table 3.2: Verification test

3.3. Set-up for validation

In contrast to verification, validation gives an answer to the question of whether the correct model has been created (van Dam et al., 2013). In social simulations, the link between the micro behavior and the macro outcome is predominant (Friedman et al., 2008). Whereby, the micro behavior may be defined as individual behavior of agents (Moss & Edmonds, 2005). In contrast, macro behavior relates to the overall outcome of the model due to the interaction of agents (Moss & Edmonds, 2005). Squazzoni (2012) argues that in sociology multi-level validation may increase the trust in the model. Therefore, macro and micro validation are performed. Thus, in this research, micro validation is defined as **the process of determining the degree to which the individual behavior of agents in the model represents the real world**. While Macro validation is described as **the process of determining the degree to which the model's outcome represents the real world**.

For macro validation, the evacuation time is compared to empirical data from Haghani et al. (2019). For micro validation the validation tests by Ronchi et al. (2016) are followed. Whereby each core behavior is contrasted to empirical data found in literature or due to face validation. In total, five different tests are employed for the pre-movement behavior, social force heuristic, group behavior, queuing and the flow rates at exits. All data and methods utilized are outlined in Table 3.3.

Validation	Core component	Core behavior	Data	Method
Macro	**Overall behavior**	**Evacuation time**	Haghani et al. (2019)	Data comparision
Micro	**1**	**Pre-Movement**	Lovereglio et al. (2019)	Data comparision
	2	**Social force heuristic**	Rinne et al. (2010); Helbing et al. (2007)	Data comparison
	2	**Group behavior**	Köster et al. (2014); Lee, Cheng, et al. (2020)	Face validation
	2	**Queuing**	Haghani et al. (2019); Wagoum et al. (2017); Hu et al. (2018); Xie, Lee, Cheng, et al. (2020)	Face validation
	5	**Flow rates**	Rinne et al. (2010)	Data comparison

Table 3.3: Macro and micro validation tests

The final step to increase the trust in the system is a sensitivity analysis. In addition, higher trust in the built model and increased validity of the model may be achieved with a sensitivity analysis (Smith et al., 2008). If the model is sensitive to parameters that also occur in the real world, the trust in the model increases (Smith et al., 2008). Thus, a Sobol sensitivity analysis is conducted with 1000 samples, leading to 22000 different parameter combinations. Every combination was repeated 50 times. A detailed description why the Sobol method was chosen can be found in Chapter A.3 in Appendix A.

4

The agent based model

To answer the research question, an agent-based model was developed. In this chapter, the developed agent-based model is explained in more detail, with its uncertainties, verification, and validation. Finally, the chapter ends with the experimental setup to receive the results.

4.1. Model representation

In order to provide a structural presentation of the developed model, the Overview, Design concepts, and Detail (ODD) protocol is followed. The ODD protocol was established to stipulate a general framework to describe individual-based and agent-based models independent from their structure in combination with the mathematical language (Grimm et al., 2006). Its division into overview, design concepts and details is employed as a structure in this chapter. Therefore, first the purpose of the model is explained, followed by the state variables and states as well as the process overview and scheduling. Then the design concepts are described in more detail, and finally, the ODD finishes with the details phase including initialization, input and submodels. The model and the related notebooks are available on request at https://github.com/JIRnic.

4.1.1. Purpose of the model

The purpose of the model is to investigate how specific leader-follower behavior may influence the evacuation, response time and intragroup distance inside buildings. In particular, three behaviors are examined in more detail: (1) backtracking, (2) group gathering before the evacuation, and (3) the flexibility of followers to change to another leader. The reason for choosing these behaviors lies in different group structures and evacuation phases. In order to test how these behaviors may influence the evacuation time and response time as well as intragroup distance inside buildings, while considering the uncertainty of evacuation models, an exploratory modeling approach is employed. The goal is to receive a robust result regarding these three behaviors in buildings with the help of exploring the uncertainty space of an evacuation process. Therefore, an agent-based evacuation model in a building is developed. The environment may represent a public building such as a museum or a community hall. However, the model may be applied to other facilities as well.

The scope of the model

During an evacuation, a broad range of behaviors may be encountered. This ranges from individual behaviors, such as herding behavior, to various group behaviors including consensus or conform decision-making (Haghani et al., 2019). However, the model's focus is related to leader-follower behavior in groups. Therefore, only this behavior is included in the model. The model's scope is summarized in Figure 4.1 whereby the different rings illustrate the core behaviors, which are always included in the model, the additional behavior, which needs to be defined and can be changed in the model, and other behaviors that are out of scope. A detailed description of the model and behaviors follows in this chapter.

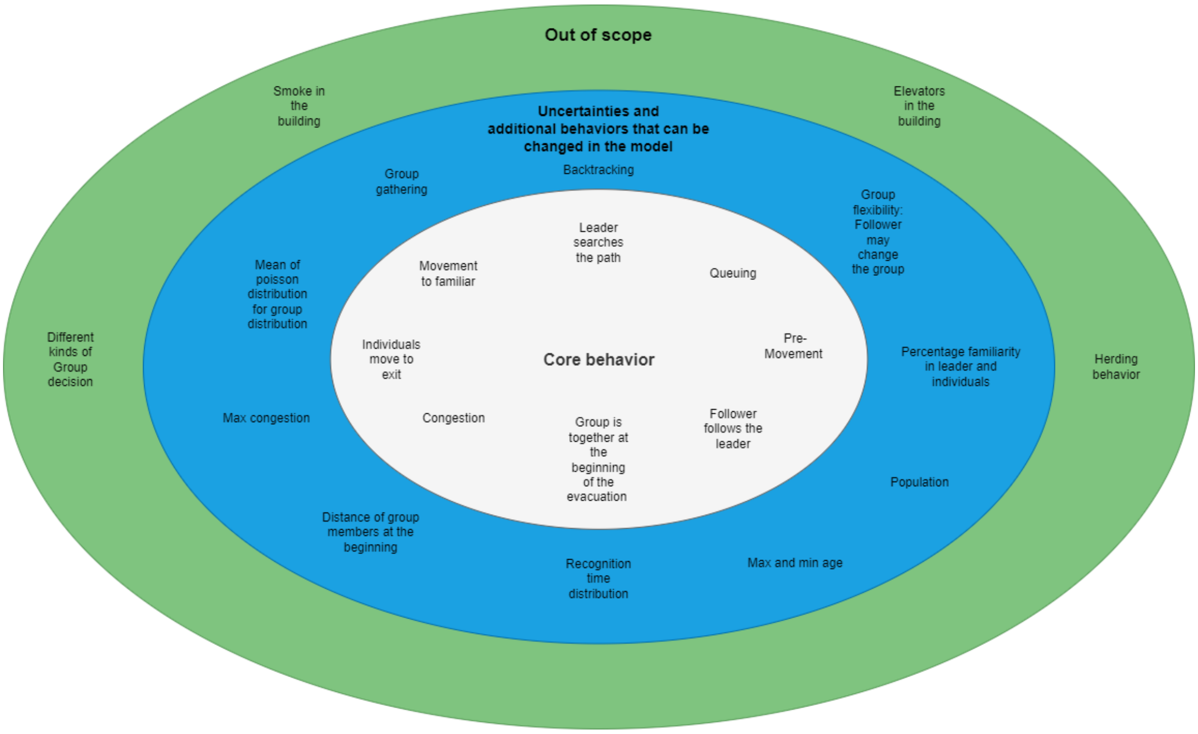


Figure 4.1: Scope of the model

4.1.2. State variables and states

In order to describe the structure of the model, the state variables and states are explained in more detail. Overall, the model consists of three hierarchical levels: the individual level of each agent, the spatial level and the environment (Grimm et al., 2010). Therefore, first, the agents states as individuals and in groups are explained in more detail, followed by the spatial dimensions. Finally, the environment is elucidated.

Agents

The model consists of three different agents: the leaders, followers, and individual evacuees. All of them are assigned with various states and variables. The variables may be classified as fixed properties, set parameters (set values), and variables which may change over time. Fixed properties embrace the shape and color of agents. The parameters may vary for every agent. However, age and gender were defined for all agents. Both are needed in order to set the maximum available speed for each agent.

The familiarity of evacuees is another crucial parameter that affects the evacuation process. The "movement to familiarity" was already found in various studies, and is thus included in the model (Kinateder et al., 2018; Sime, 1983). In behavioral theory, evacuees tend to move to the familiar exit. In case the evacuee does not know the building or is visiting the building for the first time, the familiar exit represents the main exit. In the model, only leaders and individuals are supplied with this parameter as the follower only follows the leader to the exit (Mao et al., 2019; H. Zhang et al., 2018). Furthermore, the exit is known by all agents. Nevertheless, only the leader and individuals know the path to the exit and the follower only moves towards the exit on his own, when the leader has already left the building.

In contrast to the parameters described above, the following values vary over time. First, the current speed for each agent fluctuates, depending on the current congestion as depicted in Chapter 4.1.7. Moreover, group members receive a group speed representing the minimum speed among group members. Furthermore, all agents are assigned with a premovement timer, which consists of a recognition and response timer. The premovement process is explained in more detail in Chapter 4.1.7. Finally, after the agents premovement is finished, its state changes to leaving. Both leaders and followers belong to a group with an unique group ID. Only one leader is determined per group, while one group contained one follower or more. The leader may be determined randomly (Mao et al., 2019; J. Wang

Name	Agent	Values	Description
Parameters (set values)			
Gender	Leader, follower, individuals	Male / female	Sets the gender of the evacuee.
Age	Leader, follower, individuals	10-85	Random normal distribution with 50 and standard deviation 20: Minimum age 10 and maximum age 85.
Speed_max	Leader, follower, individuals	0,61 - 1,69 m/s	Sets the maximum speed of each agent. Depends on age and gender.
Familiarity	Leader, individuals	True or false	If familiarity is true, the agent knows all exits and chooses the closest to him.
Exit	Leader, follower, individuals	Patch	The exit the agent is moving to. Depends on familiarity.
Variables (values changing over time)			
Current_speed	Leader, follower, individuals	0 - 1,69 m/s	Is the current speed of the agent. Depends on the congestion on the patch.
Group_ID	Leader, follower	1 – Number of groups	Specific group identifier for each agent.
Recognition_timer	Leader, follower, individuals		Counts down the recognition time.
Response_timer	Leader, follower, individuals		Counts down the response time.
Leaving?	Leader, follower, individuals	True or false	If true, the agent is leaving towards the entrance.
Status_moving	Leader, follower, individuals	True or false	If true, the agent is moving. Otherwise the agent waits.
Leader	Follower	Agent	Current leader of the follower.
Leaders_path	Follower	Patch-set	Sets the shortest path towards the leader.

Table 4.1: Parameters and variables for each agent

et al., 2015) or based on the group member's location whereby the leader is the one closest to the exit (Qin et al., 2018). In addition, the follower knows the leader of the group and the path towards the leader. The leader may wait in case backtracking is activated, leading a deactivation of the status moving. All agent related variables are summarized in Table 4.1.

The spatial level and map

As already explained above, the influence of leader-follower behavior was investigated in a building. The building chosen in the model represents an environment, corresponding to a museum or municipality hall. It holds five exits whereby the main exits are located on the left and right sides of the main hall. The three other emergency exits are positioned at the top and bottom of the 2D plan. The width of each exit was set to two meters. Black cells represent walls and obstacles, which need to be avoided by agents. The building is illustrated in Figure 4.2. A symmetrical layout was utilized to minimize the influence on the evacuation performance of where groups and individuals are placed.

Environment

The environmental level refers to stable external variables that do not change while running the model (Grimm et al., 2010). It includes the scale and time dimension of the model. The software Netlogo represents the environment as a grid in which one patch represents an area of 1x1 meter in real-life. In addition, time is epitomized by ticks. For each tick, an agent follows specific rules. In the model, one tick symbolizes one second in real time.

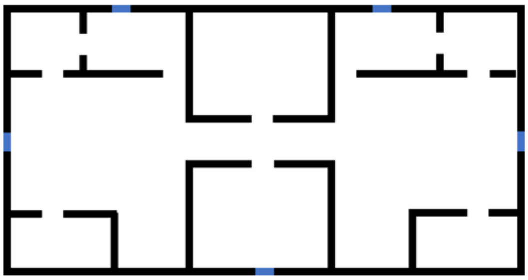


Figure 4.2: Building layout

4.1.3. Process overview and scheduling

The following chapter describes which agent does what and in what sequence (Grimm et al., 2010). It describes the overall procedure for each agent from the start until the end of the evacuation, supported by references for each process. Overall, the model may be divided into the pre-movement and movement phases, as Ronchi (2021) recommended, representing the engineering timeline in evacuation models. The pre-movement step may further be subdivided into the recognition and response time (Ronchi, 2021; Forssberg et al., 2019). After the pre-movement process, agents move towards the exit. Before leaving the building, the agents need to queue as the door may be blocked by other agents (Ng and Chow, 2006; Okazaki and Matsushita, 1992; Kunwar et al., 2016). The three different leader-follower behaviors may be additionally added to the pre-movement and movement phase. All processes are explained in more detail in Chapter 4.1.7. The overall high-level process is shown in Figure 4.3

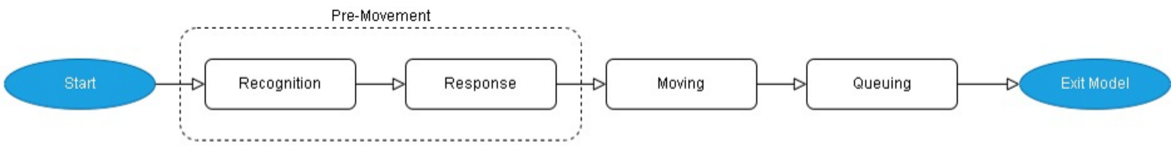


Figure 4.3: The overall process

4.1.4. Design concepts

The design concepts relate to key concepts included in agent-based models identified by Grimm et al. (2006). Hence, this chapter follows the specific framework developed to describe and design an individual-based or agent-based model. In total, seven design concepts were incorporated into the model, which are explained in more detail.

Emergence

In complex adaptive systems, emergent phenomena are those that are not directly implemented in the model but may be identified on the system level (Grimm & Railsback, 2005). The emergence of the model is the crowd's behavior leading to a final evacuation and response time of the building. All agents comply with specific rules while interacting with other agents and the environment. However, the overall crowd behavior emerges from these bottom-up interactions. These crowd behaviors are the flow towards the exit, the group distance and the queuing in front of doors.

Adaption

Adaption relates to the agents' choices due to the changing environment (Grimm & Railsback, 2005). In the model, agents adapt their movement in case their way towards the exit is blocked by other agents. They step to a neighboring patch with a lower density and lower distance to the door. This phenomenon may be encountered inside the building and in front of the exit.

Objectives

The goal of each agent is to leave the building on the fastest possible route. With the help of the path-finding algorithm, leaders and individuals achieve their objectives of escaping from the building as quickly as possible. At this, followers calculate the shortest path towards the leader and follow the leader towards the exit. All agents try to improve their fitness and move towards a patch with a lower distance to the doorway.

Interaction

Interaction relates to the process of internal communication between agents (Grimm & Railsback, 2005). It investigates how communications take place (Grimm & Railsback, 2005). Interactions of agents implemented in the model may be divided into the intragroup exchange and individual transmission. For the intragroup interaction, locations of other group members are communicated which is utilized to keep a certain distance between the leader and followers. Between evacuees, only the communication between neighbors occurs in order to safeguard the maximum congestion for each patch and to simulate the queuing behavior.

Stochasticity

Stochasticity is predominant in agent-based models using Netlogo. The stochasticity is present in the model during the distribution of locations and scheduling of agents' actions. In addition, the recognition time and response time are drawn randomly from a log-normal or log-logistic distribution. Finally, the number of group members is influenced by stochasticity. A random number drawn from a poisson distribution defines the number of group members for every group.

Collectiveness

Collectiveness is related to clusters of individuals in models (Grimm & Railsback, 2005). During the evacuation, groups are composed of a leader and followers. These groups were imposed at the beginning of the model, and thus, do not emerge. In contrast to individuals, groups are assigned with unique variables such as the group ID and the group members as a set of agents.

Observations

Observations are associated with the collected data and graphic patterns of the model (Grimm & Railsback, 2005). For an evacuation, observations of interest are the total evacuation time, response time, and the distance between group members. The key performance indicators are explained more precisely in Chapter 4.5.1.

4.1.5. Initialization

During initialization, it is defined how agents and the environment are set up in the model (Grimm et al., 2006). In the present model initialization is structured as follows: First, the floor plan is imported into the model. Then, the closeness to the familiar exit and the main exit are calculated for each patch as it is explained in Chapter 4.1.7. After the environment is set up, the agents are created. In the beginning, all agents are dispersed randomly in the building. The next step is the creation and redistribution of groups whereby the number of group members per group is randomly chosen from a poisson distribution as proposed by Moussaïd et al. (2010). However, the mean of the distribution may be uncertain as further explained in Chapter 4.2. After every group member has received a group ID, followers and leaders are relocated to stand close to each other. Hereby a random group member is chosen, and other group members are moved to a random patch in a circle around the selected group member. Nevertheless, the distance between group members at the beginning of the evacuation may differ depending on the situation (Moussaïd et al., 2010), leading to uncertainty. Finally, the leader for each group is assigned. Depending on the structure, the leader may be randomly appointed or chosen due to his spatial position whereby the closest group member to the exit is employed as the leader. After all agents have been placed on the map, the age, gender and familiarity are distributed.

The age assigned to the agents is normally distributed with a mean of 50 years and a standard deviation of 20 years as recommended by the "Richtlinie für Mikroskopische Entfluchtungsanalyse e. V. (RiMEA)", the German organization Guideline for Microscopic Evacuation Analysis (Rimea, 2016).The minimum age is set to 10 and the maximum age to 85. Furthermore, the population is divided into 50% female and 50% male evacuees (Rimea, 2016). Of course, if the model would be used to analyze a specific case, age and gender may vary.

Age and gender determine the maximum speed for each evacuee. Weidmann (1993) proposed a model which determines the maximum walking speed depending on gender and age whereby the average maximum walking speed for male evacuees is defined as 1.42 m/s, and for female evacuees it is set to 1.27 m/s. Depending on the age, evacuees may reach between 40% and 120% of this average walking speed. This is implemented in the model as shown in Table 4.2. Each agent receives a random value in the respective range according to its age and gender.

Gender	Age	Max Speed (m/s)
Woman	10-20	1,12 – 1,52
	20-30	1,39 - 1,52
	31-50	1,27 - 1,39
	51-70	0,87 - 1,27
	71-85	0,61 - 0,87
Man	10 -20	1,23 – 1,69
	20-30	1,62 – 1,69
	31-50	1,48 - 1,62
	51-70	1,02 - 1,48
	71-85	0,71 - 1,02

Table 4.2: Maximum speed of an agent depending on gender and age

After the individual velocities are set, each group receives a group speed, depending on the lowest speed of the agents within that group as recommended by Köster et al. (2014). Then, the familiarity is distributed randomly to individuals and leaders depending on the percentage initialized. The last step consists of the distribution of the recognition and the response time. The value for each variable is explained in chapter 4.1.7. The setup for the model is visualized in Figure 4.4

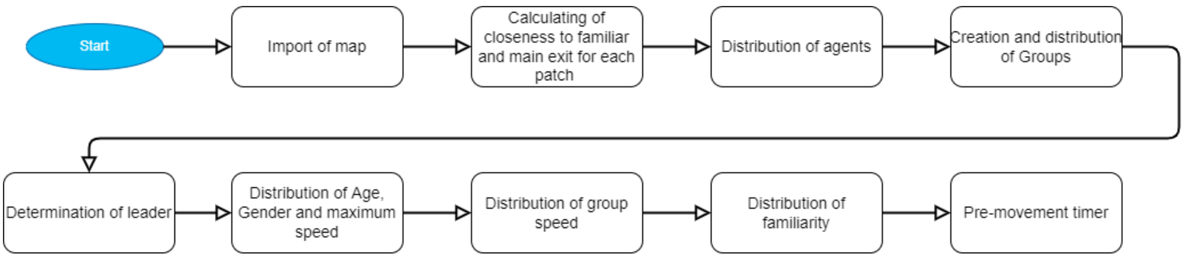


Figure 4.4: The Setup of the model

4.1.6. Input data

The input data of the ODD protocol relates to external data, which needs to be imported into the model to ensure its function (Grimm et al., 2010). For the evacuation model, the only data input is the building environment shown in Figure 4.2. To allow proper upload to the respective file it needs to be located in a "Data" folder in the exact location of the model.

4.1.7. Submodels

The model designed for this research consists of four different submodels: the pre-movement, the movement, the queuing, and the leader-follower behavior. All are explained in detail in this chapter.

Pre-movement

The pre-movement time embodies the time an evacuee requires before moving towards the exit and starting the evacuation (Ronchi, 2021). This phase may be generally divided into the recognition and response time (Ronchi, 2021; Forssberg et al., 2019). The recognition time relates to the duration before the evacuee decides to escape (Lovreglio et al., 2015). In the recognition phase, various actions were observed in people during real-life evacuations, such as "looking around", "searching for further information," or "being instructed by someone" (Forssberg et al., 2019). After finishing these actions, people undertake the decision to act and reduce the consequences of the disaster (Ronchi, 2021). The response time includes the period from that decision until the actual movement towards a safe place (Lovreglio et al., 2015). During the response phase, evacuees, for instance, "gather family and friends", "instruct others", or "collect personal belongings" (Forssberg et al., 2019) before leaving.

In evacuation models, three different methods to simulate the pre-movement time may be distinguished (E. Kuligowski, 2013). The first relates to assigning a random time from a distribution discovered in experiments or observations. In this method, agents remain stationary and only start to move after the time has passed. However, specific actions from leaders and followers may not be included in this method. Secondly, modelers may allocate specific actions to agents. The advantage is that it is possible to simulate particular tasks that may interrupt the activities of other agents. In addition, explicit activities from leaders and followers may be incorporated. Each action is related to a specific time, which must be terminated before leaving the building. Finally, the last method is a predictive model. Unique cues may stimulate different kinds of behaviors, such as smoke levels or alarms. The advantage of the last method is that a distribution does not need to be selected beforehand which reduces uncertainty (Ronchi, 2021). However, a high number of data sets are required in order to calibrate this method (Ronchi, 2021). Due to the missing data in evacuation research (Ronchi, 2021), the unspecific building environment of the model (Lovreglio et al., 2015), such as the given alarm system, the difficulties in implementing leader-follower behavior before the evacuation, and the focus of the model on this specific behavior lead to neglecting the predictive method. In addition, the goal of the model to investigate the change of pre-movement time with additional leader-follower behavior such as group gathering compared to the base case does not lead to the need to develop a predictive behavioral model. After weighing up the advantages and disadvantages, the second method is utilized to represent the pre-movement process.

Jones and Hewitt (1986) found various pre-movement behaviors of leaders and followers, as already explained in Chapter 2. Depending on the situation, the leader was alerted by a group member about the situation, or the leader was the first one to recognize the fire (Jones & Hewitt, 1986). Therefore, all group members receive a random recognition time from a distribution proposed by Forssberg et al. (2019). The group member who finishes its recognition time first alerts all other group members to evacuate. Then, each group member starts with its response task. Jones and Hewitt (1986) observed that the leaders notify other group members and advise them to “collect their personal belongings”, while shutting down some equipment. Further observations showed that the leader tries to call the emergency line and instruct others to “lock-up”. In all observations, the group left together after everyone finished their task. Hence, all these observations are utilized to represent the pre-movement time of a leader-follower group. For each action, a random number from a log-normal distribution observed by Vistnes et al. (2005) is assigned. The means and standard deviations for each delay action are summarized in Table 4.3.

Action	Mean	SD
Notify others	10	3
Shut down equipment	20	6
Call fire brigade	30	9
Collect belongings	30	9

Table 4.3: Means and standard deviations of the agents’ actions from Vistnes et al. (2005) for a log-normal distribution

For individual evacuees, the pre-movement differs. They also receive a response and recognition time. However, they may follow all actions detected by Vistnes et al. (2005). The process is summarized in figure 4.5

Movement

Overall, the movement phase in models may be divided into the route/exit choice modeling and the movement itself (Ronchi, 2021). The first aspect of the model consists of the exit choice of the agent and a path-finding algorithm. The latter incorporates the moving of the agents including congestion, the group movement and the queuing. Therefore, the following aspects are exemplified in more detail in the following chapter.

Exit choice of agents

As already explained above, the “movement to familiarity” (Sime, 1983) determines the exit choice of the agent. If the leader or the individual agents are familiar with the building, they comprehend the location of all exits. Therefore, they select the closest exit as their end of the escape route. Otherwise,

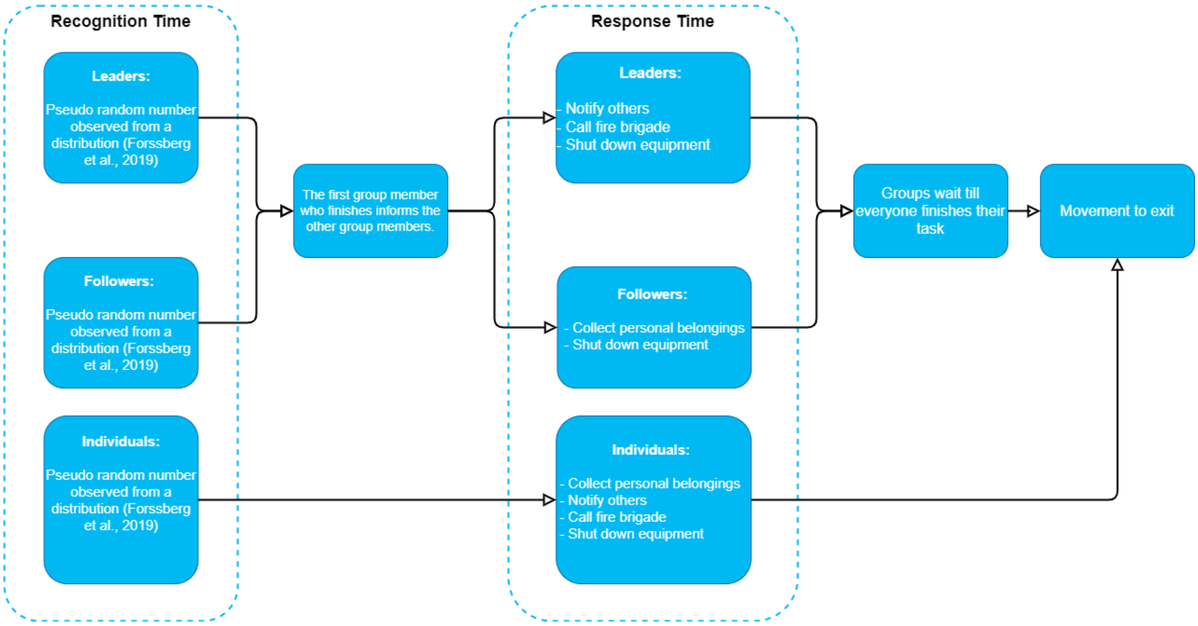


Figure 4.5: The pre-movement process for each agent

leaders and individuals without familiarity are moving towards one of the main exits nearest to them. Followers only follow the leaders, and thus do not need familiarity. These aspects are incorporated in the model. The respective process is outlined in figure 4.6.

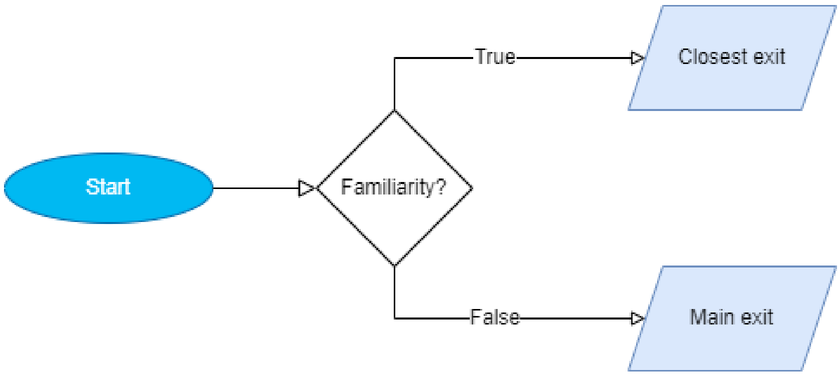


Figure 4.6: The exit choice of leaders and individuals

Path-finding algorithm
In total, four distinct route planning strategies in evacuation models may be observed (Ronchi, 2021). It ranges from the shortest path to the fastest path and from conditional to user-defined paths. As most of the current evacuation models implement the shortest path (Ronchi, 2021), this strategy is utilized in the described model. Various methods to calculate the shortest path exist, such as a distance map, Dijkstra, and the A* algorithm (Ronchi & Nilsson, 2016). However, the Dijkstra and A* algorithms are currently not widely employed in evacuation research, in contrast to the distance map algorithms (Ronchi & Nilsson, 2016). An advantage is the lower computation time compared to other algorithms, which is necessary for a time-expensive exploratory modeling approach. Therefore, this method is executed in the model. A distance map assigns different values for spatial areas. In Netlogo, the distance towards the exit is allocated to each patch whereby a patch receives two values. The first represents the value for the closest exit for familiar agents, and the second exemplifies the distance toward the main door.
Moving
The movement of each agent is influenced by its speed and direction calculated by the path-finding algorithm. However, the maximum desired speed of each agent, may not always be achieved in a crowd. Various researchers observed that an increasing density around each agent affects the velocity and

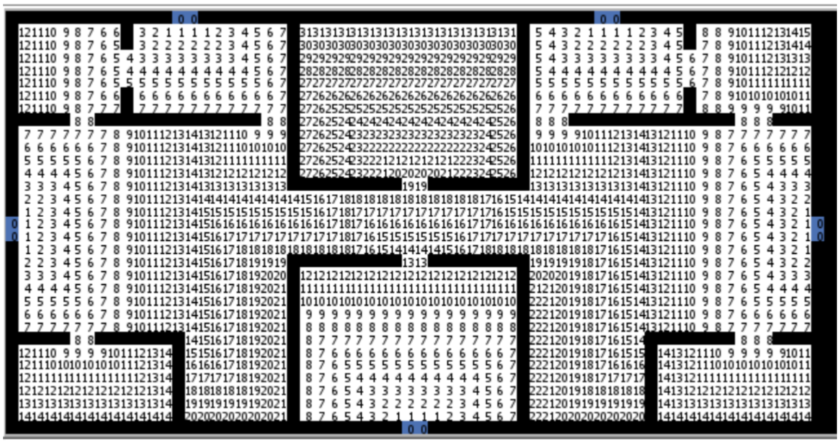


Figure 4.7: The path finding algorithm for the familiar exit

reduces the maximum speed (Weidmann, 1993; Ibrahim et al., 2016). Therefore, a heuristic function of the social force model is utilized for the locomotion behavior of evacuees. Depending on the crowd density, a certain maximum speed may only be reached. The velocity for each density is adapted from Weidmann (1993) as shown in Table 4.4 whereby the maximum congestion is a parameter of uncertainty, which is explained in more detail in Chapter 4.2
The maximum congestion determines if an agent is able to move toward this region. This phenomenon is widely known in evacuation research and has been investigated by various authors (Weidmann, 1993; Ibrahim et al., 2016; Still, 2014). New agents may not enter a specific area with a critical density and need to wait or move aside.

Density (P/m2)	Max speed (m/s)
1	1.02
2	0.55
3	0.31
4	0.2
5	0.12

Table 4.4: Maximum speed for each density

Group movement

The leader-follower behavior determines how the group moves during an evacuation. Xie, Lee, Cheng, et al. (2020) observed that the leader-follower group showed a vertical movement compared to other groups. In addition, the leader moved at the forefront (Xie, Lee, Cheng, et al., 2020) . As already explained in chapter 2, the core of the leader-follower behavior contains the leader searching the path, and the follower shifting towards the leader (H. Zhang et al., 2018; Wei et al., 2014; Y. Li et al., 2021). Therefore, these observations are the basis for the leader-follower behavior implemented in the model. First, only the leader knows the path towards the exit. Thus, he moves at the forefront of his group to search the path whereby the follower follows its leader. However, the follower strives to avoid the leader's path, as proposed by Fachri et al. (2017), in order to prevent the path's blocking. This was implemented by maintaining a minimum distance from the leader. The threshold for this distance was investigated by Moussaïd et al. (2010). They observed that the distance between pedestrians and the group center is dependent on the group size. The group center of the mass is represented by the location of the leader in our model. The minimum distance is defined by the formula $\frac{N-1}{2}$. If the distance is lower compared to the value initiated, or if the follower is located closer to the entrance than the leader, the follower waits for the leader to pass. Otherwise, the shortest path towards the leader is calculated and followed. However, if another group member already blocks the path, the follower tries to move around the group member to avoid any lump formation (Fachri et al., 2017). As already explained above, each group member exhibits the same group speed in line with the suggestion of Köster et al. (2014). Nevertheless, in case a group member loses connection to the group, the group member may increase its velocity, if possible, to catch up. The group movement is summarized in figure 4.8.

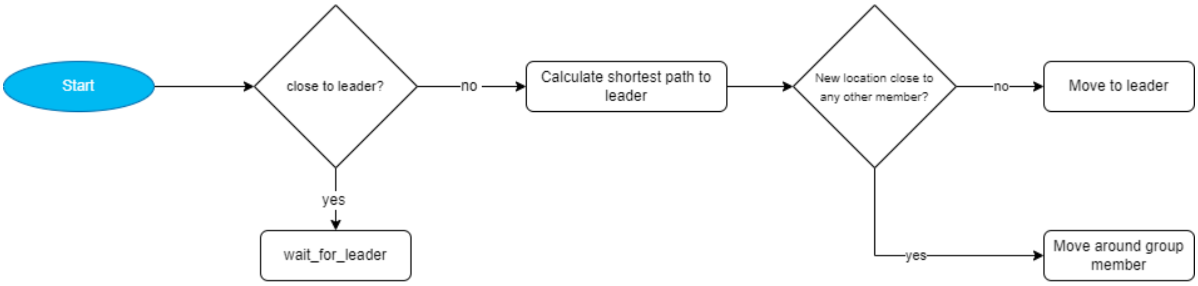


Figure 4.8: Group movement of follower

Queuing

The queuing phenomenon was perceived and studied in various experiments and real-life fire evacuations and needs to be implemented in the model (Daamen and Hoogendoorn, 2010; Seyfried et al., 2007). Overall, it describes the crowd behavior in front of an exit or stairs. Queuing may occur if the current flow of the crowd surpasses the capacity of a restricted passage (Ng & Chow, 2006). In the model, this capacity is defined as two people per second per meter as recommended by Still (2014). In case the exit is blocked by other agents, the evacuee slows down and waits until movement is possible (Ng and Chow, 2006; Okazaki and Matsushita, 1992). Thereby, a typical half-circle emerges in a bulk queue due to side-stepping and overtaking behavior (Ng and Chow, 2006; J. Zhang et al., 2008). In order to implement this behavior, a radius of four meters around each exit was defined as a queuing area. If the exit exceeds the capacity of people, evacuees try to move to an empty spot in this area with the closest distance to the exit. Hence, a half-circle of evacuees emerges. In case no place is available, agents wait until a spot is free. After evacuees pass the doorway, a new agent may fill this capacity. Whereby one evacuee closest to the exit may move towards the door. Figure 4.9 summarizes the queuing behavior.

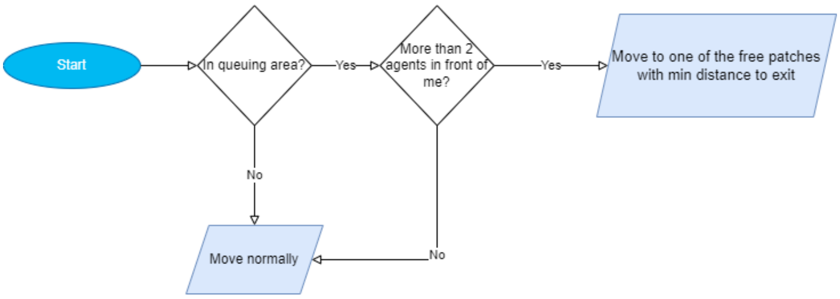


Figure 4.9: Queuing behavior in the model

Leader-follower behavior

Three different kinds of leader-follower behaviors are included in the model: backtracking, group gathering before the evacuation, as well as flexibility of the group. Therefore, their implementations are explained in the following paragraph.

Backtracking

Backtracking is a behavior that has been observed by leaders in social groups. A social group may consist of close friends and family (Köster et al., 2014). In these groups, the group members try to stay together throughout the whole evacuation process (Sime, 1995; Köster et al., 2014). However, a group member may depart from the group in the rush of the evacuation or due to interaction with other evacuees (Lu et al., 2017). In order to cope with this loss of connection, the leader reduces its speed and delays its evacuation for the lost member to catch up (Lu et al., 2017). In the model, the leader waits for a group member in case the distance of the furthest group member passes a certain threshold. This threshold is defined as the maximum distance between group members at the beginning of the evacuation. The process of backtracking is displayed in Figure 4.10.

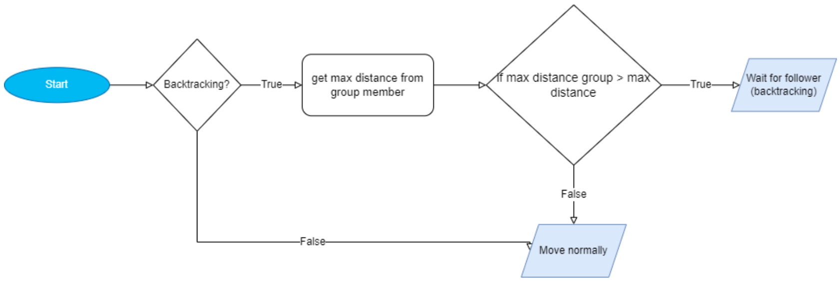


Figure 4.10: Backtracking of the leader

Group gathering
Group members may have different actions during the recognition and response time, as already described in the pre-movement chapter. After every group member finishes their task, social groups may gather before escaping together (Jones and Hewitt, 1986; Forssberg et al., 2019). In the model, every group member moves towards the leader. Only if every group member is close enough, the leader starts evacuating. Here, the threshold is represented with the same formula as for the group movement, observed by Moussaïd et al. (2010). Figure 4.11 summarizes the group gathering process. As group gathering may be allocated to the pre-movement process (Forssberg et al., 2019). Thus, it is added to the total pre-movement time.

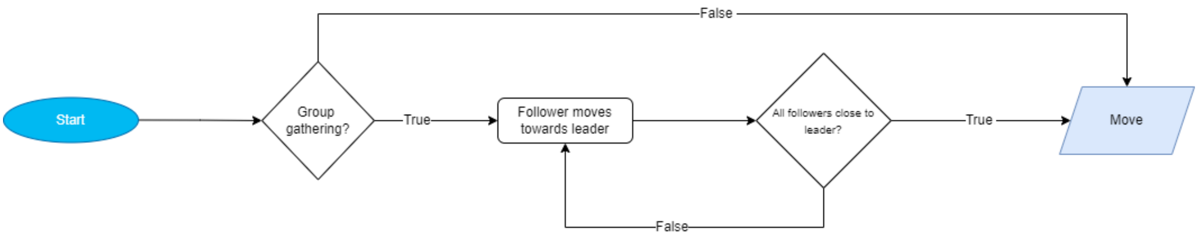


Figure 4.11: The group gathering process

Flexibility of the group
Groups may not only exist before the evacuation, but may also arise during the evacuation (Quarantelli, 1995). Hereby, leaders with specific properties, such as authority (Jones & Hewitt, 1986) or certain spatial positions (Lombardi et al., 2020; Nagy et al., 2010), may emerge. The emerging groups may be distinguished from social groups with high intragroup social relations, such as family and friends. The difference between these groups is the steadiness and the attachment among group members and leaders (Fang et al., 2016). Phenomena such as backtracking may be found in social groups (Lu et al., 2017), while emergent groups may only last temporarily, and spatial distances may divide group members from the leader (Fang et al., 2016). In a dynamic group, a follower may change to a new leader if another leader is closer to the follower (Ji & Gao, 2007) and within its visibility (Mao et al., 2019) whereby the visibility in a room without smoke may be defined as up to 20 meters (Xie, Lee, Cheng, et al., 2020) with an angle of 120 degrees, as proposed in Mao et al. (2019). Figure 4.12 illustrates the total process in the model.

Figure 4.12: The "flexibility of the group" process

4.2. Uncertainties in the model

Chapter 2 displayed general uncertainties in evacuation models. Now, this chapter focuses on the uncertainties included in the designed model. The first uncertainty relates to the familiarity of the agents. The familiarity in a crowd may change depending on the time and location of the building. For example, Elaine et al. (2007) observed different percentages of familiar students in a college. In addition, King et al. (2016) encountered higher values in a hospital compared to the first observation. This indicates uncertainty as a precise percentage may not be determined for a specific location at a particular time. Therefore, input data uncertainty is clearly predominant. Secondly, the population inside the building may be seen as uncertain as it may change over time. For instance, Rimea (2016) proposes various densities of persons per square meter at the beginning of the simulation. However, it may vary between 0,04 to 2,00 $\frac{persons}{m^2}$ depending on the location. The location and time may also influence the group percentage in the crowd. For example, depending on the time, the rate of groups may vary from 55% to 70% (Moussaïd et al., 2010). The model implements the group distribution as a poisson distribution with a specific mean. Many researchers encountered this distribution in various locations (Moussaïd et al., 2010; James, 1953). Nevertheless, contracting means were observed at different times and by distinct authors (Moussaïd et al., 2010; James, 1953), leading to input data uncertainty for this parameter. Likewise, for the maximum crowd density, contracting surveillance's may be found. The values range from 5 to 8 $\frac{persons}{m^2}$ (Still, 2014; Weidmann, 1993; Ibrahim et al., 2016).

Moreover, the maximum distance of group members at the beginning of the evacuation may be uncertain. For example, Moussaïd et al. (2010) found that the intra-group distance may vary depending on the crowd density in a shopping street without evacuation. In addition, not enough data regarding the distance of groups at the beginning of the evacuation could be found. Therefore, this parameter relates to input data uncertainty. Another uncertainty may be observed for the minimum and maximum age. In some areas and times during the day, no elderly or children may be present (Daamen & Hoogendoorn, 2010). Moreover, the recognition time distribution is another uncertainty. Nevertheless, it relates to the model structure as more than one model formulation may represent the real system. Different recognition distributions may be encountered in the literature (Forssberg et al., 2019; Lovreglio et al., 2019).

Finally, the determination of the group leader is a structural uncertainty in the model. Different structures can be witnessed in the literature, such as random distribution, closest to the exit or due to social relations (Mao et al., 2020; Qin et al., 2018; B. Liu et al., 2018). The first ones were included in the model. Nonetheless, the described uncertainties may only display a small portion of the uncertainty in the model. Structural uncertainty regarding the behavior of agents is predominant. Nevertheless, the described uncertainties are the most important ones and are thus implemented in the model. All uncertainties are summarized in Table 4.5.

4.3. Model verification

As already explained in Chapter 3, various tests from Ronchi et al. (2016) were performed in order to verify the model. The tests and results are explained in more detail in this chapter. They are structured by the core behavior of the test. For further explanations of the test, see Chapter A.1 in the appendix A.

4.3.1. Pre-evacuation time

In order to verify the distributions of parameters included in the model, the model was executed 50 times. Whereby the focus lay on the response time of each agent. The response time at the beginning of the modeled evacuation followed a log-normal distribution which was compared to a random log-normal distribution with the same mean and standard deviation. Figure 4.13 demonstrates both distributions. It clearly shows that the values of the model follow a log-normal distribution.

4.3.2. Movement and navigation

Proper movement and navigation of the agents were verified by two independent tests. First, the movement around a corner was verified. Second, the group behavior of the model was tested.

Uncertainty	Location of uncertainty	Explanation	Value range in the model	Found values in literature
Familiarity	Input data uncertainty	The familiarity may change depending on the time and location of the building (Elaine et al., 2007)	0 - 100	15.5% – 21.7% (Elaine et al., 2007) 28% (King et al., 2015)
Population	Input data uncertainty	Depending on the building use and time, the population inside the building may change	100 - 1600	0.04 – 2.00 Persons/m^2 (Rimea, 2016)
Percentage groups	Input data uncertainty	Depending on the building and time, the group percentage may differ	0-100	55% - 70% (Moussaïd et al., 2010)
Group distribution	Input data uncertainty	Different means for a poisson distribution could be found in the literature.	0.5 – 1.5	0.83, 1.11 (Moussaïd et al., 2010) 1.46 (James, 1953)
Max crowd density	Input data uncertainty	Different maximum crowd densities can be found in literature	5-8	8: (Ibrahim et al., 2016) 6: (Weidmann, 1993) 5: (Still, 2014)
Max distance group members	Input data uncertainty	The max distance between group members may vary	1-6	4-6 m (Gwynne et al., 2016) 0,54 - 2,6m (Moussaïd et al., 2010)
Min_age	Input data uncertainty	In some areas, no children may be present (Daamen & Hoogendorm, 2010)	10	10-20 (Daamen & Hoogendorm, 2010)
Max_age	Input data uncertainty	In some areas, no elderly may be present (Daamen & Hoogendorm, 2010)	65-85	65-85 (Daamen & Hoogendorm, 2010)
Recognition time distribution	Structural uncertainty	Different recognition time distributions may be found depending on the location and source.	Department Store, restaurant, office	Location: Distribution mean (min-max) SD (Forssberg et al., 2019) Department store: Lognormal 25.2 (4-64) 10.5 Restaurant: Lognormal 27.3 (13-56) 9.9 Office: Loglogistic 46.6 (6-111) 27.4
Determination of group leader	Structural uncertainty	In literature, various methods to determine the group leader were encountered.	Random, closest to the exit	Random, closest to the exit

Table 4.5: Uncertainties in the model

Movement around corners
The movement around the corner test illustrated that the model operates within the system's boundaries (Ronchi et al., 2016). Figure 4.14 demonstrates the movement around a corner for successive ticks in the model. It displays that agents stir around the corner to reach the other side. In addition, unit tests regarding the movement on walls are included in the model.

Group behavior
In order to verify group behavior, Ronchi et al. (2016) proposed a verification test in a squared room of a size of 15 m by 20 m with a 1 m exit. The goal of the test was to examine whether group members stay together and reach the door within 10 seconds. Four of the five group members located near the wall opposite the exit were assigned the same speed with 1.25 m/s. The remaining group member received a velocity of 0.5 m/s. In contrast, the group in the middle of the room obtained a constant speed of 0.2 m/s. The test was repeated 50 times. Figure 4.15 illustrates the room implemented for the test and the maximum time difference for each run. It clearly indicates that the difference between the first and the last agent reaching the exit never exceeded 6 seconds. Thus, the group behavior is verified.

4.3.3. Exit usage
In order to verify the exit choice of each agent, an exit choice allocation test was performed as proposed by Ronchi et al. (2016). This test is recommended to be carried out in a room featuring two exists. One was only assigned to the agents with familiarity, and the other exit was designated for agents without familiarity. Figure 4.16 shows the results of the test with 50 repetitions. It clearly indicates that all familiar agents also chose their allocated doorway. Therefore, the exit choice allocation test is passed leading to verification of the exit usage.

4.3.4. Flow conditions
Two different aspects of the flow conditions were verified. These aspects relate to testing the maximum congestion and the maximum flow rate.

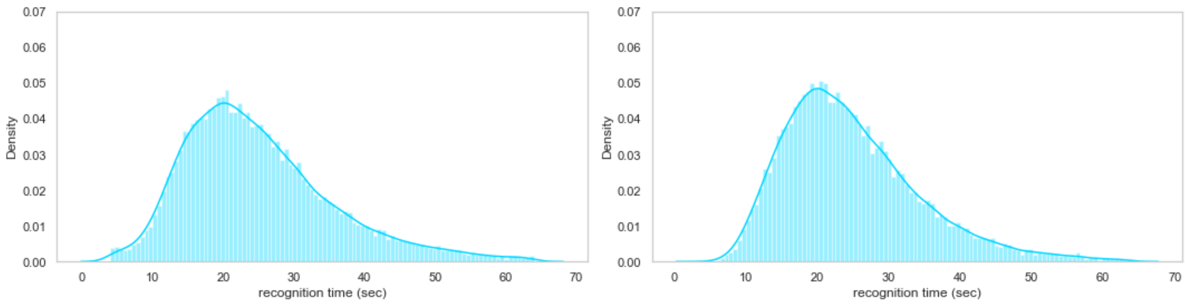


Figure 4.13: Density plot of the response time of the model (left) in comparison to a density plot of a random log-normal distribution (right) mean=25.2 SD=10.5 as implemented in the model

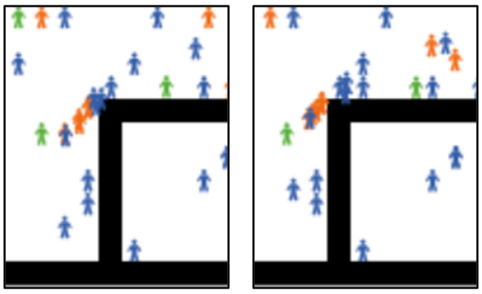


Figure 4.14: The movement around the corner for successive ticks

Congestion
In order to verify that the model simulates congestion, the maximum congestion during the evacuation was recorded for 50 repetitions. The results show that congestion occurs with a maximum of six people per patch. However, the maximum congestion of six people is never surpassed. Figure 4.17 displays that congestion is simulated in the model and verifies the maximum congestion in the model.

Maximum Flow rates
The maximum flow rate through an exit was determined with two people per meter. In order to verify this rate at each door, the results of the model need to be compared with the predefined maximum capacity (Ronchi et al., 2016). Therefore, the flow rate for each patch at the exit was documented during the complete evacuation with 50 repetitions. Figure 4.18 displays that the maximum flow rate per patch, which represents 1 m, never exceeds two people. Thus, the flow rate is verified. In addition, a unit-testing was implemented in the model to check the flow rate during every run.

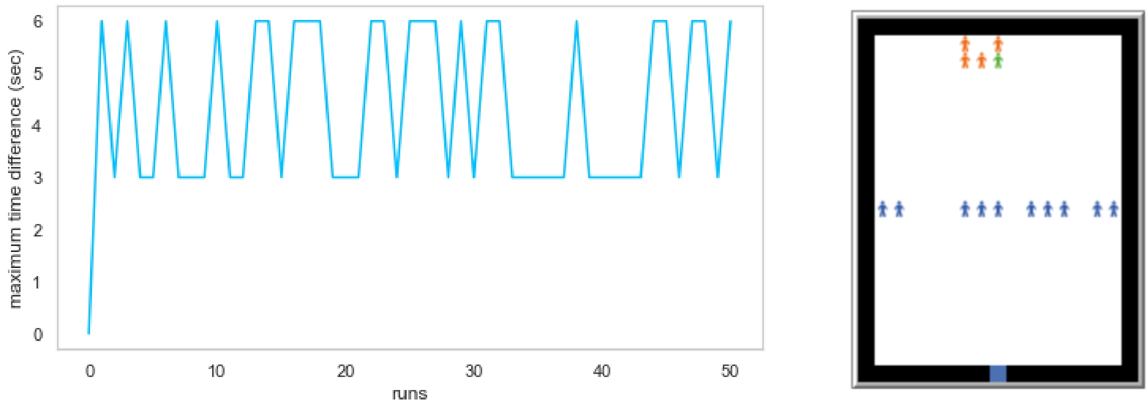
4.4. Model validation and sensitivity analysis

The validation of the model is divided into a micro validation of unique behaviors and a macro validation, whereby the outcome of the model is compared to an empirical study by Haghani et al. (2019). Finally, the chapter ends with a sensitivity analysis.

4.4.1. Micro validation

For the micro validation, five unique behaviors were either compared with data or observations obtained in empirical studies. Thus, the pre-movement and the social force heuristic validation with empirical data are explained in more detail. Then, the group and queuing behavior were validated with the help of face validation. Finally, micro validation finished with the data comparison of flow rates. Additional information about the experiments conducted in Netlogo may be found in A.2 in Appendix A.

Pre-movement
In order to validate the pre-movement time of the model in comparison to real-life data, the database from Lovreglio et al. (2019) was utilized to compare the outcome of the model with the data found in empirical studies. Observed data at an assembly occupancy, such as a theatre or a restaurant,



Maximal time difference between the first and the last group member

The set up of the test

Figure 4.15: Group behavior set up and results

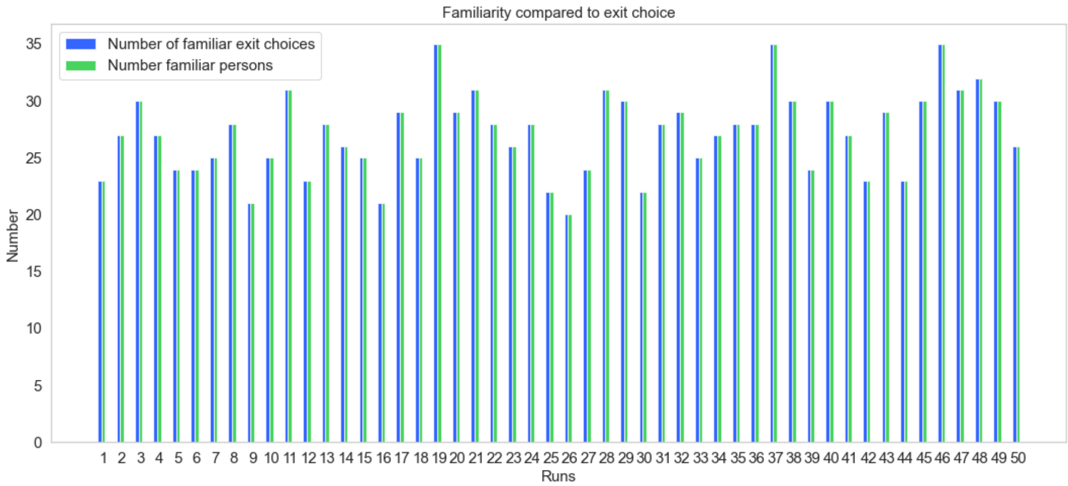


Figure 4.16: The exit choices of familiar people compared to number of people at the familiar exit

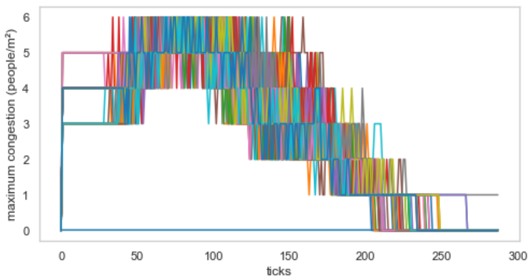


Figure 4.17: The maximum congestion for each tick in the model with 50 repetitions

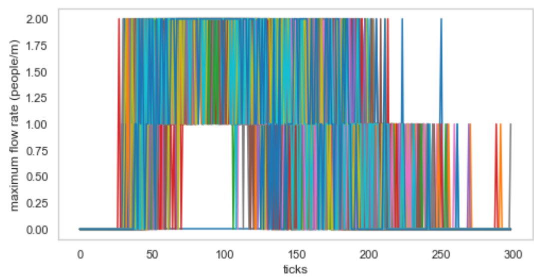


Figure 4.18: The flow rate for each tick in the model with 50 repetitions

was applied. Lovreglio et al. (2019) collected pre-movement times from various empirical studies and converted them into a pre-movement distribution. Figure 4.19 shows the data collected for specific clusters of assembly occupancies on the left. In contrast, on the right, the total pre-movement times resulting from the model are presented for 50 repetitions and 100 agents. It illustrates that the pre-movement time of the model is within the range of the empirical data. However, it only indicates that the pre-movement time in the model is in range with one empirical study. Different empirical studies show contradicting results, seen in Figure 4.19, leading to a structural uncertainty regarding the pre-movement behavior.

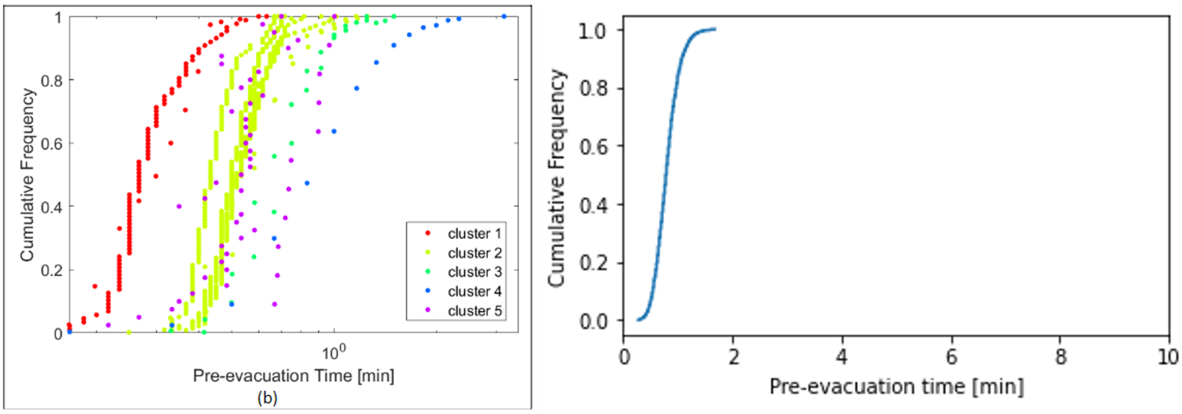


Figure 4.19: Cumulative frequencies of pre-evacuation times as observed in empirical studies by Lovreglio et al. (2019) (left) and as simulated by the model (right)

Social force heuristic

In order to validate the social force heuristic included in the model, the implementation is compared to empirical data found by Rinne et al. (2010) and Helbing et al. (2007). Rinne et al. (2010) monitored the walking speed depending on the crowd density in a stadium. In contrast, Helbing et al. (2007) performed their experiment on a bridge and collected additional data from other authors for comparison. Figure 4.20 shows that the implemented values in the model revealed the same pattern compared to empirical data. However, it also indicates the high scatter of values for each density in empirical studies, which may influence the total evacuation time.

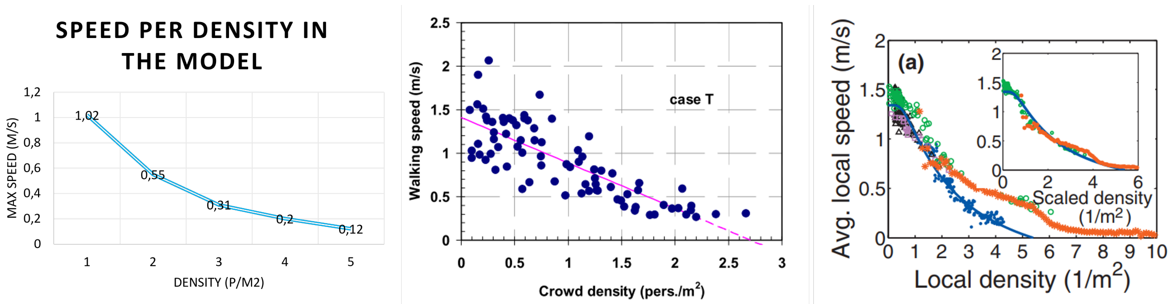


Figure 4.20: Social force heuristic implemented in the model (left) in comparison with empirical data by Rinne et al. (2010) (middle) and Helbing et al. (2007) (right)

Group behavior

In order to validate the group behavior, face validation is utilized to compare the behavior of groups with empirical observations. First, results of Xie, Lee, Cheng, et al. (2020) about the vertical movement are contrasted with the surveillance in the model. Figure 4.21 illustrates the vertical movement of groups in the model on the right side. In contrast, the vertical motion in the empirical study is shown on the left side.

In addition, the observations by Köster et al. (2014) were utilized for the validation of the group behavior. The verification test of the group behavior illustrated in Figure 4.15 already demonstrated that a group member reaches the exit within a minimum of six seconds. In addition, the intragroup distance in the model within a social group with backtracking was investigated. Therefore the model was repeated 50 times with a population of 500 people whereby the intragroup distance was monitored for one group. Figure 4.22 demonstrates that the intragroup distance between a social group with backtracking amounts up to 6 m due to the congestion during an evacuation. However, it decreases afterwards due to backtracking and the increased speed of followers. In addition, this test was performed without backtracking. The results also indicate the same phenomenon. Nevertheless, the distance between group members are higher because the follower is able to increase the speed needed to follow

Figure 4.21: Comparison of the behavior observed in empirical study by Xie, Lee, Cheng, et al. (2020) compared to behaviors simulated in the model

the leader after the agent loses connection due to congestion. This phenomenon was also observed in an empirical study by P. Zhang et al. (2021). Therefore, the group behavior validation was successful.

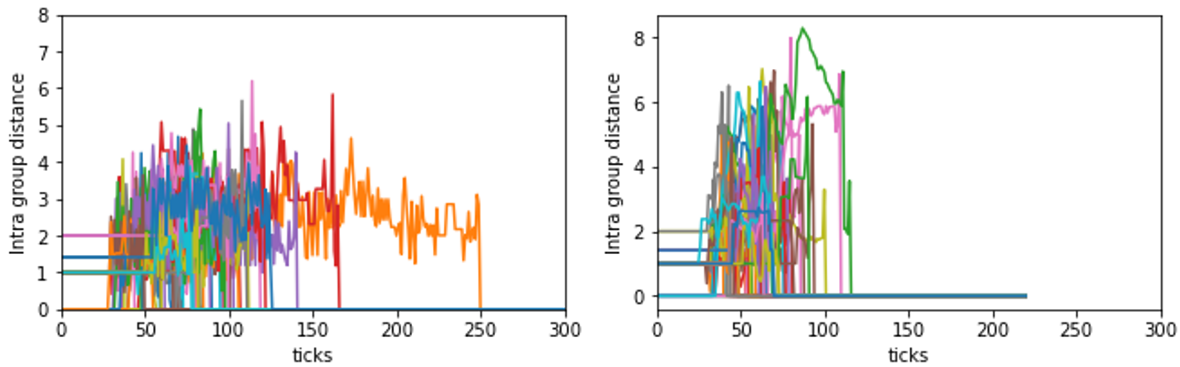


Figure 4.22: Intragroup distance between groups in the model with (left) and without backtracking (right).

Queuing behavior

Validation of the queuing behavior is achieved by comparing the emergent patterns of the model with observations in empirical studies namely by Haghani et al. (2019) Wagoum et al. (2017), Hu et al. (2018), and Xie, Lee, Cheng, et al. (2020) display queuing behavior in front of a exit. (Figure 4.23)

Figure 4.23: Queuing behavior observed in different empirical studies (Haghani et al., 2019; Wagoum et al., 2017; Hu et al., 2018; Xie, Lee, Cheng, et al., 2020)

In comparison, Figure 4.24 illustrates the queuing behavior in the model during which a half-circle emerges. Thus, the queuing behaviour simulated by the model appeared representative of queuing patterns observed in empirical studies.

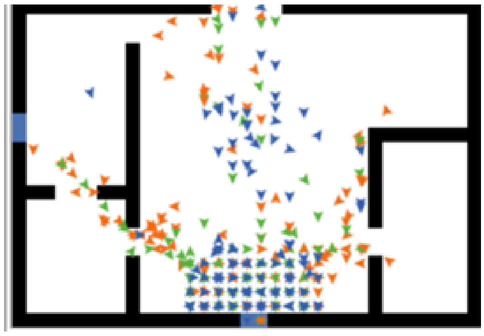


Figure 4.24: Queuing behavior observed in the model

Flow rates

The validation of the flow rate is achieved with the help of empirical data found in Rinne et al. (2010). They observed various flow rates during queuing in front of a door with a width of 2 m, as implemented in the model. It varied from 1.029 pers./s to 1.849 pers./s with 20 to 100 persons per exit. In order to examine whether the model demonstrates the same behavior, an experiment with 50 repetitions and 100 people was performed. No pre-movement timer was set and no familiarity of the people was allocated. Hence, one exit was utilized resulting in an average of 100 people per exit in accordance with the empirical study. Finally, the average flow rate for the exit during the whole run was monitored and compared to the data found by Rinne et al. (2010). Figure 4.25 outlines the result. It indicates that the flow rates in the model are within the ranges observed in the empirical study. Thus, the modeled flow rates may be seen as valid.

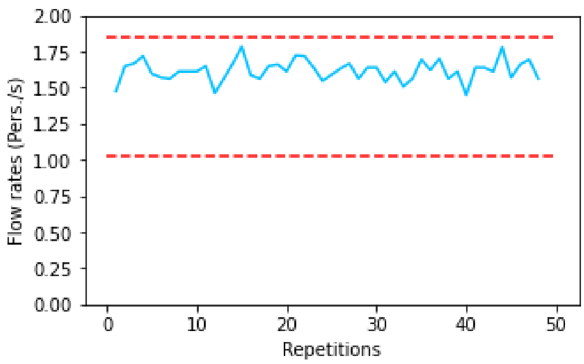


Figure 4.25: Flow rates in the model for different repetitions in comparison with the found values by Rinne et al. (2010) as indicated with the red lines

4.4.2. Macro validation

The model's micro validation already increased the trust that the right model had been built. For further validation, the model outcome was compared to empirical data collected by Haghani et al. (2019). First, the empirical study by Haghani et al. (2019) is explained, then the implementation in the model, and finally, the results are presented.

The empirical study

In an experiment in a basketball hall at the University of Melbourne in Australia, a squared room with a squared barriere in its center was utilized to test the effect of group size and stress level on evacuation behavior. The layout of the empirical study is shown in Figure 4.26. During this experiment, one of the four exits was randomly closed after the start signal to reduce the biased positioning close to an

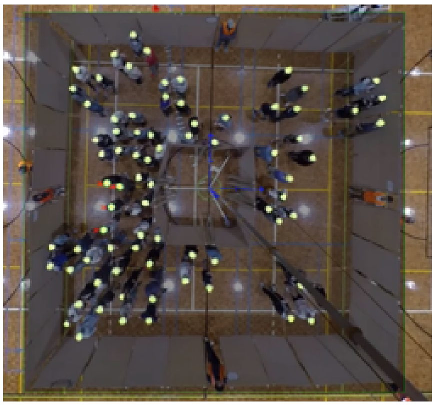


Figure 4.26: The layout of the empirical study by Haghani et al. (2019)

Figure 4.27: The layout for macro validation in the model

exit by students. In total, 16 experiments with different group sizes and stress levels were executed, whereby the group sizes ranged from one member to four members per group. The group's goal was to leave the room as quickly as possible. All group experiments were performed with two stress levels: high and low-stress levels. In the high-stress scenario, the first member who exited the room received a monetary prize. Furthermore, two different groups of students were employed, summing up to 16 experiments as shown in Table 4.6. However, as different stress levels are not present in the model, only the data from high-stress level experiments were utilized, as they simulate an actual evacuation situation.

Scenario no.	Team	Group size size	Treatment
1	Yellow	2	High stress
2	Green	2	High stress
3	Yellow	2	Low stress
4	Green	2	Low stress
5	Green	3	High stress
6	Yellow	3	High stress
7	Green	3	Low stress
8	Yellow	3	Low stress
9	Green	4	High stress
10	Yellow	4	High stress
11	Green	4	Low stress
12	Yellow	4	Los stress
13	Green	1	High stress
14	Yellow	1	High stress
15	Green	1	Low stress
16	Yellow	1	Low stress

Table 4.6: The 16 different experiments conducted by Haghani et al. (2019) and utilized for the macro validation

The implementation in the model

In order to reproduce the experiment by the model, a squared room was implemented. However, due to the assumption that one patch in Netlogo represents one square meter, the exact room with the same dimensions could not be replicated. Therefore, the room was slightly modified and rounded to full numbers. The room's layout is displayed in Figure 4.27 In this room, 50 repetitions were performed. The time interval of interest was the period between deciding to leave and exiting the building. Therefore, no pre-movement was included in the model to simulate this time. As a result, all agents immediately started to move towards the exit.

The results of macro validation
Figure 4.28 illustrates the results of the model in comparison to the results of the empirical study. The distributions of the evacuation time were broader than those found in the empirical research with a maximum evacuation time of 30 s resulting from the model and of 20 s observed in the experiments. This may be due to the modified room, different decision-making behaviors in the empirical study or other assumptions in the model. However visual comparison indicates that the results of the model are within the range estimated in the empirical study. This increases confidence that the correct model was created. However, it also shows that the capacity of the door, in particular, influences the overall performance and must be considered when analyzing the results.

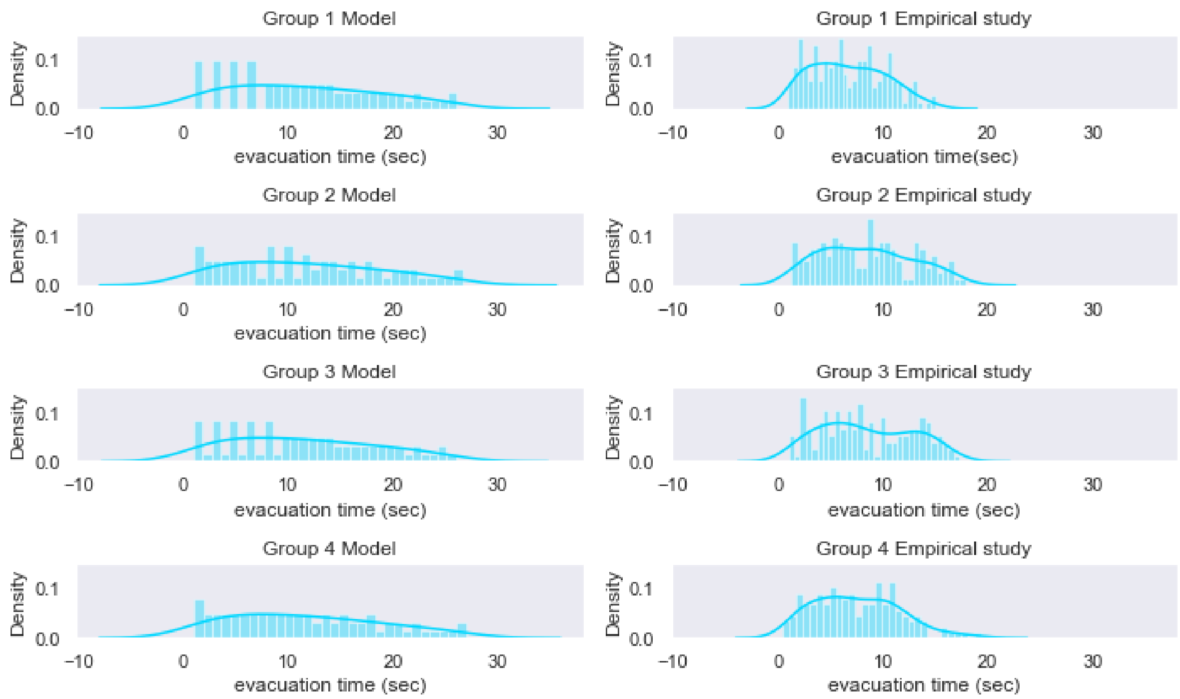


Figure 4.28: Comparison of evacuation times resulting from the model and observed in empirical studies for each group size

A fully valid model may never be achieved as no empirical study exists on different leader-follower behaviors. Nevertheless, the validation tests outlined in this chapter increases the confidence in the built model.

4.4.3. Sensitivity analysis

Sensitivity analysis may aid in providing insights into the emergent behavior of the model and its robustness regarding parameters (ten Broeke et al., 2016). In addition, higher trust in the built model and increased validity of the model may be achieved (Smith et al., 2008). If the model is sensitive to parameters that also occur in the real world, the trust in the model increases (Smith et al., 2008). Sobol sensitivity analysis provides the possibility of conducting a global sensitivity analysis (the reason for choosing sobol over other methods may be found in Chapter A.3 in Appendix A). The Sobol method quantifies the contribution of each input parameter to the outcome variance (X. Y. Zhang et al., 2015; Nossent et al., 2011). This is accomplished with the help of sensitivity indices. These indices exemplify fractions of the model output variance (Nossent et al., 2011). S1 can be seen as the first-order effects related to the given parameters on its own, while ST indices include the interaction effects. For the sensitivity analysis, first, the parameter sets using a low-discrepancy sequence are created, which has the advantage of a more uniform distribution compared to pseudo-random numbers (X. Y. Zhang et al., 2015). A deeper explanation of the Sobol methods can be encountered in Sobol (2001). For this model, the sensitivity analysis was conducted with 1000 scenarios from the whole parameter space, leading to 22000 runs in the developed model. Every run was conducted with 50 repetitions. Figure 4.29 demonstrates that the evacuation time is mainly influenced by the population, the recognition time and the percentage of familiar agents. If the interaction with other parameters is included, the share of the output variance increases for every parameter. However, for familiarity and population, the confidence bounds (the black lines in Figure 4.29) are still broad with the selected sample size. For the response time, the most significant uncertainty is the group distribution. This indicates that groups and individuals show contradicting response behaviors. Finally, for the mean intragroup distance, different parameters influence the variance of this KPI. Excluding the interaction effects, only the mean poisson distribution from which the group size is drawn, the distance of group members at the beginning of the evacuation and the population size impact the intragroup distance. However, with the inclusion of the interaction effects, the familiarity, the maximal congestion, and the number of groups influence this KPI. To conclude, the influence of parameters on the main KPIs is logical and thus, increases trust that a suitable model for its purpose was built. A more detailed description of the sensitivity analysis may be encountered in Chapter A.3 in Appendix A.

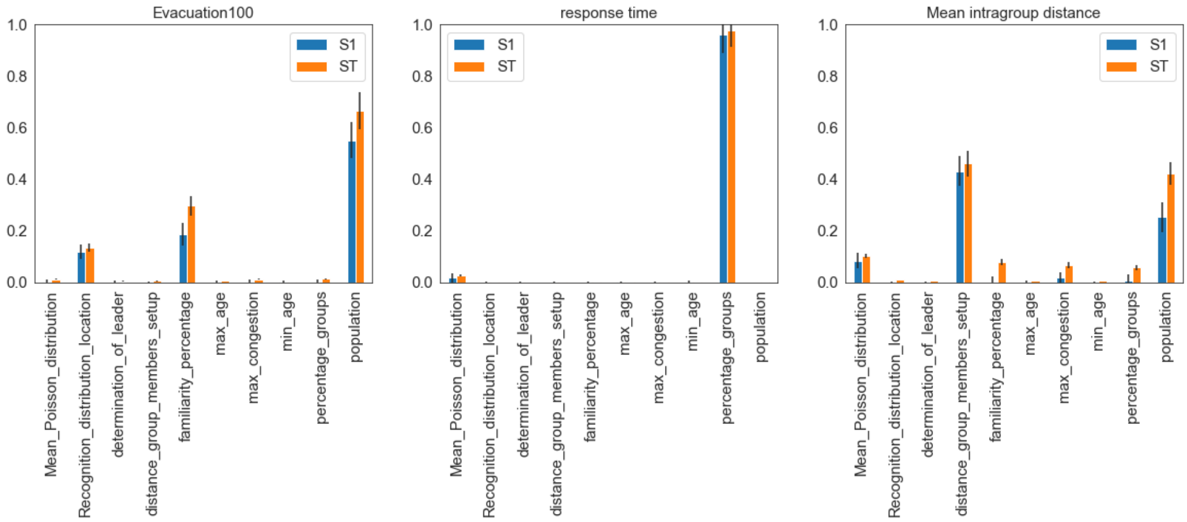


Figure 4.29: Results of the sensitivity analysis for the KPIs evacuation time (left), response time (middle) and intragroup distance (right). It indicates the influence of uncertainties on the variance of the KPIs. S1 relates to the influence of the parameter on its own, while ST includes interaction effects with other parameters.

4.5. Set-up for experimentation

As the research aimed to investigate how specific leader-follower behavior may influence the evacuation and response time as well as the intragroup distance under uncertainty, four experiments were conducted to answer the research question. The first may be seen as a base exploratory experiment to investigate how the model reacts under the variation of all parameters and investigate the influence of uncertainty on leader-follower groups. The second experiment described a hypothesis-driven experiment with a base ensemble. Thirdly, multivariate behavior testing on the base ensemble was performed. Finally, the environment was changed to an empty room, and the last experiment was repeated. All experiments were conducted with the EMA Workbench. The EMA Workbench in python allows performing experience in a complex environment and under uncertainty. A detailed description of the EMA Workbench may be found in J. H. Kwakkel (2017). The experiments are summarized in Table 4.7 with the reason for conducting each experiment. In this chapter, first, KPIs for each experiment are defined. Then the repetitions are specified, and finally, the experiments are exemplified in more detail.

Experiment	Definition	Scenarios	Samples	Behavior	Reason for this experiment
Base Experiment for open exploration	Exploratory experiment to investigate the influence of uncertainty on the core leader-follower behavior.	Uncertainty space	4000	No additional behaviors	- Investigate the influence of uncertainty on the core leader-follower behavior. - Find policy-relevant parameters, that may be utilized to design policies for locations with a high distribution of leader-follower groups.
Hypothesis driven experiment with base ensemble	Base ensemble is utilized to investigate the hypothesis.	Base ensemble	1000	Backtracking, group gathering, flexibility of the group	- To provide a better understanding and discover new insights about how backtracking, group gathering and the group's flexibility influence the evacuation performance. - This may aid modelers in evacuation research in modeling this behavior.
Multivariate behavior testing on base ensemble	Base ensemble is utilized to investigate all possible combination of behaviors.	Base ensemble	1000	8 unique behavioral combinations with three behaviors	- To provide a better understanding how combinations of leader-follower behavior influence the overall evacuation performance.
Multivariate behavior testing on base ensemble in an empty room	Base ensemble is utilized to investigate all possible combination of behaviors in an empty room.	Base ensemble	1000	8 unique behavioral combinations with three behaviors	- The goal is to test the pure behavior without interaction with obstacles and minimise the environment's influence on the results. - Provides more trust in the received results.

Table 4.7: The experiment plan for this research

4.5.1. Key performance indicator

Rimea (2016) proposed various KPIs of repeated simulation runs for evacuation models, such as the average, minimum and maximum evacuation time as well as the standard deviation. In order to calculate these KPIs, the evacuation time (Evactime100) for each run was received. However, a complete evacuation may not always be accomplished (Han et al., 2007). Hence, the 95% percentile of the evacuation time (Evactime95) may be more representative for evacuation efficiency (Han et al., 2007) and was, therefore, included in the KPIs for the experiments. As the research aims to investigate how the different leader-follower behaviors influence the evacuation and response time in buildings, the response time was measured for each run. The response time includes the time frame from the recognition phase to leaving the building, whereby the average, standard deviation, minimum and maximum response time for each run were collected. Furthermore, to receive an overview of the behavior inside the group, and about how it may vary with additional policies, the mean intragroup distance between the groups was monitored. In order to see the differences per group size, the mean intragroup distance for groups sizes two, three, four, and five were examined. The KPIs are summarized in Table 4.8.

KPI	Explanation	Unit
Evactime100	The time between the start of the evacuation and the last agent leaving the building	Second
Evactime95	The time between the start of the evacuation and 95% of the agents have left the building	Second
Mean ResponseTime	The mean response time of all agents.	Second
SD ResponseTime	The Standard deviation of the response time of all agents.	Second
Min ResponseTime	The minimum response time	Second
Max ResponseTime	The maximum response time	Second
Mean Intragroup distance total	The mean intragroup distance between all groups	Meter
Mean Intragroup distance G2	The mean intragroup distance between groups with 2 group members	Meter
Mean Intragroup distance G3	The mean intragroup distance between groups with 3 group members	Meter
Mean Intragroup distance G4	The mean intragroup distance between groups with 4 group members	Meter
Mean Intragroup distance G5	The mean intragroup distance between groups with 5 group members	Meter

Table 4.8: Key performance indicator for each experiment

4.5.2. Repetitions

Due to the chaotic property of an agent-based model, it is never possible to trust a single run (van Dam et al., 2013). Therefore, repetitions are needed to gain confidence in the results of the experiments. In order to achieve this confidence, a convergence test was performed with a Latin hypercube sampling for nine different scenarios as proposed by van Dam et al. (2013), whereby the mean evacuation time was utilized to investigate when the outcome of repetition stabilized. In addition, a variance stability test was conducted to assess the uncertainty surrounding the variance (Lee et al., 2015). Thus, the coefficient of variance (Cv) is calculated for every run, which is influenced by the standard deviation (σ) as well as the mean (μ). It is represented by the following formula (Lorscheid et al., 2012):

$$C_V = \frac{\sigma}{\mu}$$

If the coefficient of variance stabilizes, the minimum runs may be retrieved. Figure 4.30 shows the convergence test, and Figure 4.31 summarizes the coefficient of variance. All results may be found in Figure A.3 and Figure A.4 in Appendix A. Both tests demonstrated stability after 50 runs which was, thus, employed for the experiments.

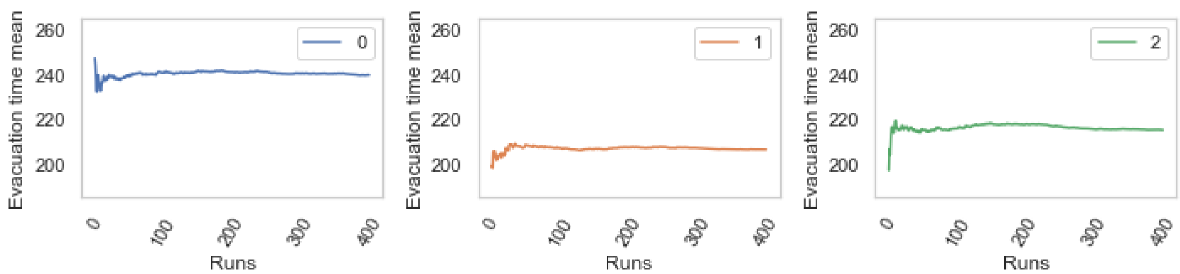


Figure 4.30: The evacuation means for different runs and three samplings

4.5.3. Base experiment for open exploration

The base experiment may be seen as an exploratory experiment. In order to explore the influence of the model uncertainties on the core leader follower behavior, an uncertainty analysis may be utilized (Blower et al., 1994). In particular, this may aid in measuring the importance of uncertainties (Thiele et al., 2014). In addition, it may aid in finding policy-relevant parameters that may be utilized to design policies for locations with a high density of leader-follower groups. A full factorial experimental design

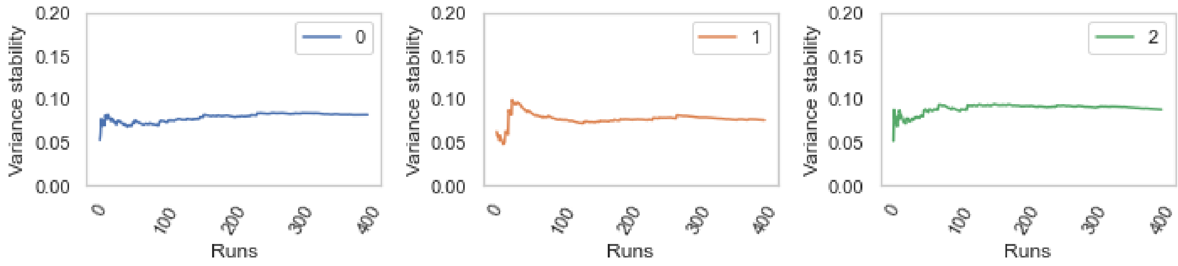


Figure 4.31: The variance stability for different runs and three samplings

was, however, not possible due to the limited amount of time and computer capacity. Instead a sampling technique was utilized (van Dam et al., 2013). Various sampling techniques exist to conduct an exploratory experiment, such as simple random, Latin hypercube and Monte Carlo sampling (Thiele et al., 2014; van Dam et al., 2013). In the base experiment, the Latin hypercube sampling was utilized to receive the most representative set of parameters (van Dam et al., 2013). For this experiment, 4000 samples were created for the uncertainty ranges described in Table 4.5.

4.5.4. Hypothesis driven experiment with base ensemble

In order to investigate how the selected leader-follower behaviors influence the evacuation and pre-movement time, a hypothesis-driven experiment was performed. This experiment aims to provide a better understanding of additional behaviors and discover new insights into the underlying pattern. van Dam et al. (2013) proposed a base case for hypothesis testing. However, due to the presence of various uncertainties in the model, a base case may not be suitable or not available to obtain robust conclusions regarding the influence of each behavior (Lempert et al., 2006; Auping, 2018). Therefore a base ensemble was utilized to investigate the effect of each behavior. The base ensemble is shown in Table 4.9 with value ranges retrieved from literature, whereby a Latin hypercube sampling was employed with 1000 samples. Finally, the hypothesis for each behavior is displayed in Table 4.10.

Parameter	Change of value
Familiarity	0-30
Population	100-1200
Percentage groups	55%-70%
Group distribution	0,83-1,4
Max crowd density	5 - 8
Max distance group members	1-6
Min_age	10-20
Max_age	65-85
Recognition time distribution	Department store, restaurant, office
Determination of group leader	Random, closest to the exit

Table 4.9: Base ensemble

4.5.5. Multivariate behavior testing on base ensemble

Due to the behavioral uncertainty in evacuation models, more than just one behavior may be observed during the evacuation process. Backtracking, group gathering and flexibility of the group may all emerge during an evacuation process in real life whereby the combinations of behaviors may influence the KPIs. Hence, the goal of this experiment was to investigate when, how or whether certain behavioral combinations impact the evacuation process. Therefore, an experiment of 1000 Latin hypercube samplings with eight distinct behavioral combinations was performed.

Behavior	Definition of the behavior	Default setting	Variation	Hypothesis
Backtracking	Leaders slow down and wait for the follower to catch up.	Off	On	**H1: Backtracking of the leader has a negative influence on the evacuation time,** as the slowest member of the group determines the speed of the group.
Group gathering before the evacuation	The group is gathering near the leader before they follow the leader.	Off	On	**H2: Group gathering negatively influences the evacuation time and increases the response time.** The reason behind choosing this assumption is that some valuable time will be lost during the gathering process.
Flexibility of the group: A follower may change to another leader if the other leader has more influence.	Every follower may change the leader, if another leader is closer.	Off	On	**H3: The possibility to change the leader does not influence the overall evacuation time.** The reason behind this hypothesis is that the leader needs to leave the building with or without a group following him.

Table 4.10: Hypothesis for each behavior

4.5.6. Multivariate behavior testing on base ensemble in an empty room

As the environment and building layout highly influence the outcome of an evacuation (Berseth et al., 2015), the above experiment was additionally conducted in an empty room. The goal was to test the pure behavior without interaction with obstacles and minimise the environment's influence on the results. Figure 4.32 indicates the environment representing the empty room. In this environment, multivariate behavior testing with a base ensemble was conducted to strengthen the results of the above-conducted experiment.

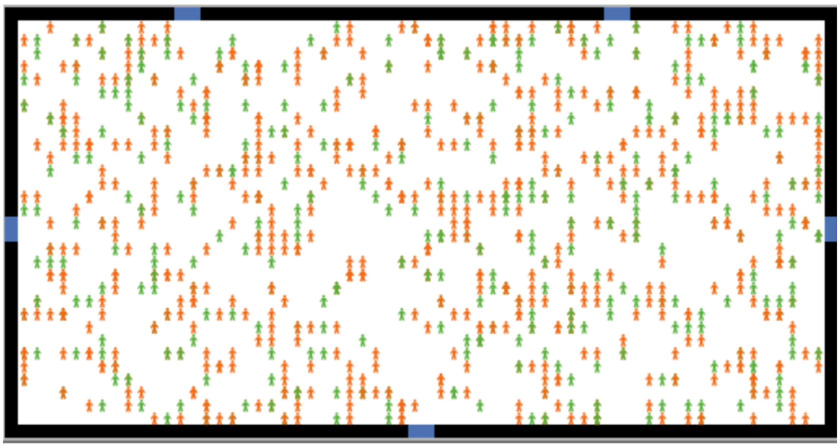


Figure 4.32: The environment utilized for multivariate behavior testing on base ensemble in a squared room

5

Results

5.1. Open exploration about leader-follower behavior without additional behaviors

The goal of open exploration was to investigate the influence of uncertainty on the overall behavior of the model. In addition, it demonstrates how uncertainty impacts the core leader-follower behavior. Therefore, first, the general behavior is explained in more detail, then the influence of uncertainties is explored with the help of (1) a visual analysis, (2) feature scoring and (3) scenario discovery.

5.1.1. Overall behavior

The overall behavior is summarized in Figure 5.1. The plots show resulting distributions of the different KPIs. First, it illustrates that the evacuation time for each scenario ranges from 105.72 seconds to 271.70 seconds, while the median lies at around 145.58 seconds. The same emergent behavior may be unearthed for the 95% percentile of the evacuation time. In contrast, the mean response time may not be as sensitive as the evacuation times regarding the uncertainties. However, it shows that the model's maximum and minimum response time varies largely. It ranges from 4.42 to 77.20 seconds. The reason of the variability in the resulting response times are different pre-movement actions for each member with different distributions. Finally, the intragroup behavior was studied. The mean intragroup distance varies largely between the scenarios. In addition, the intragroup distance increases with the number of group members. Overall all KPIs show a sensitivity regarding the uncertainties and indicate strongly diverging results between scenarios.

5.1.2. Influence of uncertainties on the core leader-follower behavior

Overall, the model demonstrates that uncertainties highly influence the outcome of an evacuation. For instance, the evacuation time varies more than two minutes, depending on the scenario. This difference may increase or decrease fatalities enormously in case a fire occurs. Hence, it needs to be investigated which uncertainties influence KPI's the most. For this purpose, feature scoring was utilized to identify relevant influences of uncertainties on the KPIs. Finally, a scenario discovery is performed to receive policy relevant areas in the uncertainty space. In addition, plots for each uncertainty against the KPIs and a detailed visual analysis may be found in Appendix B.

Feature scoring for the whole uncertainty space

The above results demonstrate that uncertainties highly impact the outcome of an evacuation. Feature scoring helps to identify the relevance of uncertainties on the KPIs (D. Y. Yang & Frangopol, 2020). A higher score in Figure 5.2 indicates a greater influence on the KPI.

Feature scoring displays that the **evacuation time** and its 95 percentile are influenced by the recognition distribution location, familiarity and the population. The highest impact has the **population size**, as more agents need to leave the building leading to longer queuing times. Moreover, the increased density leads to a lower speed of evacuees. In addition, the recognition time has a substantial influence. A higher **recognition time** distribution may create longer recognition times and thus impacts

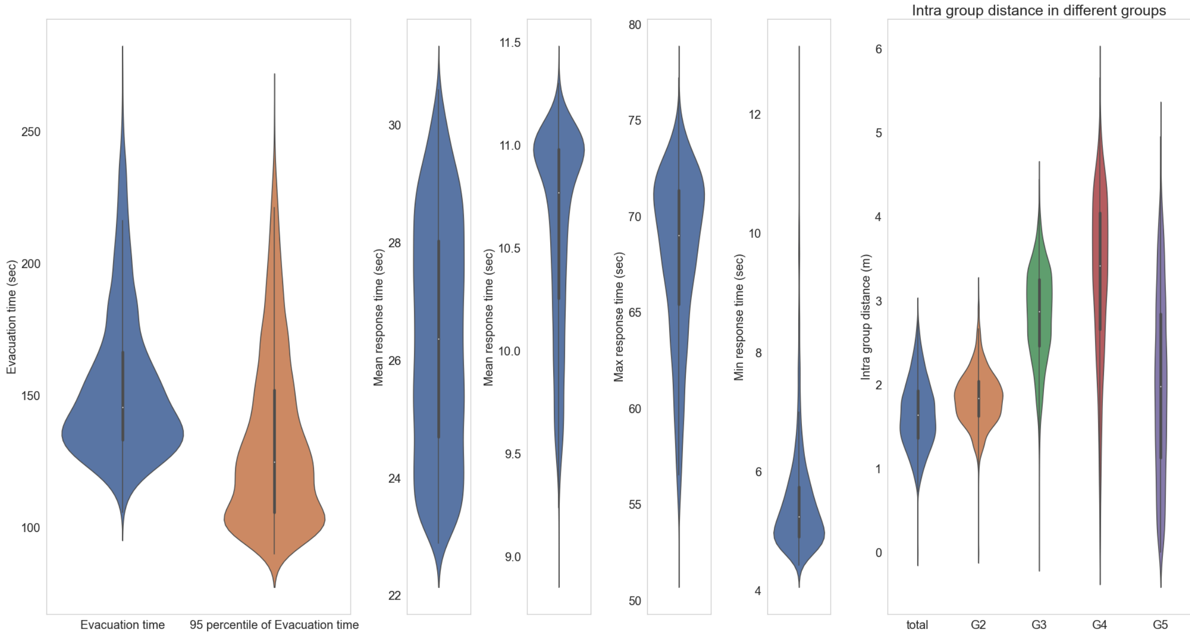


Figure 5.1: The overall behavior for each key performance indicator. The evacuation time and its 95 percentile on the left, the mean, standard deviation, maximum and minimum of the response time in the middle, as well as the intragroup distance for different groups on the right

the total evacuation time. For instance, the distribution in an office indicates a higher mean than in a department store or restaurant. In addition, its maximum value of 111 seconds is higher compared to the other distributions, leading to longer evacuation times. Finally, feature scoring indicate the impact of familiarity. An increasing **familiarity** may lead to lower evacuation times, as evacuees are utilizing all exits to leave the building. Therefore, lower queuing times emerge, which decreases the evacuation time. Other uncertainties have non or only a marginal influence on the evacuation time. Thus, it indicates that bigger groups (higher "mean for the poisson distribution") or more groups (higher value for the "group percentage") may not be as influential as the population size or familiarity.

The mean and standard deviation of the **response time** is mainly influenced by the **group percentage**, while the **population size** affects the maximum of the response time. This reveals that groups and individuals show a different response behavior. A higher group percentage in the model increases the mean response time, indicating that groups exhibit a higher response time overall, as they wait for every member to finish their task. However, the standard deviation of the response time decreases. The reason for this observation is that groups remain for every group member to complete their actions and then receive the same response time, leading to a lower deviation of the mean. Lastly, the minimum response time is impacted by the group percentage and only minimally by the population size as group members indicate a higher response time.

Finally, the intragroup distance is shaped by the **separation at the beginning** of the evacuation and by the **population** due to higher congestion. Moreover, the overall mean distance is affected by the **mean of the poisson distribution** for the group size as an increase of this parameter leads to larger groups with higher group distances. Furthermore, the **familiarity** percentage has a minor influence on smaller groups. If evacuees are very familiar with their surrounding, the congestion decreases as all exits are utilized. Therefore, group members may not lose connections and stay together, which leads to a lower mean intragroup distance.

Scenario discovery

In evacuations, people must leave the building before the fire leads to fatalities. This time is defined as the ASET. For instance, the European Union recommended that 2 minutes for leaving a building should not be extended (DIN EN 13200-1, 2012, cited in Rimea, 2016). Consequently, scenario discovery may be utilized to find policy-relevant regions with uncertain parameter space in evacuation models (Bryant & Lempert, 2010) as already explained in Chapter 3.1.3. Parameter combinations that may lead to a ASET exceeding 2 minutes need to be investigated, and can guide the restriction of visitor numbers

Figure 5.2: Feature scoring for the uncertainties. A higher number indicates a greater influence on the Key performance indicator.

or safety training for staff members. Different values recommended for the ASET could be found in the literature. It highly depends on the size and structure of the building. However, diverging ASET recommendations for a building have been published. As already mentioned, the European Union recommends an ASET of 2 minutes (DIN EN 13200-1, 2012, cited in Rimea, 2016). In contrast, Van De Leur (2005) proposed an ASET of 3 minutes, and the Vereinigung Kantonaler Feuerversicherungen (VKF) (1999, cited in Rimea, 2016) reported a maximum ASET between 3 and 5 minutes. Due to the different recommendations, three scenarios are created to find the policy-relevant parameter space: a low ASET scenario with 2 minutes, a middle ASET with 3 minutes, and a high ASET with 4 minutes. The scenarios are depicted in Figure 5.3, whereby the blue line indicates the cumulative frequency of all evacuation times encountered in the base experiment with 4000 samples.

For all three scenarios, boxes are encountered, which are explained and shown below. These boxes illustrate a location in the uncertainty space and exhibit the parameters and values that need to be restricted in order to achieve the desired evacuation time.

2-minute scenario

The results for the 2-minute scenario showed that three different uncertainties need to be restricted in order to assure the evacuation within 2 minutes. Thus, the **familiarity percentage** must be over 50 percent, the **population size** under 321 persons and the distribution for a restaurant or department store may be utilized for the **recognition time distribution**. Overall, the scenario covers 78% of the cases of interest. However, when restricting all these parameters to the respective boundaries, only 57.9% of all restricted cases have an evacuation time below 2 minutes. The other 42,1% of the restricted cases have a higher evacuation time (Figure 5.4).

3-minute scenario

The second scenario for the middle ASET scenario requires restricting the **population size** to a maximum of 865 persons and the **mean of the poisson distribution** for sampling the group size to 1.45. A density of 1 and coverage of 58.3% was achieved with the help of the prim algorithm. Figure 5.5a

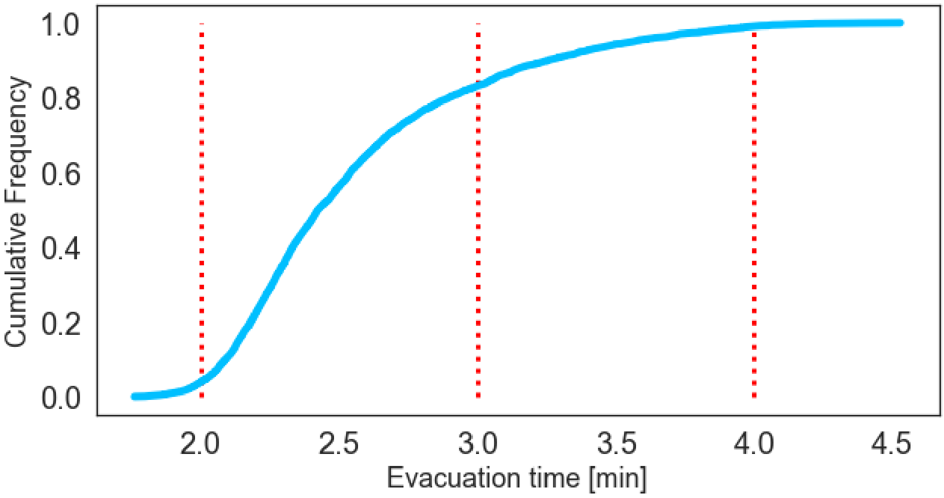


Figure 5.3: Three different scenarios (red line) are plotted against the cumulative frequency of evacuation times in the base experiment with 4000 samples.

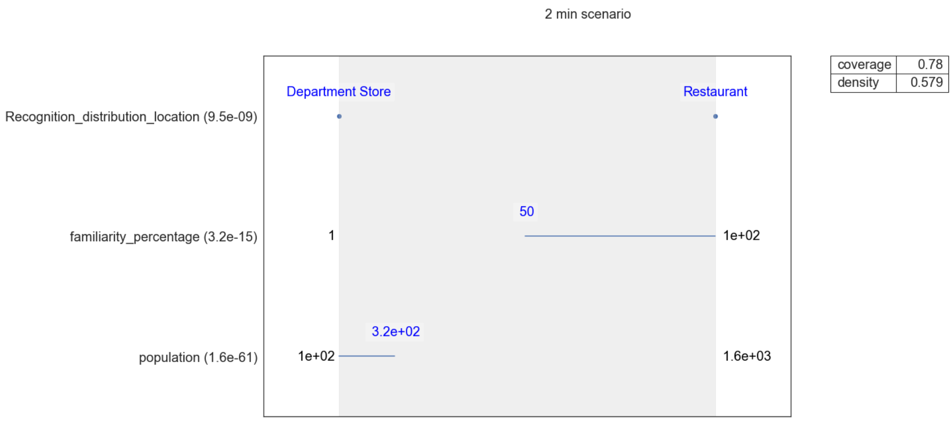


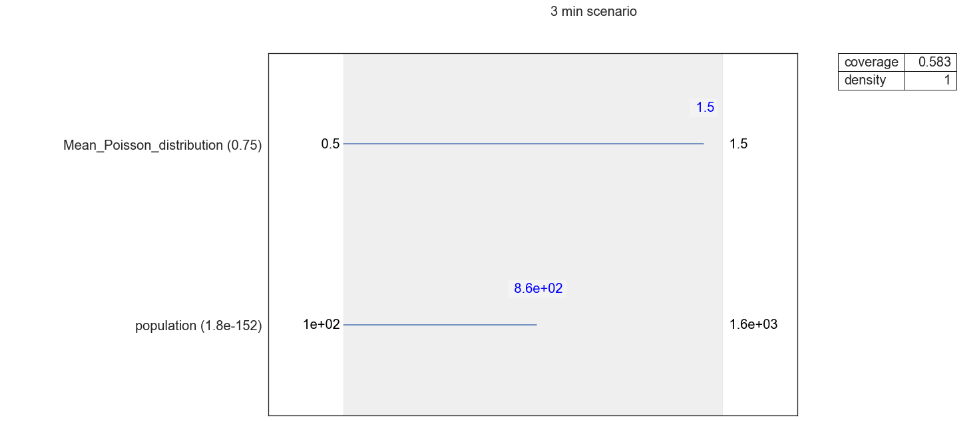
Figure 5.4: The values of restricted uncertainties of the 2 min scenario that covers 78% of the cases under 2 minutes and 57.9% of all restricted cases are cases with an evacuation time lower than 2 minutes

summarizes the scenario. Another box for the remaining cases below 3 minutes could be found with a density of 1 and coverage of 16.6% (Figure 5.5b). It includes the restriction of **familiarity** to over 40% and the population size under 1348 persons. In addition, the distribution of the **recognition time** for the office may not be utilized. Another box with the threshold of 0.9 could not be observed. With these two boxes 74.9% of all cases of interest are covered.

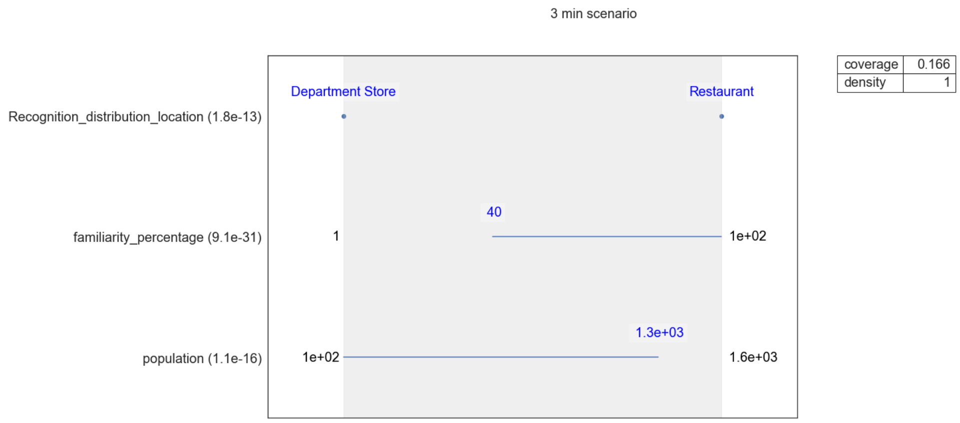
4-minute scenario

Finally, in order to achieve an ASET under 4 minutes, the **capacity of the building** ought to be restricted to 1320. In addition, the people's **familiarity** should not drop below 9 percent. This box covers 75.6% of the cases of interest with a density of 1. For the remaining cases another box could be encountered. It covers additional 12.9% of the cases of interest which are not covered by the first box. Also, the density of 1 indicates that it covers only cases with an evacuation time below 4 minutes with the help of restricting the familiarity, the maximum congestion and recognition distribution location. Finally, a third box with a lower density of 94,3% s displayed that includes the remaining cases. Here, the maximum age and population size need to be restricted to 84 years and 1552 persons. All values for all boxes are summarized in Table 5.1. In total 3904 cases of 3964 cases of interest are covered with these 3 boxes.

Overall, scenario discovery with the help of the PRIM-algorithm reveals a strong influence of **familiarity, population size and recognition time distribution** on the evacuation time for a leader-follower



(a) The values of restricted uncertainties of box 1 of the 3 min scenario with a density of 1 and coverage of 58.3%



(b) The values of restricted uncertainties of box 2 of the 3 min scenario with a density of 1 and coverage of 16.6%

Figure 5.5: The different boxes of the 3-minute scenario

group. In addition, for higher ASET, the **maximum congestion** influences the evacuation performance. Other uncertainties found in the boxes, such as the age or the mean of the poisson distribution for selecting the group size, only show a high quasi p-value, indicated behind the parameter name. These high quasi p-values demonstrate the statistical significance of the constraint parameter (or uncertainty) (Bryant & Lempert, 2010). A lower quasi p-value reveals a higher statistical significance. In particular, these results confirm the observations of the extra-tree algorithm for feature scoring and reveal that the most significant uncertainties in buildings with leader-follower groups are **familiarity, the population size and the recognition time**.

Box	Density	Coverage	Restricted parameters		quasi p-value
Box1	1	0.756	Population Familiarity_percentage	<= 1320 >= 9	< 0.01 0.4
Box2	1	0.129	Familiarity_percentage Max_congestion Recognition_distribution_location	>= 2 >= 5 [Department store, restaurant]	0.15 0.041 < 0.01
Box3	0.943	0.100	Max_age Population	<= 84 <= 1552	0.42 0.16

Table 5.1: The different boxes for the 4-minute scenario and their restricted parameters

5.2. Three unique leader-follower behaviors

After the core leader-follower behavior was investigated in more detail, this chapter focuses on the influence of additional leader-follower behaviors. Figure 5.6 compares the three different leader-follower behaviors with the base case (the plot for all KPIs are illustrated in Figure B.11 in the Appendix B). It shows the difference between the three behaviors for different KPIs. In addition, a Mann-Whitney U test was performed in order to examine how and if the hypothesis for each leader-follower behavior may be accepted or declined. The Mann-Whitney U test allows comparing a variable between two groups (McKnight & Najab, 2010). The H_0 hypothesis is that the two groups have the same evacuation time. In case a p-value of the Mann-Whitney U test above 0.05, the H_0 hypothesis cannot be rejected. First, for each behavior the hypothesis test and the results for each KPI are presented. The main findings and their explanation with regard to the structure of the model are summarized at the end in Table 5.5.

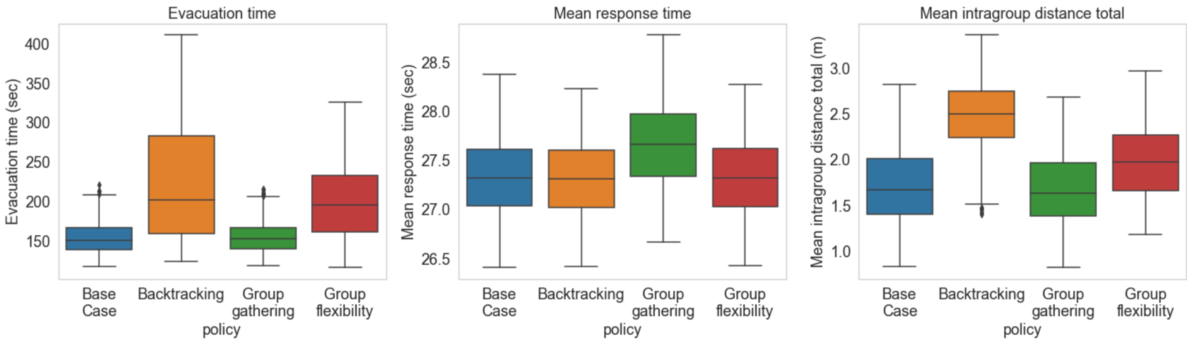


Figure 5.6: The total evacuation time (right), the mean response time (middle) and the mean intragroup distance (left) for additional leader-follower behavior.

5.2.1. Backtracking

The first behavior in focus is backtracking. According to the hypothesis formulated in Chapter 4 prolongation of the evacuation time due to backtracking was explored.

H1: The backtracking of the leader has a negative influence on the evacuation time

Figure 5.6 already indicates that the scenario with backtracking of the leader increases the evacuation time when compared to the base case. This is confirmed by statistical comparison with the Mann-Whitney U test. Furthermore, the difference between the medians (150.77 seconds for the base case and 202.31 seconds for the scenario with backtracking) indicates a negative influence on the evacuation time. Therefore, the research hypothesis H1 is confirmed. The backtracking of the leader may reduce the speed of groups leading to a higher evacuation time.

Moreover, the respective comparison of the time needed to evacuate 95% of the population confirms the negative impact of backtracking, although, the difference between the base case and the backtracking scenario is lower than for the total evacuation time. This pattern might appear due to fewer but larger groups during the evacuation. In these groups, the leader must wait longer for group members to decrease the gap between the leader and the followers. The response time is not affected by backtracking. This is logical, as backtracking may only be observed in the movement phase. However, the intragroup distance varies in comparison to the base case. A significant difference is observed for groups with 2 and 4 persons, but not for groups with 3 and 5 persons. Backtracking reduces the distance for smaller groups, as the leader waits for the follower to reduce the distance. Conversely, in larger groups, backtracking increases the intragroup distance, as the leader waits for all group members to catch up. Followers step aside which leads to a higher distance between group members in larger groups. All the results for backtracking are summarized in Table 5.2.

In order to analyze which uncertainty influences the results about the impact of the backtracking scenario the most, feature scoring was utilized for the different samplings with backtracking. The results are displayed in Figure B.12 in Appendix B. It becomes clear that backtracking is highly influenced by the distance between group members at the beginning of the evacuation. The same value is utilized as the threshold for backtracking and has thus the greatest impact on the evacuation time. The distributions

KPIs	Mann-Whitney U Test: p-value	Median base case	Median backtracking	Result
Evactime100	<0.01	150.77	202.31	Significantly different
Evactime95	<0.01	129.57	149.48	Significantly different
Mean ResponseTime	0.82	27.32	27.31	Not significantly different
SD ResponseTime	0.62	10.61	10.60	Not significantly different
Min ResponseTime	0.79	5.40	5.40	Not significantly different
Max ResponseTime	0.94	67.05	67.00	Not significantly different
Mean Intragroup distance total	<0.01	1.67	2.50	Significantly different
Mean Intragroup distance G2	<0.01	1.85	1.77	Significantly different
Mean Intragroup distance G3	0.06	2.91	2.78	Not significantly different
Mean Intragroup distance G4	<0.01	3.63	4.03	Significantly different
Mean Intragroup distance G5	0.67	2.35	2.26	Not significantly different

Table 5.2: Comparison of the KPIs between the scenario with backtracking and the base case with a significance level of 0.05

of the evacuation time depending on the threshold distance for backtracking in comparison to the base case are shown Figure 5.7. It indicates that a lower threshold for backtracking increases the influence of backtracking. If the largest accepted distance between the leader and follower for backtracking is lower, the leader must wait more often and extend the stay until followers catch up. However, if a higher threshold is chosen, backtracking may not have any influence as the leader's waiting time decreases.

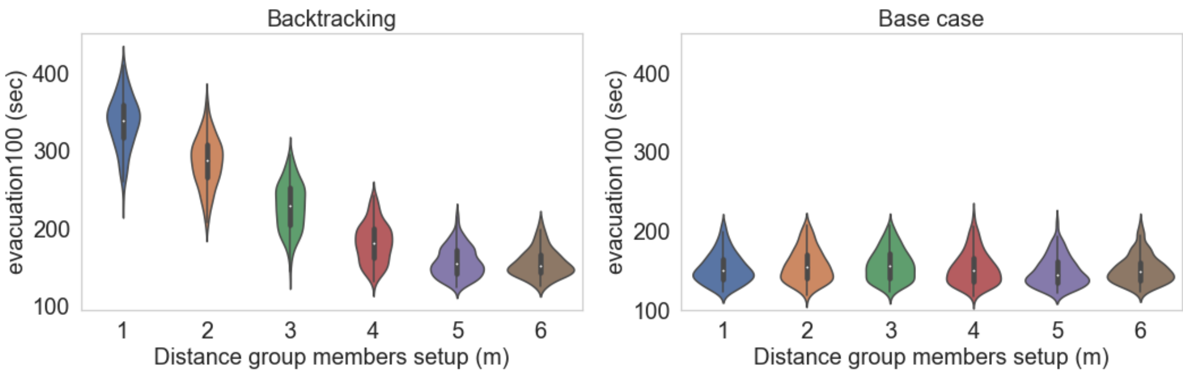


Figure 5.7: The influence of group distance at the beginning of the evacuation on the evacuation time for backtracking (left) and for the base case (right)

5.2.2. Group gathering

The following hypothesis was tested regarding the influence of group gathering on an evacuation process:

H2: Group gathering negatively influences the evacuation time and increases the response time.

Figure 5.6 provides a first indication that group gathering does not have any influence on the overall evacuation time. The p-value of the Mann-Whitney U test for the respective comparison with the base case lies above the threshold of 0.05. Furthermore, the difference between the medians (150.77 for the base case and 152.21 for the scenario with group gathering) does not represent a relevant difference. Hence, the first part of the hypothesis needs to be rejected. The second part of the hypothesis, that group gathering would affect the response time, must be accepted. The response time is slightly higher with group gathering when compared to the base case. Nonetheless, the difference is only minimal. The reason for this small difference lies in the distribution of the agents. If group members are already located close to each other before the evacuation, not much time is necessary for the final group formation. But if group members are situated further apart, the process of group gathering adds to the response time. The same pattern was observed for the standard deviation of the response time. The reason for this is that groups and individuals indicate distinct response times. Overall, the perceived response time of individuals is lower compared to groups in the model. However, with the addition of group gathering, the response time of groups increases, which expands the gap between the response time of individuals and groups, leading to a higher standard deviation.

Furthermore, the distance within groups of two, three, four, and five people is significantly different between the scenario with group gathering and the base case. The reason for this observation is that groups stand tighter together when they start evacuating. This results in a lower intragroup distance for the whole evacuation. However, the overall mean intragroup distance is similiar as bigger groups may also be present at the beginning of the evacuation, depending on the mean of the poisson distribution for group size selection, which may influence the group distribution. The values for each KPI are summarized in Table 5.3

KPIs	Mann-Whitney U Test: p-value	Median base case	Median group gathering	Result
Evactime100	0.25	150.77	152.21	Not significantly different
Evactime95	0.43	129.57	130.11	Not significantly different
Mean ResponseTime	<0.01	27.32	27.66	Significantly different
SD ResponseTime	<0.01	10.61	10.72	Significantly different
Min ResponseTime	0.88	5.40	5.40	Not significantly different
Max ResponseTime	0.02	67.05	67.38	Significantly different
Mean Intragroup distance total	0.10	1.67	1.63	Not significantly different
Mean Intragroup distance G2	<0.01	1.85	1.78	Significantly different
Mean Intragroup distance G3	0.01	2.91	2.86	Significantly different
Mean Intragroup distance G4	<0.01	3.63	3.46	Significantly different
Mean Intragroup distance G5	0.02	2.35	2.29	Significantly different

Table 5.3: Comparison of the KPIs between the scenario with group gathering and the base case with a significance level of 0.05

Also, for group gathering, the influence of the uncertainty was analyzed with the help of feature scoring. Results regarding the impact of uncertainties on the KPIs are shown in Figure B.13 in Appendix B. The mean of the poisson distribution for group size selection was plotted against the response time for the base case and the group gathering scenarios. Figure 5.8 indicates a steeper slope of the group gathering scenarios in comparison to the base case. The reason is the increasing number of bigger groups with a higher value of the mean poison distribution. Bigger groups need a longer time to gather around the leader before they start evacuating.

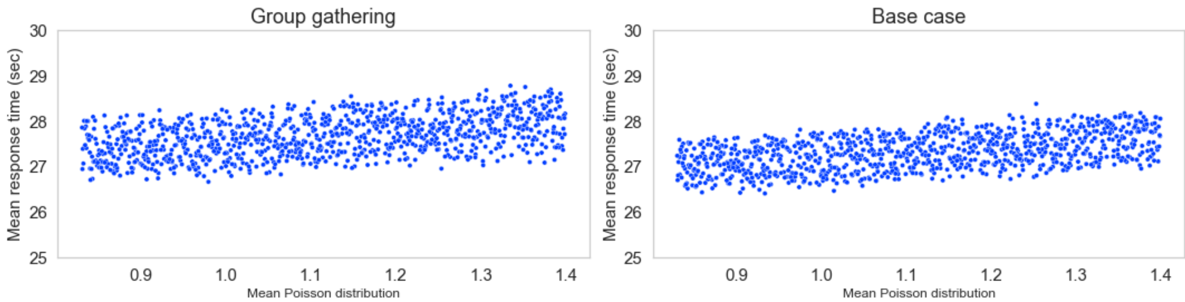


Figure 5.8: The influence of the mean poisson distribution of group distribution on the response time for group gathering (left) and for the base case (right)

5.2.3. Flexibility of the group

The final hypothesis, relating to the behavior of flexibility is as follows:

H3: The possibility to change the leader does not influence the overall evacuation time.

The group's flexibility clearly raises the evacuation time. Figure 5.6 displays the difference between the base case and the scenario with flexibility of the group. The Mann-Whitney U test verifies this difference ($p = <0.01$). Therefore, the hypothesis must be rejected.

The explanation for the rise in evacuation time is that few but large groups emerge when the group's flexibility is activated. Bigger groups exhibit a lower speed, leading to higher evacuation times. This pattern is also confirmed by the 95 percentile of the evacuation time. The gap between the base case and the group flexibility scenario is lower compared to the overall evacuation time. This indicates that a few bigger groups emerge, which need a longer time to arrive at the exit.

In contrast, the group's flexibility does not impact the response time, as it may be encountered only in the movement phase. However, the overall intragroup distance may increase. Flexibility in changing the leader may lead to bigger groups. Overall, these groups demonstrate a higher intragroup distance and lower walking speed, leading to higher evacuation times and larger overall intragroup distance. Nevertheless, for small groups, the flexibility of groups decreases the mean intragroup distance. Only groups with a smaller intra-group distance stay together, as otherwise, the followers could switch to another leader.

KPIs	Mann-Whitney U Test: p-value	Median base case	Median flexibility of group	Result
Evactime100	<0.01	150.77	195.56	Significantly different
Evactime95	<0.01	129.57	135.94	Significantly different
Mean ResponseTime	0.97	27.32	27.31	Not significantly different
SD ResponseTime	0.75	10.61	10.61	Not significantly different
Min ResponseTime	0.82	5.40	5.40	Not significantly different
Max ResponseTime	0.64	67.05	67.26	Not significantly different
Mean Intragroup distance total	<0.01	1.67	1.97	Significantly different
Mean Intragroup distance G2	<0.01	1.85	1.71	Significantly different
Mean Intragroup distance G3	<0.01	2.91	2.62	Significantly different
Mean Intragroup distance G4	<0.01	3.63	3.14	Significantly different
Mean Intragroup distance G5	<0.01	2.35	2.87	Significantly different

Table 5.4: Comparison of the KPIs between the scenario with groups flexibility and the base case

Finally, the impact of uncertainty was investigated with the help of feature scoring for the group's flexibility. It indicates a more significant influence on the uncertainty of maximal congestion compared to the base case (Figure B.14 in Appendix B). Figure 5.9 reinforces this result. This phenomenon is explained by the higher chance of the follower finding a closer leader due to more agents in the same area. As a result, bigger groups with a lower speed are created. However, even with a lower value for the maximum congestion, the influence of the group's flexibility may be observed. The reason is that followers still maintain a high probability of encountering a closer leader with maximum congestion of five people per patch. Hence, group flexibility increases the evacuation time even with a lower value of maximum congestion.

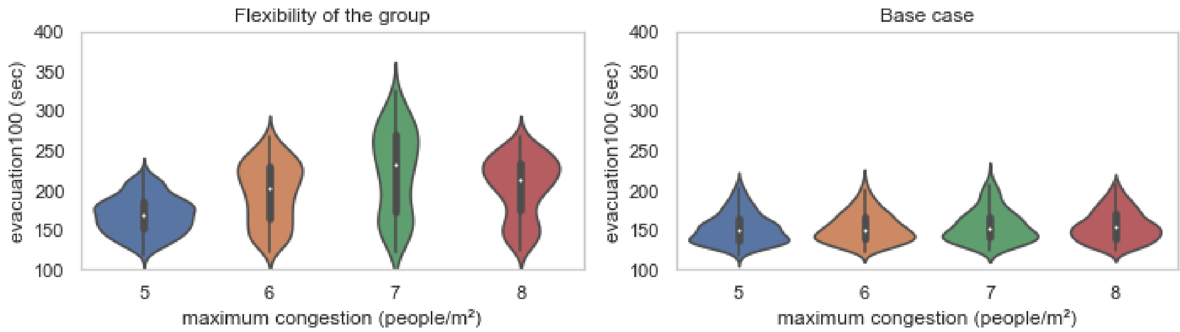


Figure 5.9: The influence of uncertainty maximum congestion on the evacuation time for flexibility of the group (left) and for the base case (right)

Behavior	Result	Structural explanation of the pattern in the model
Backtracking	**Backtracking increases the evacuation time.**	The backtracking of the leader may reduce the speed of groups leading to a higher evacuation time.
	For the 95 percentil, the difference between the backtracking scenario and the base case is lower compared to the total evacuation time.	This pattern might appear due to larger groups, where only a few are present during the evacuation. In these groups, the leader must wait longer for group members to decrease the gap between the leader and the followers.
	The mean intragroup distance varies in comparision to the base case.	As the leader waits for all group members to catch up, followers step aside, which leads to a higher distance between group members in larger groups, increasing the overall mean.
	For smaller groups the intragroup distance decreases.	Backtracking reduces the distance for smaller groups as the leader waits for the follower to reduce the distance.
	The evacuation time is highly influenced by the threshold for leaders to utilize backtracking.	If the largest accepted distance between the leader and follower for backtracking is lower, the leader must wait more often and extend the stay until followers catch up. However, if a higher threshold is chosen, backtracking may not have any influence as the leader's waiting time decreases.
Group gathering	**The response time is slightly higher with group gathering when compared to the base case. Nonetheless, the difference in only minimal.**	The reason behind the slight difference lies in the distribution of the agents. If group members are already located close to each other before the evacuation, not much time is necessary for the final group formation. But if group members are situated further apart, the process of group gathering adds to the response time.
	The standard deviation of the response time increases.	The reason behind this is that groups and individuals indicate distinct response times. Overall, the perceived response time of individuals is lower compared to groups in the model. However, with the addition of group gathering, the response time of groups increases, which expands the gap between the response time of individuals and groups, leading to a higher standard deviation.
	The distance within groups of two, three, four, and five people is significantly different between the scenario with group gathering and the base case.	The reason is that groups stand tighter together when they start evacuating, resulting in a lower intragroup distance for the whole evacuation.
	The overall mean intragroup distance is similar.	Bigger groups may also be present at the beginning of the evacuation, which also influence the mean intragroup distance .
	A higher influence of the mean poisson distribution for the group gathering scenario compared to the base case.	The reason is the increasing number of bigger groups with a higher value of the mean poison distribution. Bigger groups need a longer time to gather around the leader before they start evacuating.
Flexibility of the group	**The group's flexibility raises the evacuation time.**	Few bigger groups emerge when the group's flexibility is activated. Bigger groups exhibit a lower speed, leading to higher evacuation times.
	The gap between the base case and the group flexibility scenario for the 95 percentil is lower compared to the overall evacuation time.	This indicates that a few bigger groups emerge, which need a longer time to arrive at the exit.
	The overall intragroup distance increases.	Flexibility in changing the leader my lead to bigger groups, increasing the mean intragroup distance.
	The intragroup distance for smaller groups decreases.	Only groups that have a lower intragroup distance stay together; otherwise the follower can change to another leader.
	The uncertainty of maximal congestion has a higher influence compared to the base case.	A higher chance of the follower finding a closer leader due to more agents in the same area.

Table 5.5: The summary of findings of additional leader-follower behavior and their explanation in the structure of the model

5.3. Multivariate behavior testing

In order to test, how combinations of behaviors influence the KPIs, a Multivariate behavior experiment was conducted. In this chapter for each KPI the results are explained. Table 5.6 summarizes the different medians and indicates if the KPI differs significantly when compared to the base case. The plots for all KPIs and the visual analysis may be found in Appendix B.3.

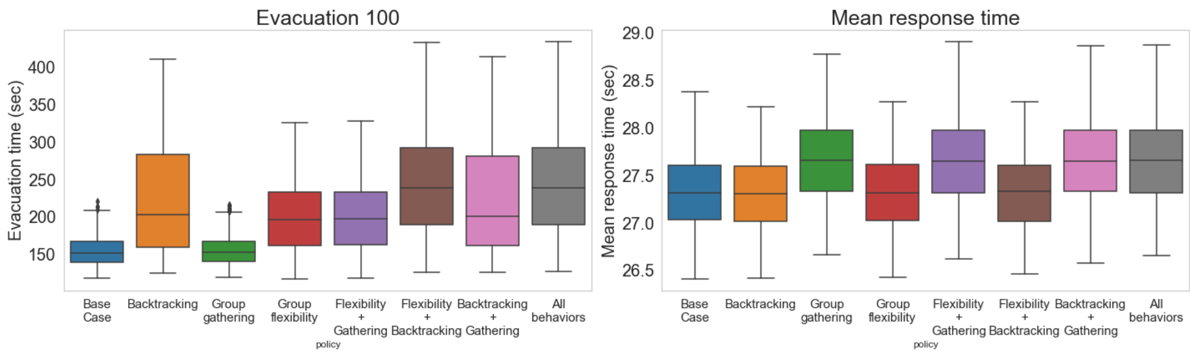


Figure 5.10: Results the evacuation and response time for different combinations of leader-follower behavior

KPIs	Base case (median)	Flexibility + gathering (median)	Flexibility + backtracking (median)	Backtracking + gathering (median)	All behaviors (median)
Evactime100	150.77	197.40*	238.18*	200.78*	237.89*
Evactime95	129.57	136.80*	159.88*	149.29*	159.32*
Mean ResponseTime	27.32	27.65*	27.33	27.64*	27.65*
SD ResponseTime	10.61	10.72*	10.61	10.72*	10.71*
Min ResponseTime	5.40	5.40	5.40	5.40	5.40
Max ResponseTime	67.05	67.41*	67.15	67.39	67.49*
Mean Intragroup distance total	1.67	1.93*	2.28*	2.42*	2.26*
Mean Intragroup distance G2	1.85	1.65*	1.61*	1.71*	1.58*
Mean Intragroup distance G3	2.91	2.58*	2.55*	2.75*	2.52*
Mean Intragroup distance G4	3.63	3.06*	3.44*	3.92*	3.37*
Mean Intragroup distance G5	2.35	2.80*	2.66*	2.22*	2.63*

Table 5.6: The medians for different combinations for each KPI. Significant values with a significance level of 0.05 are marked with *

5.3.1. Evacuation time

Figure 5.10 indicates that certain combinations of behaviors increase the evacuation time compared to the implementation of one leader-follower strategy and the base case. In particular, combinations of group flexibility and backtracking result in the largest increase. The explanation is the higher number of agents per group due to the possibility of changing to another leader. This leads to longer waiting times for the leader as group members may get lost in congestion. The 95 percentile of the evacuation time confirms this explanation. The difference between the combinations is lower compared to the total evacuation time. This indicates that only the evacuation time is determined by few big groups that emerge due to the possibility of changing to another leader.

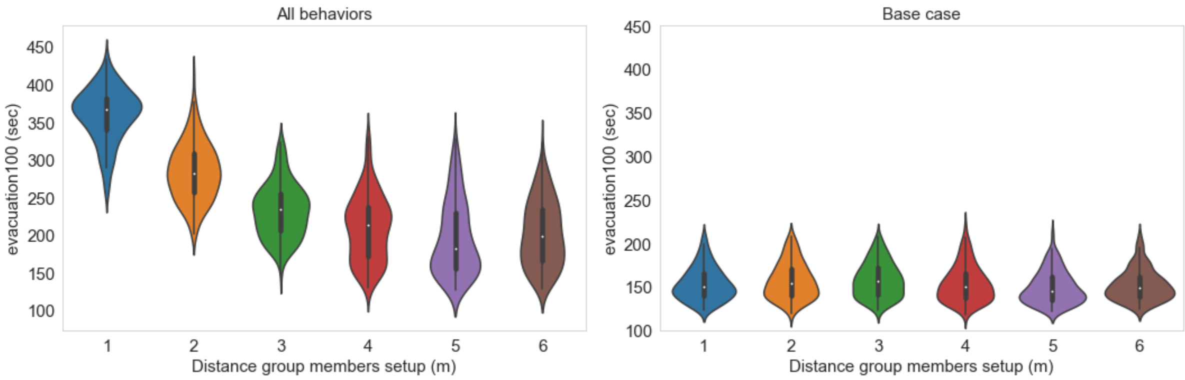


Figure 5.11: The influence of uncertainty distance group member setup on the evacuation time for the all behavior scenario (left) and for the base case (right)

The box plots in Figure 5.10 indicate that the difference between the maximum and minimum evacuation time for all behaviors varies extremely compared to the base case. The reason behind this observation it is the influence of uncertainties. Therefore, feature scoring was also utilized to discover the most significant uncertainties in combinations (Figure B.16 in Appendix B). The strongest influence for the "All behavior" case is the parameter **distance group members setup**, which functions as the threshold in the backtracking behavior for leaders to wait for followers to catch up. Figure 5.11 indicates that a lower value leads to higher evacuation time. The reason is that leaders need to wait more often for followers to catch up. In particular, this reinforces the result that backtracking has the strongest influence on the evacuation time and, thus, is the most dominant behavior. However, compared to the scenario where only backtracking is activated (Figure 5.7), this parameter is not the only substantial uncertainty. In addition, the **maximum congestion** impacts the evacuation time. However, this parameter has a lower influence compared to the distance of group members at the beginning of the evacuation. Overall, it indicates that the influence of uncertainties on the additional behaviors is more extensive compared to the base case, leading to a higher sensitivity.

5.3.2. Response time

Only combinations featuring group gathering have an increased mean, maximum and SD of the response time. This is logical, as the group gathering strategy exclusively adds to the response time. However, the difference is only minimal. None of the behaviors affects the minimum response time. The reason behind this is the implemented response time of individuals, as they are not affected by the behavior implementation. Consequently, they determine the minimum of the response time.

5.3.3. Intragroup distance

Finally, the intragroup distance is largest if backtracking is included in the combination of behaviors. The addition of flexibility of the group as well as group gathering slightly blunts the effect of backtracking on this KPI, as lower mean distances were observed compared to backtracking on its own. The reason behind this phenomenon is that followers may change to another leader in case the distance between the leader and follower increases if the group's flexibility is additionally activated. If group gathering is included in the combination, the closer distance at the beginning of the moving phase reduces this effect. All behaviors decrease the intragroup distance for smaller groups.

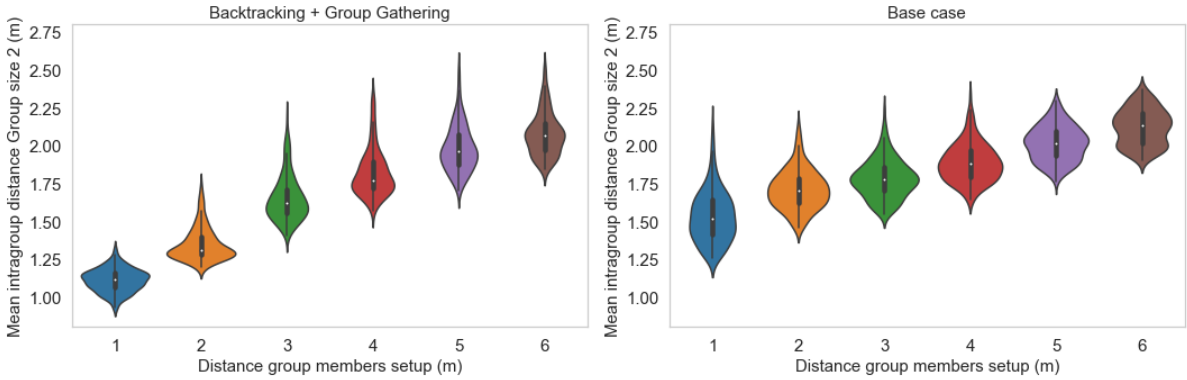


Figure 5.12: The influence of uncertainty distance group member setup on the intragroup distance for the scenario with backtracking and group gathering (left) and for the base case (right)

However, some scenarios may lead to higher intragroup distances. Scenarios with backtracking revealed a larger variance for the distance between groups with two members compared to the base case. This variance results from the changing threshold for backtracking, which determines the parameter "Distance group member setup". This can be seen in Figure 5.12. In particular, a lower value leads to a decreased intragroup distance for groups with a size of two people. While a higher threshold for backtracking leads to higher intragroup distances. This increases its variance compared to the base case without backtracking. This change in variance may only be observed for groups with two people. For bigger groups with four or more members, the intragroup distance increases, especially for backtracking. The reason is the model implementation that group members avoid the patch of other members.

5.4. Multivariate behavior testing in an empty room

In order to test the influence of the environment on the results and provide a more robust solution, the multivariate behavior testing was repeated in an empty room. Table 5.7 indicates that results of the statistical comparison are different only for a few KPIs compared to the utilized environment at the beginning. This affects mainly KPIs with p-values close to 0.05 in the first place. In particular, for the maximum response time, these observations may result due to the stochastic elements in the agent-based model. However, the same pattern for all KPIs arose in both experiments which increases the confidence in the results presented above. If a KPI shows a higher value in the initial environment, the same can be observed in the empty room.

KPIs	Base case (median)	Backtracking (median)	Group gathering (median)	Group flexibility (median)	Flexibility + Gathering (median)	Flexibility + Backtracking (median)	Backtracking + Gathering (median)	All behaviors (median)
Evactime100	139.86	183,79*	140.82	144.03*	145.51*	182.32*	180.89*	180.25*
Evactime95	123.59	141.17*	124.26	125.81*	126.64*	143.12*	140.83*	142.72*
Mean ResponseTime	27.30	27,29	27,64*	27.29	27.64*	27.29	27.65*	27.65*
SD ResponseTime	10.61	10.60	10.71*	10.61	10.72*	10.61	10.71*	10.72*
Min ResponseTime	5.40	5.40	5.40	5.40	5.40	5.40	5.40	5.40
Max ResponseTime	67.38	67.07	67.42	67.14	67.6*	67.12	67.46	67.50
Mean Intragroup distance total	1.54	2.21*	1.50*	1.63*	1.60	2.13*	2.11*	2.06*
Mean Intragroup distance G2	1.78	1.68*	1.73*	1.70*	1.64*	1.60*	1.64*	1.55*
Mean Intragroup distance G3	2.79	2.71	2.73*	2.59*	2.54*	2.57*	2.65*	2.52*
Mean Intragroup distance G4	3.49	3.95*	3.35*	3.11*	3.03*	3.54	3.79*	3.40*
Mean Intragroup distance G5	2.36	2.31	2.31*	2.89*	2.85*	2.68*	2.27*	2.63*

Table 5.7: The medians for different combinations for each KPI for a squared room. Significant values with a significance level of 0.05 are marked with * and differences of statistical test results compared to the experiment in the base environment are colored in red

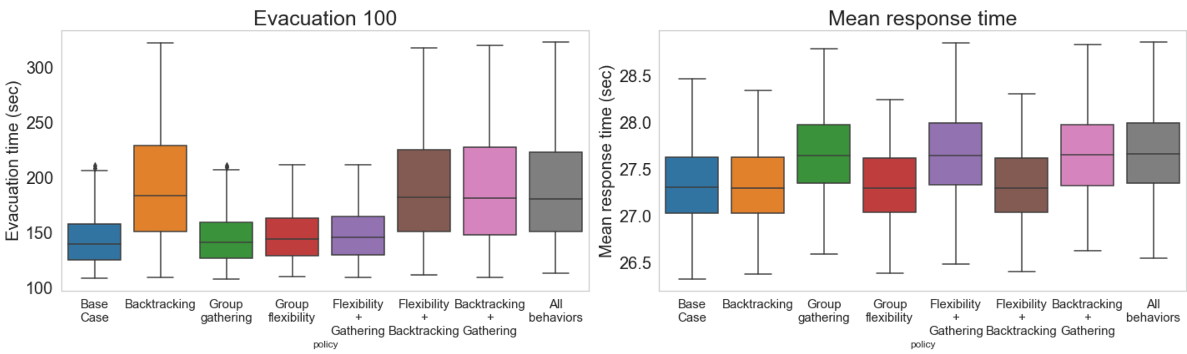


Figure 5.13: Results the evacuation and response time for different combinations of leader-follower behavior in an empty room

An interesting observation is the reduced influence of the group's flexibility. The difference between the scenarios with and without flexibility was smaller in the empty room than in the base environment (Figure 5.13). The most possible reason for this observation is the absence of bottlenecks and barriers in the empty room compared to the base environment. In the base environment, a higher density of people may be encountered in areas where agents need to leave a room to reach the main exit. This phenomenon stimulates the evacuees to change their groups leading to larger groups in the base environment. These larger groups also influence the mean intragroup distance for this behavior. Therefore a lower value may be encountered in an empty room. A comparison of the influence of the parameter

”maximum congestion” on the impact of group flexibility clearly supports this observation. Maximum congestion had impacted the outcome of the group flexibility in the original layout, Figure 5.14 displays a lower influence of this parameter in comparison to Figure 5.9 , which compares the behavior in the original layout with the base case. The plots and the visual analysis for all KPIs can be found in Figure B.17 in Appendix B.3.

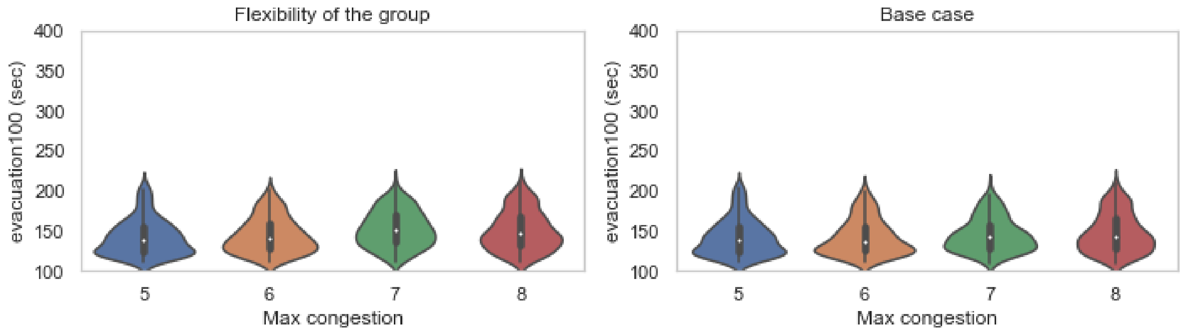


Figure 5.14: The influence of uncertainty max congestion on the evacuation time for flexibility of the group(left) and for the base case (right) in an empty room

6 Discussion and conclusion

Understanding leader-follower behavior and its influence on the evacuation process is crucial as leadership may be seen as one of the essential underlying patterns in group decision-making (Haghani et al., 2019). A better understanding of this behavior aids evacuation models in preparing buildings for emergencies and reducing fatalities. Different behaviors are currently implemented in models, but no comparison about their influence is available. The project presented here, closes this research gap and answers the question of how different leader-follower behaviors in groups, especially backtracking, group gathering and flexibility of the group, influence the evacuation and response time as well as intragroup distance inside buildings. An agent-based model in combination with exploratory modeling was developed in order to answer the research question. In this chapter, the results are discussed, which are divided into three aspects: the leader-follower framework, the influence of uncertainties on leader-follower groups and the comparison of additional leader-follower behaviors. Then the societal relevance, strengths, limitations, and implications are further elaborated.

6.1. A leader-follower framework

The overall goal of the leader-follower framework, developed in Chapter 2, was to help modelers and researchers to model leader-follower behavior. In this chapter, the framework is discussed and evaluated regarding three aspects: conceptual soundness, completeness, and usefulness. All limitations of the framework may be encountered in Chapter 6.5.

6.1.1. The conceptual soundness

The framework was based on an extensive literature review of models and empirical studies in peer-reviewed journals investigating and implementing leader-follower behavior. Hence, only behavior and structures observed in these articles were incorporated into the framework, increasing the conceptual soundness. Currently, many evacuation models are not based on valid assumptions about the behavior of individuals (Aguirre et al., 2011). Yet, evacuation models may only provide valuable insights if the implemented behaviors are grounded on real world data, such as field observations or empirical findings (Aguirre, 2005). Thus, by using colors, the framework clearly highlights which findings were encountered in models, and which structures and behavior were observed from empirical studies. Nonetheless, the overall framework still needs to be validated with experts' help to increase the framework's conceptual soundness.

6.1.2. The completeness

As the framework is limited to the behaviors identified in the literature review, the completeness may be questioned, as other leader-follower behaviors and influential structures may occur in certain evacuation circumstances that have not yet been investigated. However, achieving a complete framework was also not the goal in the first place. The framework may be seen as the starting point for providing an overview of leader-follower behavior and may aid researchers in modeling this behavior. With increasing knowledge, the framework can be expanded and adapted to current research.

6.1.3. The usefulness

The developed agent-based model in this research was based on the framework. Hence, it indicates its usefulness and provides one possible example of its utilization. Of course, leader-follower behavior may only be one behavior in an evacuation model, and additional behaviors and structures need to be added in order to achieve a valid evacuation model. Nonetheless, the usefulness lies in helping researchers and modelers in modeling this behavior.

6.2. The influence of uncertainties on the core leader-follower behavior

Overall, the obtained results illustrate that uncertainties strongly influence the evacuation and response time of the core leader-follower behavior. The most significant uncertainties for **the evacuation time** are familiarity, population size and the distribution of the recognition time. These results are in line with results of other researchers. For instance, D. Li and Han (2015) observed a faster evacuation with a higher familiarity. Congestion at the exit is lower if there is a higher degree of familiarity leading to shorter evacuation times. In addition, the influence of an increasing population on the evacuation time was witnessed by J. Wang et al. (2013). Finally, the reason for the influence of the distribution of the recognition time is that the recognition time is a part of the evacuation time. A higher mean or a different distribution directly impacts the evacuation time (Siikonen & Hakonen, 2003). It also indicates that bigger groups or more groups in the crowd may not be as influential as the three parameters mentioned above.

In contrast, the percentage of groups available affects the **response time** which indicates that groups exhibit a different behavior compared to individuals. A group might not start moving before the last person has not finished his or her task or collected belongings. This delays the response time of all other group members, and the average response time increases. This occurrence of social influence on the pre-movement behavior was also observed by Bode et al. (2015) and ,thus, is in line with current research.

Finally, the **mean intragroup distance** between the groups is mostly influenced by the intragroup distance at the beginning of the evacuation. This can be explained by the larger separation at the start. In addition, the intragroup distance at the beginning of the evacuation determines the threshold for followers to increase the speed to catch up. Furthermore, the intragroup distance grows with a higher number of group members per group. This observation was also documented in Moussaïd et al. (2010). A lower value for the intragroup distance for groups with five people is observed as not always such groups are present in all scenarios, reducing the mean intragroup distance. The availability of these groups depends on the mean of the poisson distribution, which determines the size of the groups.

6.3. The influence of three unique leader-follower behavior

The results show that the selected leader-follower behaviors **influence the evacuation and response time**. In particular, the group's flexibility and backtracking increase the evacuation time, with **backtracking** having the most significant impact. Unfortunately, no current literature is available for group flexibility, making it difficult to compare the results. Nevertheless, group flexibility increases the group size of a few groups, leading to a longer evacuation time. The pattern of an increased evacuation time due to bigger groups was also observed in Köster et al. (2011). The effect of backtracking is also consistent with other research on social groups (L. Z. Yang et al., 2005). In addition, an increasing threshold for the leader to wait for the follower to catch up was also observed by Pan et al. (2021) which increases the trust in the built model. No literature may be encountered on the influence of group gathering on the response time. However, the longer response time of group gathering, which may be perceived in social groups, is in line with the common observation that social groups need longer to start moving at the beginning of the evacuation (Bode et al., 2015).

Additionally, monitoring of the group distance shows that group gathering and flexibility reduce the distance between group members in smaller groups. However, the overall mean of the intragroup distance was not or minimally affected by group gathering. In contrast, flexibility even increases the total mean intragroup distance. The reason behind this occurrence is that larger groups emerge if the follower can change to another leader. For backtracking, only groups with fewer members may decrease the intragroup distance. Conversely backtracking increases the intragroup distance in larger groups as evacuees try to avoid the patch of other group members and step aside, leading to a higher distance between the group members.

Moreover, the analysis of uncertainties for these three behaviors shows that specific parameters in particular influence the outcome of the additional behaviors. For backtracking, the **threshold when leaders wait for followers to catch up** is the most influential factor on the evacuation time. An increase in this threshold leads to longer waiting times for leaders, which, of course, prolongs the evacuation time. As already mentioned above, this is in line with current research (Pan et al., 2021). For group gathering, the **mean of the poisson distribution from which group sizes are drawn** importantly influences the response time, as bigger groups need a longer time to gather before they start evacuating. Finally, the **maximum congestion** influences the evacuation time for the group's flexibility. The reason behind this pattern is the higher density of leaders closer to the follower. Thus, bigger groups with lower speeds emerge. Overall, this indicates that utilization of a base ensemble for evacuation research is essential as it provides new insights about behaviors without neglecting certain aspects, which may lead to wrong conclusions.

Multivariate behavior testing of leader-follower behavior showed that **combinations with backtracking and flexibility of the group** indicate the highest increase of evacuation time compared to the base case. The reason behind it are bigger groups that need longer time to gather if the leader waits for the follower to catch up. Moreover, combinations with group gathering only resulted in higher mean and maximum response time. No combination affects the minimum response time as it is determined by the individual pre-movement behavior in the model. These results were confirmed with an experiment in an empty room, which was utilized to focus on the pure behavior itself without obstacles and minimise the environment's influence. The statistical significance changed only for a few KPIs compared to the initially chosen environment, particularly for KPIs with a p-value close to 0.05 in the first experiment. This may be explained due to the stochastic elements included in the model. In addition, it indicated a lower influence of the flexibility of the group on the evacuation time. The reason behind are bottlenecks in the original environment, which are missing in an empty room. In these bottlenecks a higher density of people may be observed, which increases the possibility for followers to change to another leader.

6.4. Societal relevance

Overall, every research aims to contribute to the nation's social capital by improving the quality of life, changes in community attributes, informed public debate and improved policy-making as well as improvements in health safety and security (Donovan, 2008). First, this research could contribute to more suitable policies for locations with a high distribution of leader-follower groups and provides parameters that may be addressed by building policies. These parameters relate to the familiarity, the recognition time, and the population of the building. At the same time, other parameters may not be as influential. With this knowledge, the research results aid in improving people's safety in buildings, leading to a high social impact. Secondly, it contributes to the public debate about modeling this behavior. Currently, leader-follower behavior in models may only consist of the core leader-follower behavior. Nonetheless, this research indicates that additional leaders may influence the evacuation performance and thus need to be included in models.

6.5. Strengths, limitations and future research

To the author's knowledge, this is the first study to **investigate the influence of different leader-follower behaviors** on evacuation performance. Various researchers implemented the leader-follower behavior differently (Lu et al., 2017; Sirakoulis, 2014). However, their impact on the overall evacuation performance has not yet been explored. Therefore, three unique leader-follower behaviors from different group structures and behavior phases were investigated regarding their impact on the overall evacuation performance. The results found for each behavior were confirmed in an empty room. Thus, it is unlikely that results were biased by the chosen environment.

In addition, no study has yet explored the **impact of uncertainty** on the core leader-follower behavior with exploratory modeling. Therefore, an agent-based model was created to comply with structural and parameter uncertainties encountered in evacuation research. Scenario discovery and feature scoring helped to find policy-relevant areas in the uncertainty space. Moreover, a robust result regarding the uncertainty was achieved with the help of a base ensemble, leading to more trust in the final results

(Auping, 2018). The uncertainty analysis for each leader-follower behavior indicates that particular uncertainties may influence individual behavior. If these uncertainties are not varied, contradicting results may be encountered, leading to false conclusions. Therefore, a base ensemble may provide a more appropriate solution for evacuation research. Furthermore, with the help of macro and micro validation and comparison of the results with empirical data, confidence could be established that the right model was built.

Finally, the **first framework** regarding leader-follower behavior was based on the results of an extensive literature review (see Chapter 2). This framework may aid researchers in the future when modeling leader-follower behavior in evacuation models as it demonstrates the range of possible activities by leaders and followers. Depending on the situation of interest, the modeler may choose different behaviors. Additionally, it creates awareness about how structural decisions in the conceptualization phase may lead to possible inclusion or exclusion of behaviors

The strengths of the research highlighted already the importance of it. However, it comes with various **limitations** that need to be considered.

First, the **leader-follower framework** is limited to behaviors and structures found in the literature review. More behavior may be observed if additional search engines are utilized. In addition, the framework is restricted to leader-follower behaviors. Other conceptual decisions are still necessary in order to develop a complete evacuation model. Therefore, it may only be utilized to model leader-follower behavior, which is only one group decision-making process out of many. Finally, the leader-follower framework needs to be validated by experts in the field to secure the correctness of behaviors included in the framework.

Second, it is essential to remember that **a model never represents the real world**, and that certain aspects are simplified. In addition, the observations of certain leader-follower behaviors are partly a result of the implementation in the model. If their behavior is implemented differently, other results may be obtained. Overall, in evacuation research, it is naturally challenging to arrive at firm conclusions about the accuracy of the simulation results due to the assumptions in the model (El-Tawil et al., 2017). Yet, with the help of comparison with a real-life experiment, a high trust in the model was achieved. Obviously, a complete validation in evacuation research, given the uncertainties and assumptions, is not possible (El-Tawil et al., 2017). Nevertheless, it is accepted as modeling is the only way to ethically study leader-follower behavior in these critical situations and conduct quantitative research in this complex environment (El-Tawil et al., 2017). In addition, it is essential to describe the implementation in detail, as it was done in this thesis (Chappin, 2018).

Furthermore, the research is limited to **three different behaviors**, while additional leader-follower behaviors may be encountered in empirical studies and models (see Chapter 2), such as group splitting with new emergent leaders or including different authority levels for leaders. Moreover, additional group decision-making structures may be encountered in an evacuation, such as conformity or consensus (Haghani et al., 2019). The developed model only implemented one group structure. Additional group structures may also affects the evacuation performance and need to be included in order to test the evacuation time for a building. Additionally, other behaviors, such as herding behavior (Lovreglio, Fonzone, et al., 2014) or the influence of smoke inside the building (Gwynne et al., 2001) were not considered. Nevertheless, the inclusion of these structures may mask the effects of the most prominent leader-follower behaviors. Future research is needed to further clarify such interaction effects.

It is essential to keep in mind that the results are influenced by **behavioral, intrinsic, input, and measurement uncertainty** (Ronchi et al., 2014). This research tries to cope with it by sampling over the uncertainty space in order to receive robust results. Nonetheless, the structure and conceptual model's uncertainties remain predominant, and the included uncertainties are limited. For instance, different social force heuristics may be observed in empirical studies, leading to a structural uncertainty, which is not considered in the model.

The limitations already have demonstrated that further research is necessary in order to cope with limitations in this research. Therefore, various **recommendations** are given. First, it needs to be investigated how **other leader-follower behaviors** (as seen in Chapter 2) influences the evacuation performance and compare with the behavior utilized in this research. For instance, group splitting with new emergent leaders were observed by Jones and Hewitt (1986). The model may be utilized and extended with this behavior to compare it with the results observed in this study. Moreover, other behaviors or policies for locations with a high distribution of leader-follower groups can be included and tested in the model.

Moreover, the **influence of structural decisions** as outlined in Chapter 2, such as crowd and group compilation, must be examined. This research already included the determination of the leader as a structural uncertainty with two different options and showed that their influence on the evacuation time is only marginal. However, a diverse crowd or group compilation may produce a different result. Thus, it needs to be investigated how different structural uncertainties affect and interact with the core leader-follower behavior.

The second research recommendation is to include **other group decision-making structures** in the model to investigate how the analyzed behaviors may influence the performance with additional groups incorporated. For example, suppose groups with conform, or consensus decision-making may need a longer time than leader-follower groups. In that case, the influence of backtracking, group gathering, and group flexibility may only have a marginal effect on this KPI.

Finally, **empirical studies** may aid in confirming the results. Experiments need to be developed to test the different leader-follower behaviors and monitor their influence on the evacuation performance. In addition, videos of real-life evacuations or investigations may be utilized to analyze the frequency of occurrence for each behavior implemented in the model and study the evacuation performance. Currently, we only comprehend that these behaviors exist. However, not all behaviors may be encountered in all groups during an evacuation. Some groups may only gather before the evacuation, and others may employ all three behaviors. An understanding of how often these behaviors occur in a real-life evacuation may aid in creating more realistic models to prepare buildings and evacuation strategies.

6.6. Implications

This thesis aims at understanding leader-follower behavior. The following chapter discusses the theoretical and practical implications of this research.

Three theoretical implications may be derived from the results of this research. First, the literature review indicated that different leader-follower behaviors are currently implemented in models and that no consensus about an essential set of these behaviors exists. In addition, it revealed that certain structures influence the chosen behavior. Thus, a leader-follower framework was developed. **It provides a contribution for modeling leader-follower behavior by indicating necessary structures of the model that influence the behavior and demonstrate behaviors that can be added in different behavioral phases**. Also, it displayed that researchers must be aware that different structures and decisions in the conceptual phase exclude or include specific leader-follower behaviors. For example, the determination of the leader, the group and crowd compilation and the group size variability are all structures that need to be decided upon when modeling leader-follower behavior. Depending on the decision, particular leader-follower behaviors can be included or may not be implemented in the model which naturally will impact the obtained results and conclusions drawn from these results.

Secondly, the results in this study indicated that all additional leader-follower behaviors impact the evacuation performance. Thus, modelers and researchers **must include backtracking and group gathering for social groups and flexibility of the group for emergent groups in evacuation models due to their impact on the evacuation performance found in this study**. Currently, many models only implement the core leader-follower behavior and neglect the additional behaviors of leader and follower. However, only implementing the core leader-follower behavior in models may lead to wrong conclusions. Policymakers and fire safety engineers may then utilize the models with the included behaviors to prepare buildings for these critical situations and save people's lives.

Finally, in this study, the utilization of a base ensemble instead of a base case helped to find the most critical uncertainties for each behavior and resulted in a more robust result. For instance, for some scenarios, a difference between backtracking and the core leader-follower behavior may not be significant, leading to wrong conclusions. Especially a higher threshold for the distance, when backtracking occurs, undermines the result. However, with sampling over the uncertainty space, the trust in the results can be increased. Therefore, the last theoretical implication is that **a base ensemble instead of a base case may increase the trust in the results** and is needed in evacuation research where uncertainty is predominant. It may aid in finding underlying patterns and structures that influence the evacuation performance and thus, provide a better understanding of behaviors in an evacuation.

In addition, practical implications may be emanated from the results. The uncertainty analysis, including scenario discovery, showed that the evacuation time of leader-follower groups is mainly influenced by the population, familiarity, and recognition time. Other parameters, such as smaller groups or fewer groups, are not as influential and thus do not need to be tackled with policy implementations. This leads to practical implementations for buildings, with a high distribution of leader-follower groups such as offices or museums, where families are present, to **restrict the allowed persons inside and increase the familiarity with the help of safety training for staff members and visitors**. Such familiarity can easily be increased in the workplace e.g. by regular guided tours, while in public environments, signs or other measures are needed to compensate for a lack of familiarity. Depending on the building and the chosen recommendation of the ASET, the restricted population and familiarity may increase or decrease. The exact values can then be identified with the help of scenario discovery.

6.7. Conclusion

The thesis answered the research question of how three unique leader-follower behavior influences the evacuation and response time as well as intragroup distance inside buildings. It is the first study investigating different leader-follower behaviors, impact on evacuation performance. Therefore, an agent-based model was developed, and an exploratory modeling approach was utilized. The model demonstrated that backtracking and the group's flexibility increase the overall evacuation time. In addition, group gathering influences the response time. For the intragroup distance, different results for group sizes may be observed. Backtracking and flexibility of the group increase the overall intragroup distance, while group gathering does not affect the mean total intragroup distance. However, for smaller groups, all behaviors lead to a lower intragroup distance. The same is observed with combinations of these behaviors, while the most significant influence is observed with a combination of backtracking and flexibility of the group. The presented research helps modelers implement leader-follower behavior in evacuation models with the help of a framework, provide awareness about which uncertainty may influence this behavior, and identify the influence of additional leader-follower behavior on the overall evacuation performance. Overall, this study provides a better understanding of leader-follower behaviors and the influence of uncertainties. The overall purpose was to discover new insights about leader-follower behavior. These new insights may then be utilized in evacuation research for modeling this behavior. Furthermore, they can provide a valuable basis for designing policies in buildings with a high distribution of leader-follower groups as it was demonstrated that the population size and familiarity are the most influential parameters. Hence, this research may be seen as a crucial basis for researchers and modelers to implement this behavior in models and provide a better understanding for policymakers.

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A

The agent based model

A.1. Verification

This chapter provides a more detailed description of the tests conducted to verify the model and thus complements Chapter 4.3. In particular, for the pre-evacuation time, the exit usage, the congestion, and the maximum flow rate, the experiments conducted in the model with Netlogos behavior space are explained in more detail. For all experiments, only a base case received from values found in literature was employed as mostly one specific outcome is of interest, which is independent of the chosen parameters. However, in order to provide a complete description of the tests, the parameters for each test are specified in this chapter.

A.1.1. Pre-evacuation time

Table A.1 summarizes the parameters employed in the model to compare the log-normal distribution implemented in the model with a random log-normal distribution with the same parameters in python. The experiment was repeated 50 times. The log-normal distribution employed for the recognition time of a department store was utilized with a mean of 25.2, a Standard deviation of 10.5, a maximum value of 64, and a minimum value of 4. The chosen parameters in the model represent a base case for values encountered in the literature. However, as only the implementation of the log-normal distribution is of interest, the only essential parameter is the recognition time distribution. Other parameters do not have any influence on the outcome. During this experiment, the recognition time for each agent was monitored and visualized with the help of a density plot. This plot was then compared to the same plot from the distribution in python (Figure 4.13).

Parameter	Value
determination_of_leader	Random
Distribution_recognition_time	Department Store
percentage_groups	70
min_age	10
max_age	85
familiarity_percentage	29
max_congestion	6
population	500
Mean_Poisson_distribution	1.11
distance_group_members_setup	2
Group_gathering	False
Group_flexibility	False
Backtracking	False

Table A.1: Parameters for the experiment in BehaviorSpace to verify the pre-evacuation time.

A.1.2. Group behavior

In order to verify the group behavior, the model was modified. The test, proposed by Ronchi et al. (2016) was conducted in a squared room size of 15 m and 20m with a 1 m exit. Four of the five group members located near the wall opposite the exit were assigned the same speed with 1.25 m/s. The remaining group member received a velocity of 0.5 m/s. In contrast, the group in the middle of the room obtained a constant speed of 0.2 m/s. The test was repeated 50 times. Other parameters of the experiment are summarized in Table A.2. The layout is shown in Figure 4.15.

Parameter	Value
determination_of_leader	Random
Distribution_recognition_time	No premovement behavior
percentage_groups	One group with 5 people
min_age	20
max_age	85
familiarity_percentage	100
max_congestion	6
population	15
distance_group_members_setup	3
Group_gathering	False
Group_flexibility	False
Backtracking	False

Table A.2: Parameters for the experiment in BehaviorSpace to verify the group behavior.

A.1.3. Exit choice

In order to test that the agent's exit choice is consistent with its familiarity, an exit choice allocation test in the building with two exits was carried out. The layout is shown in Figure A.1. While agents with red represent the familiar person, the unfamiliar persons are colored yellow. In the building, the exit on the left represents the familiar exit. On the other hand, the exit on the right is assigned to unknown persons. In order to verify this behavior, the persons for the known exit are contrasted with the familiar persons at the beginning of the evacuation. The results are presented in Chapter 4.3.3. Table A.3 summarises the base case for this experiment.

Parameter	Value
determination_of_leader	Random
Distribution_recognition_time	Department Store
percentage_groups	75
min_age	20
max_age	85
familiarity_percentage	29
max_congestion	6
population	100
Mean_Poisson_distribution	1.11
distance_group_members_setup	2
Group_gathering	False
Group_flexibility	False
Backtracking	False

Table A.3: Parameters for the experiment in BehaviorSpace to verify the exit choice.

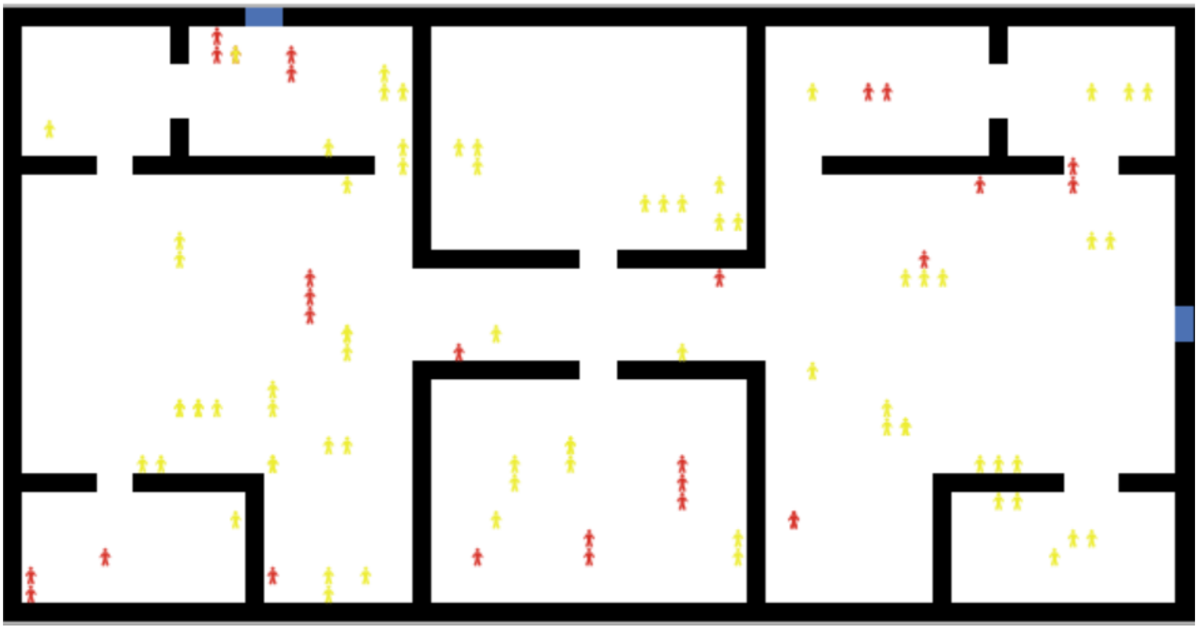

Figure A.1: The building layout to verify the exit choice.

A.1.4. Congestion

In order to test that the model complies with the maximal congestion per patch, an experiment with 50 repetitions was conducted. The parameters applied for this experiment are summarized in Table A.4. The most critical parameter is the “max congestion”, which determines the maximum number of persons per patch. This experiment verifies that the maximum number of persons per patch never exceeds the value for this uncertainty. In addition, a unit test was implemented in the model, which is performed during each run. It tests that the model always adheres to the maximum congestion. If this value exceeds, the model prints out an error message.

Parameter	Value
determination_of_leader	Random
Distribution_recognition_time	Department Store
percentage_groups	75
min_age	20
max_age	85
familiarity_percentage	29
max_congestion	6
population	500
Mean_Poisson_distribution	1.11
distance_group_members_setup	2
Group_gathering	False
Group_flexibility	False
Backtracking	False

Table A.4: Parameters for the experiment in BehaviorSpace to verify the congestion implemented in the model.

A.1.5. Maximum flow rates

The maximum flow rates experiment was conducted to test if the model adheres to the value of two persons per patch at the exit, defined in the conceptual model. The same base case as for the congestion is utilized to test this behavior (Table A.4). Also, for this core component, a unit test was implemented in the model. An error message is issued if the throughput exceeds two persons per exit patch.

A.2. Micro validation

For the micro validation, various tests were performed to increase the trust in the built model. This chapter complements Chapter 4.4.1 and explains in detail the experiments conducted in the model. Especially for the pre-movement, the group behavior, and the flow rates, experiments with Netlogos behavior space were executed. They are explained in more detail in this chapter.

A.2.1. Pre-movement

The pre-movement test was performed to compare the pre-movement time of the model with empirical data from Lovreglio et al. (2019). Thus, an experiment in the model was conducted with 100 agents and 50 repetitions. The parameters chosen for this test are summarized in Table A.5. It can be seen as a base case from values observed in the literature in the uncertainty space.

Parameter	Value
determination_of_leader	Random
Distribution_recognition_time	Department Store
percentage_groups	55
min_age	10
max_age	85
familiarity_percentage	28
max_congestion	6
population	100
Mean_Poisson_distribution	0.88
distance_group_members_setup	2
Group_gathering	False
Group_flexibility	False
Backtracking	False

Table A.5: Parameters for the experiment in BehaviorSpace to validate the pre-movement time implemented in the model.

A.2.2. Group behavior

For the group behavior, two experiments were executed to validate the behavior that groups try to stay together throughout the whole evacuation. The parameter combinations for both experiments are summarized in Table A.6. The two experiments differed in the activation of the backtracking behavior. Finally, both experiments were repeated 50 times. The outcome of interest was the intragroup distance during the whole evacuation. Thus, the intragroup distance was monitored at each tick for one group.

A.2.3. Flow rate

Finally, the last experiment was performed to validate the flow rate and compare it to the outcome of an empirical experiment. For this experiment, the parameter summarized in Table A.7 were applied. Only one exit was open in order to create a queuing behavior and reproduce the empirical study by Rinne et al. (2010). In order to assess the data, the average flow rate per square meter was monitored.

Parameter	Value
determination_of_leader	Closest to the exit
Distribution_recognition_time	Department Store
percentage_groups	70
min_age	10
max_age	50
familiarity_percentage	29
max_congestion	6
population	500
Mean_Poisson_distribution	1.11
distance_group_members_setup	2
Group_gathering	False
Group_flexibility	False
Backtracking	False/True

Table A.6: Parameters for the experiment in BehaviorSpace to validate the group behavior implemented in the model.

Parameter	Value
determination_of_leader	Random
Distribution_recognition_time	No pre-movement behavior
percentage_groups	70
min_age	10
max_age	85
familiarity_percentage	0
max_congestion	6
population	100
Mean_Poisson_distribution	1.11
distance_group_members_setup	2
Group_gathering	False
Group_flexibility	False
Backtracking	False

Table A.7: Parameters for the experiment in BehaviorSpace to validate the flow rate implemented in the model.

A.3. Sensitivity analysis

This section provides a detailed description about how the sensitivity was conducted and highlights its results.

A.3.1. Reason for conducting a sensitivity analysis

A sensitivity analysis provide the possibility to increase the validly of the model, as it provides new insights how parameter influence the variance of KPIs (X. Y. Zhang et al., 2015). If the influential parameters may surprise and may not be explained logically, a possible wrong model was built (Smith et al., 2008). In addition, it provides new insights about the emergent behavior of the model (ten Broeke et al., 2016).

A.3.2. Experimental design

Different approaches to conduct a global sensitivity analysis are currently available. For instance, weighted average of local sensitivity analysis, partial rank correlation coefficient, Multi-parametric sensitivity analysis, Fourier amplitude sensitivity analysis and Sobol sensitivity analysis (X. Y. Zhang et al., 2015). Table A.8 compares the different methods for various criteria. It clearly indicates that a sobol sensitivity analysis fulfills nearly all criteria. In particular, the criteria that no assumptions regarding model input and output is utilized and the possibility to evaluate each parameter on its own as well as interactions between parameter may be seen as an advantage (X. Y. Zhang et al., 2015). Hence, a Sobol global sensitivity analysis with the help of the EMA Workbench was conducted to receive new insights about the model.

Criteria for comparison	Commonly used global sensitivity analysis methods				
	Weighted average of local sensitivity analysis (WALS)	Partial rank correlation coefficient (PRCC)	Multi-parametric sensitivity analysis (MPSA)	Fourier amplitude sensitivity analysis (FAST)	Sobol
Discrete inputs	✓	✓	✓	✓	✓
Model independence				✓	✓
Non-linear, input-output relationship	✓	✓	✓	✓	✓
Non-monotonic input-output relationship	✓		✓	✓	✓
Robustness	✓	✓	✓	✓	✓
Reproducibility	✓	✓	✓	✓	✓
Ability to apportion the output variance				✓	✓
Higher order interaction of parameters				✓	✓
Quantitative measure for ranking	✓	✓	✓	✓	✓
Computational efficiency	✓	✓	✓		

Table A.8: Comparison of different global sensitivity analysis method, adapted from X. Y. Zhang et al. (2015)

In general, sobol sensitivity analysis consist of five steps. First, the upper and lower bound of the parameters need to be defined, which was already done in Chapter 4.2. Then parameter sets with the help of sobol sequences were created (X. Y. Zhang et al., 2015). For this model, the sensitivity analysis was conducted with 1000 scenarios from the whole parameter space, leading to 22000 runs in the developed model. Then each parameter sequence was utilized to run the model. Due to the chaotic property of the agent-based model, every run was repeated 50 times as explained in Chapter 4.5.2. The last steps are to calculate the sobol indices and analyze the sensitivity indices (X. Y. Zhang et al., 2015).

A.3.3. Results

The results for all KPIs may be seen in Figure A.2 and are explained in more detail for each KPI in the following chapter.

Evacuation time

Figure A.2 indicates that both the total evacuation time and its 95 percentile are influenced by the recognition distribution, the familiarity of the agents, and the population. Its effect increases if interactions of parameters are investigated.

Response time

The group percentage mainly influences the mean and the Standard deviation. If interactions of parameters are included, no difference in the results may be observed. In contrast, the population influences the maximum response time. If the interaction is included, other parameters may also influence the variance of this KPI. Finally, the minimum response time is sensible to the group percentage and the population. However, the group percentage has a more significant influence on the variance.

Intragroup distance

Different parameters influence the outcome of the mean intragroup distance. In particular, the first order indices show that mean poisson distribution, which increases the number of bigger groups, the distance at the beginning of the evacuation, and the population, influence the variance of this KPI. If the interactions are included, then the max congestion, the familiarity, and the group percentage also indicate some impact. For smaller groups, the main parameters are the distance at the beginning of the simulation, the familiarity, and the population. Yet, for bigger groups, the mean poisson distribution increases its influence. The reason behind this pattern is the presence of bigger groups with an increasing mean.

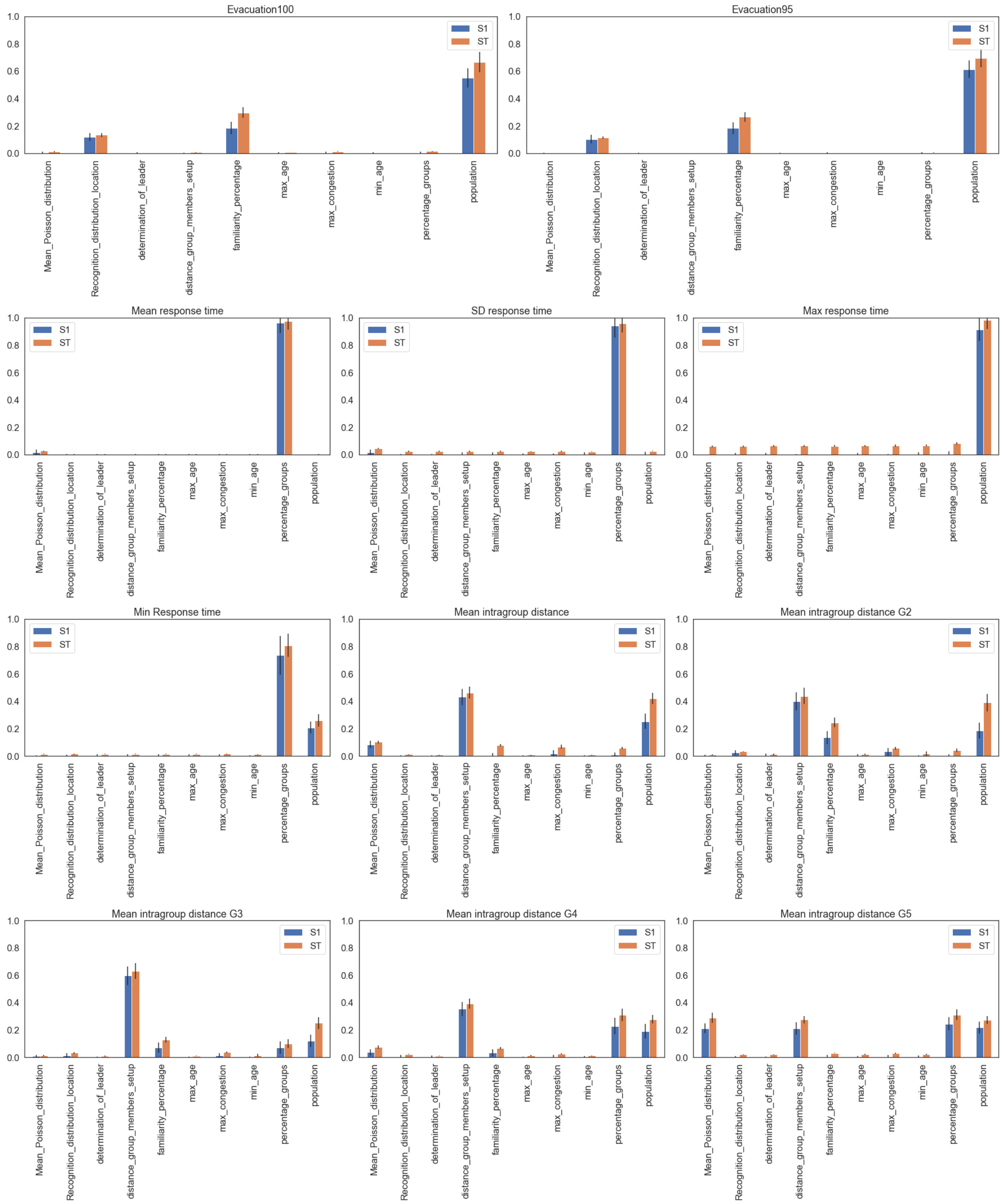

Figure A.2: The sensitivity for all KPIs. It indicates the influence of uncertainties on the variance of the KPIs. S1 relates to the influence of the parameter on its own, while ST includes interaction effects with other parameters.

A.4. Repetitions

This section provides additional graphs for the convergence and variance stability tests conducted to receive the appropriate repetitions for the experimental set-up. Chapter 4.5.2 describes the reason behind conducting these tests. Overall, nine different scenarios from a Latin hypercube sampling were chosen to test after how many repetitions the mean and variance of the evacuation time stabilized. This was achieved with the help of visual analysis of the cumulative means and variance coefficients for up to 400 repetitions. Figure A.3 indicates the means for the evacuation time, while Figure A.4 shows the variance stability. The figures indicate that the evacuation time and variance stabilize after 50 runs.

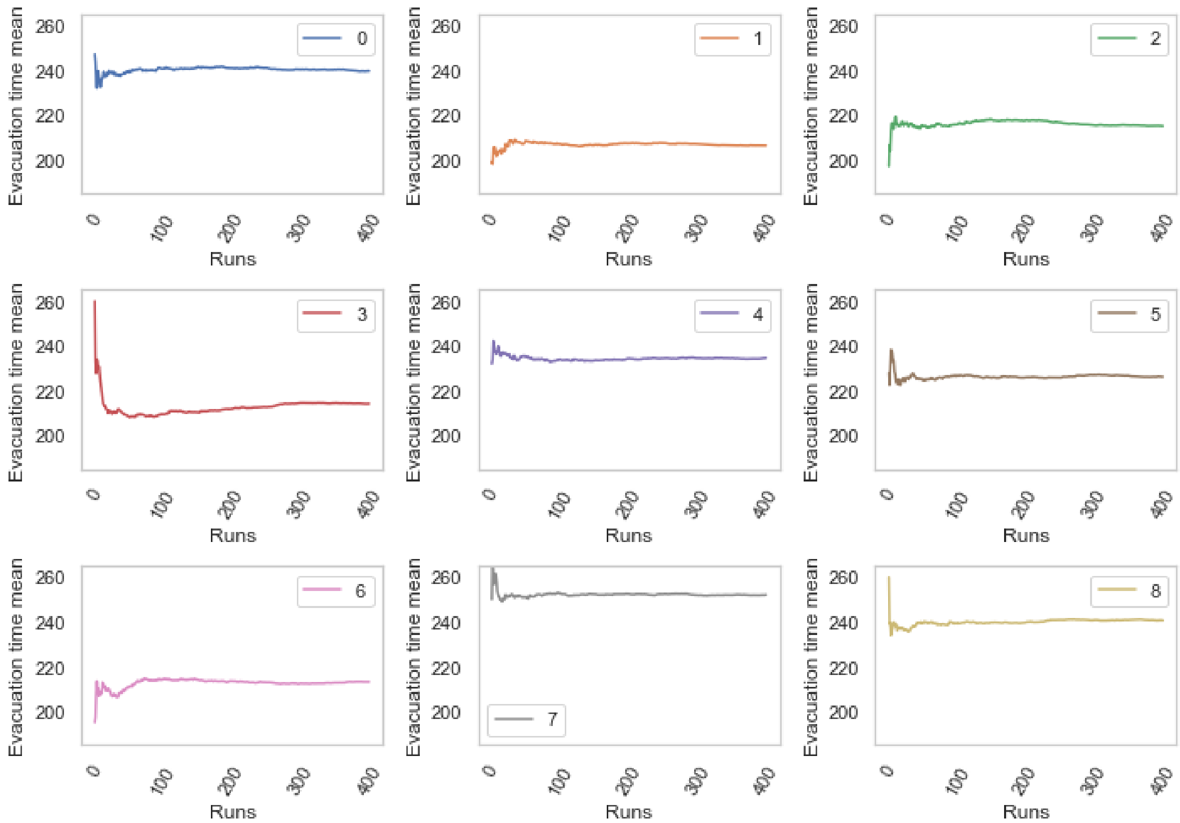

Figure A.3: The evacuation means for different runs and nine samplings

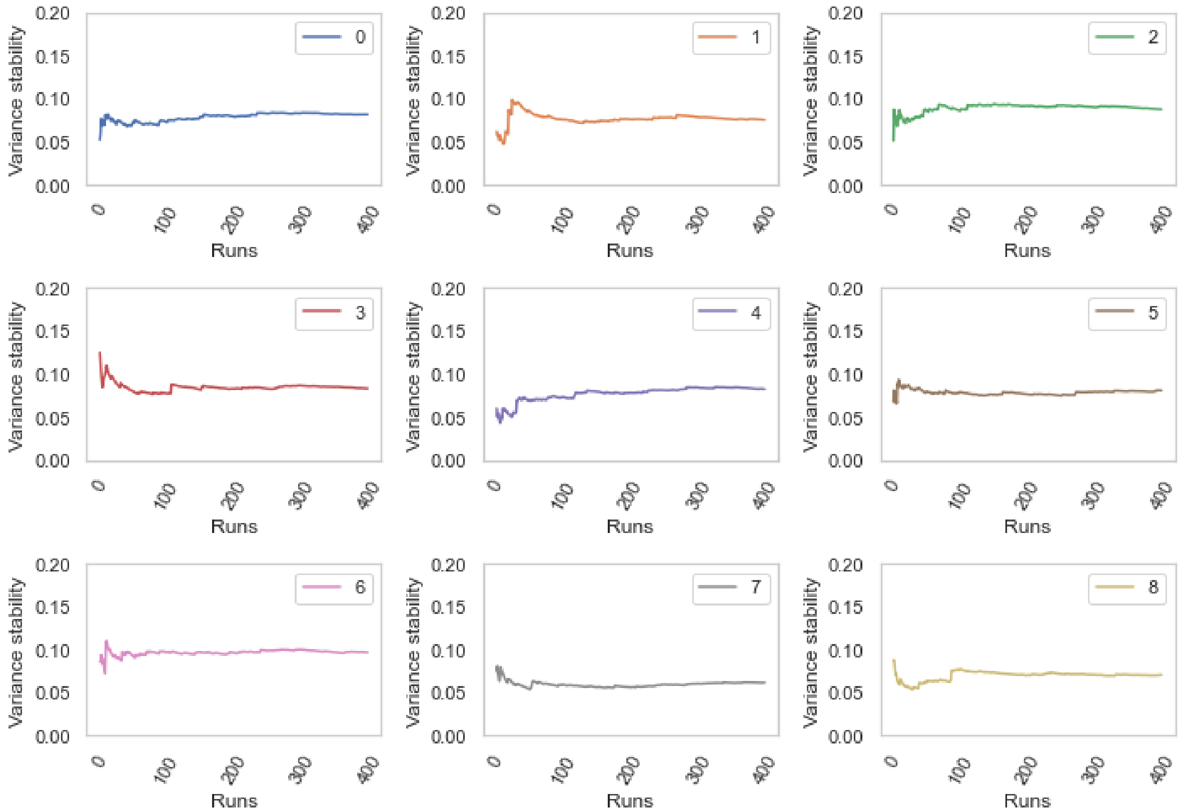

Figure A.4: The variance stability for different runs and nine samplings

B Results

In addition to the results of the agent-based model explained in Chapter 5, this chapter provides additional results about the influence of uncertainties and additional leader-follower behavior.

B.1. Uncertainty analysis

This chapter provides additional results and a visual analysis for the uncertainty. Every uncertainty was plotted against the KPIs to receive a better understanding of how the model reacts under the variation of the parameter. Visualization aids in finding patterns in the model (van Dam et al., 2013) and thus is utilized. In addition, it helped to identify essential uncertainties in combination with feature scoring.

B.1.1. Percentage groups

B.1 indicate the influence of the parameter percentage of groups in the model on the KPIs. It clearly indicates that a higher number of groups increases the mean response time and reduces the Standard deviation. This implies that groups and individuals have a different response behavior and that groups have a higher response time compared to individuals. In addition, the minimum response time is affected by this parameter. The increase of the minimum evacuation time with a high distribution of groups and, thus, fewer individuals shows that the individual response behavior determines the value of this KPI. Finally, the mean intragroup distance for bigger groups increases with a higher group percentage. The reason is that bigger groups are more likely with an increasing number of groups as the group distribution follows a poisson distribution. With only a few groups, groups with 3, 4, or 5 people may not be present. This decreases the mean intragroup distance for each group over the 50 repetitions for every scenario.

B.1.2. Population

In order to investigate how the model reacts to an increasing population inside the building, the different amounts of population are plotted against the KPIs. Chapter 5.1.2 already explained the influence of the population. Figure B.2 indicates that the evacuation time increases with a growing population. In addition, the maximum and minimum response time demonstrates the same pattern. However, the increasing population does not affect the mean and standard deviation of the response time. All groups show a slight increase in the mean intragroup distance for the group distance. The rising congestion in the building may explain this phenomenon.

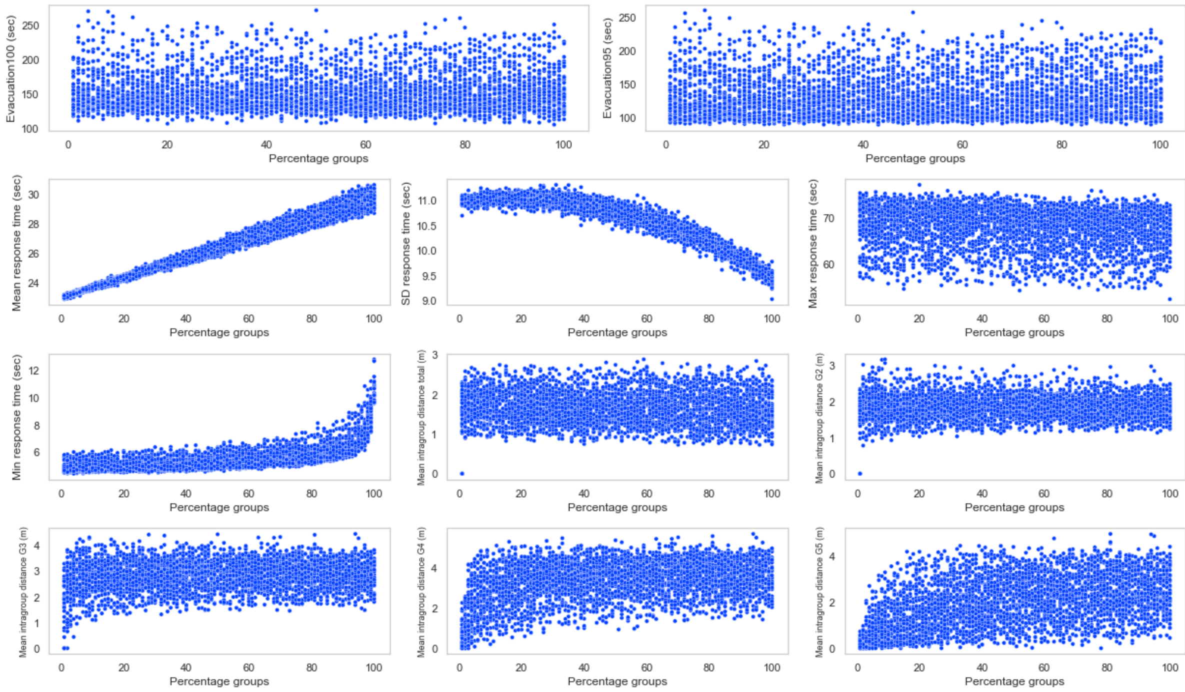

Figure B.1: The group percentage plotted for each KPI

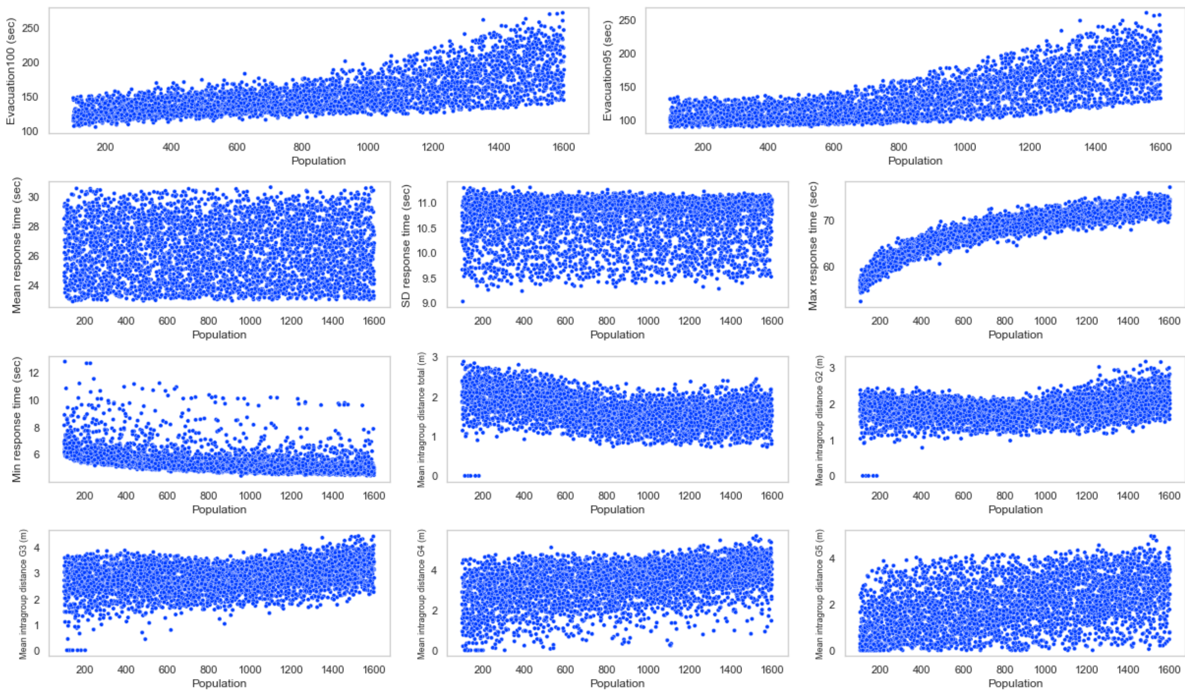

Figure B.2: The population plotted for each KPI

B.1.3. Familiarity

The familiarity has influence on the evacuation times, as illustrated in Figure B.3. In addition, the intragroup distance is affected by increasing familiarity. If a higher familiarity may be observed, the congestion decreases as all exits are utilized. Therefore, group members may not lose connections and stay together, leading to a lower mean intragroup distance. Finally, the increasing familiarity does not influence the response time of the model.

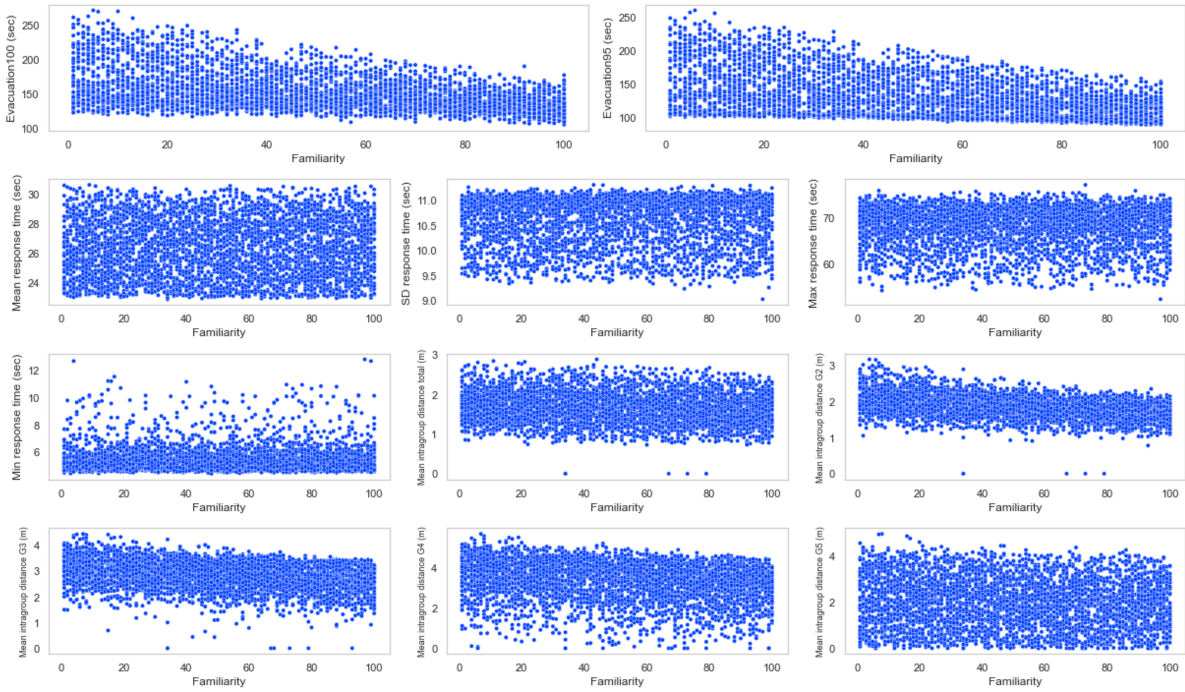

Figure B.3: The familiarity plotted for each KPI

B.1.4. Distance group member setup

An increasing group member distance may not influence the evacuation and response time. However, the distance at the beginning of the evacuation and utilized as a threshold for increasing speed by followers affects the intragroup distance in groups. If the group is situated closer together at the beginning of the evacuation, the mean distance decreases. The results are summarized in Figure B.4.

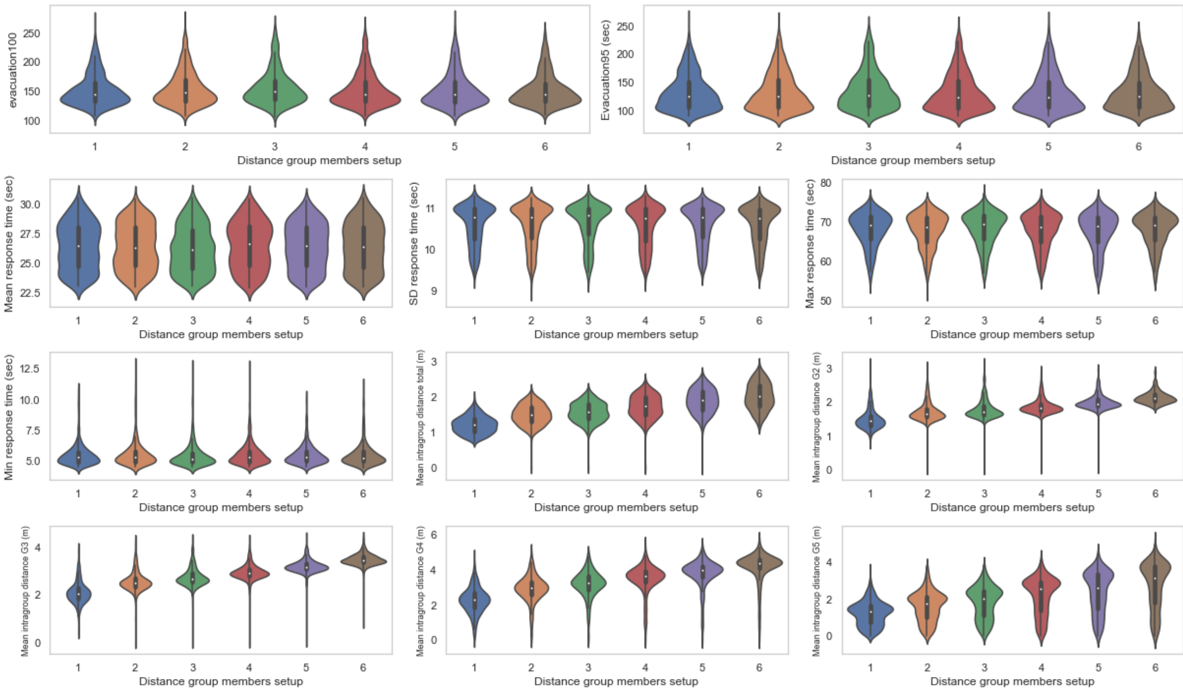

Figure B.4: The uncertainty distance group member setup plotted for each KPI

B.1.5. Mean poisson distribution

A higher mean poisson distribution leads to a higher response time and a slightly higher Standard deviation of the response time. In addition, the increasing size of groups affects the overall intragroup distance. The reason is larger groups with higher group distance. Other KPIs are not influenced by this parameter. Figure B.5 summarized the influence of the mean poisson distribution for all KPIs.

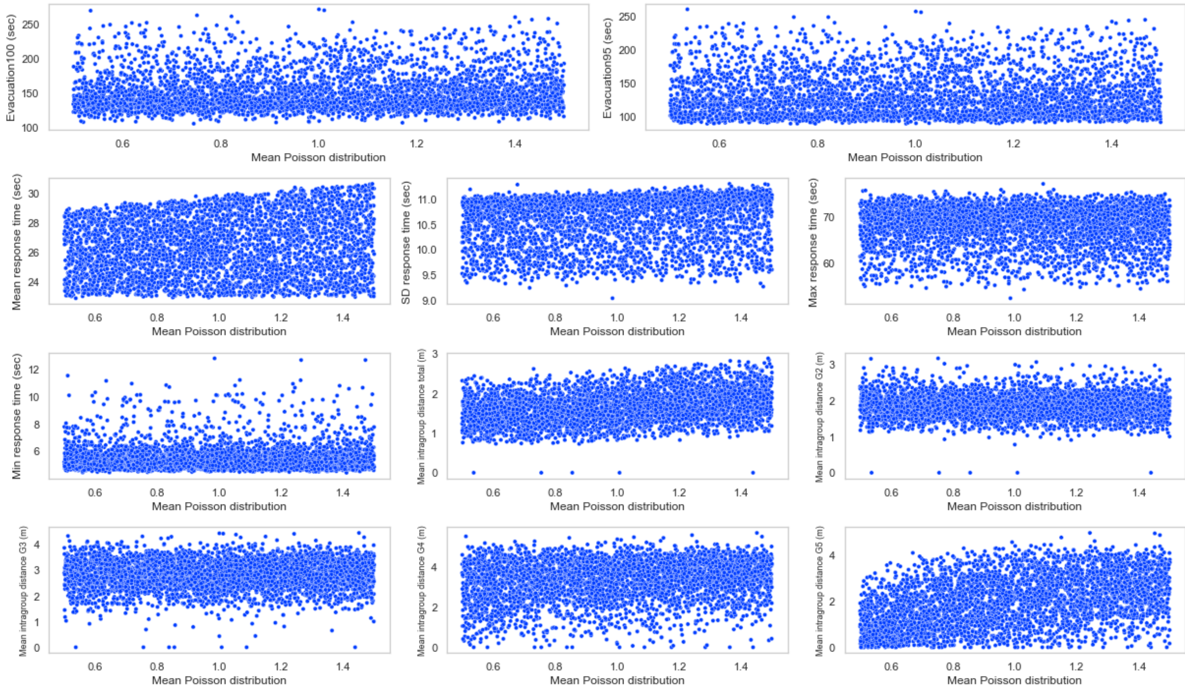

Figure B.5: The mean poisson distribution plotted for each KPI

B.1.6. Determination of leader

Figure B.6 indicated that the choice of how to determine the leader does not influence any KPI. The reason behind it is that group members are already located close to each other. Thus, the leader's location may not influence the overall behavior. To conclude, it does not make any difference if the leader is the one agent closest to the exit or randomly selected.

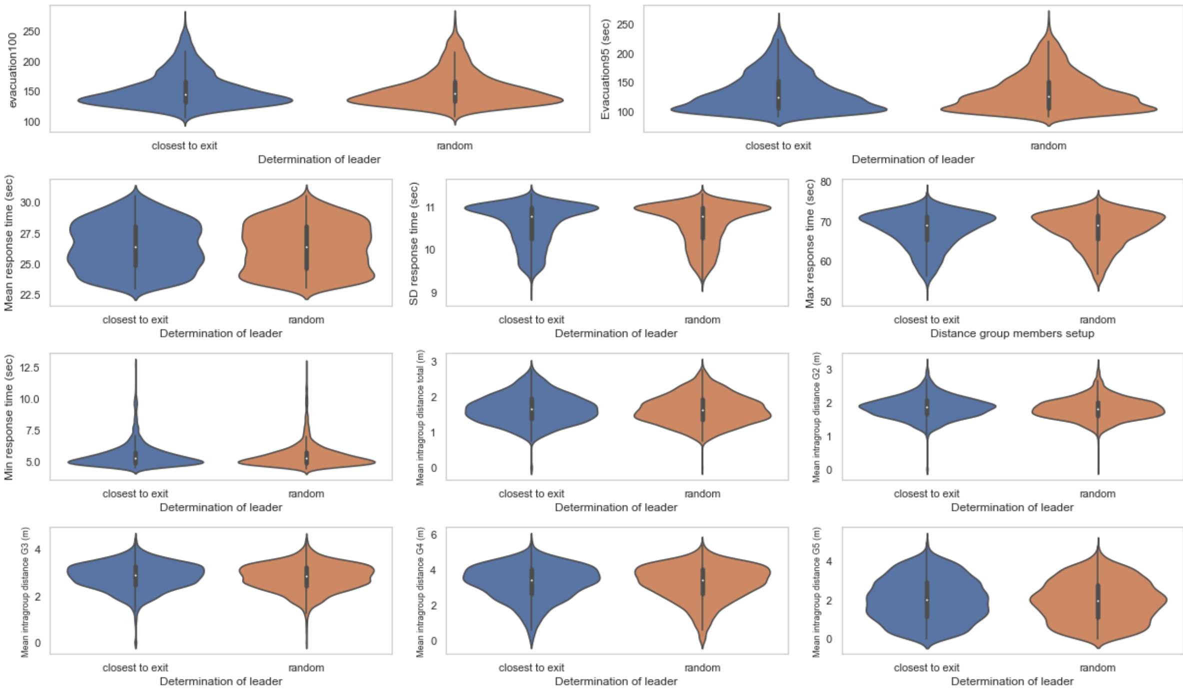

Figure B.6: The determination of leader plotted for each KPI

B.1.7. Recognition distribution location

The distribution of the recognition time influences the evacuation time and its 95 percentile. Figure B.7 indicates that the distribution for an office has the highest evacuation time. The reason behind this observation is a higher mean of 46.6 compared to 25.2 in a department store and 27.3 in a Restaurant. In addition, the maximal recognition time of 111 seconds is higher than the other distributions. Consequently, this leads to a higher evacuation time. For the other KPIs, this structural uncertainty does not show any impact.

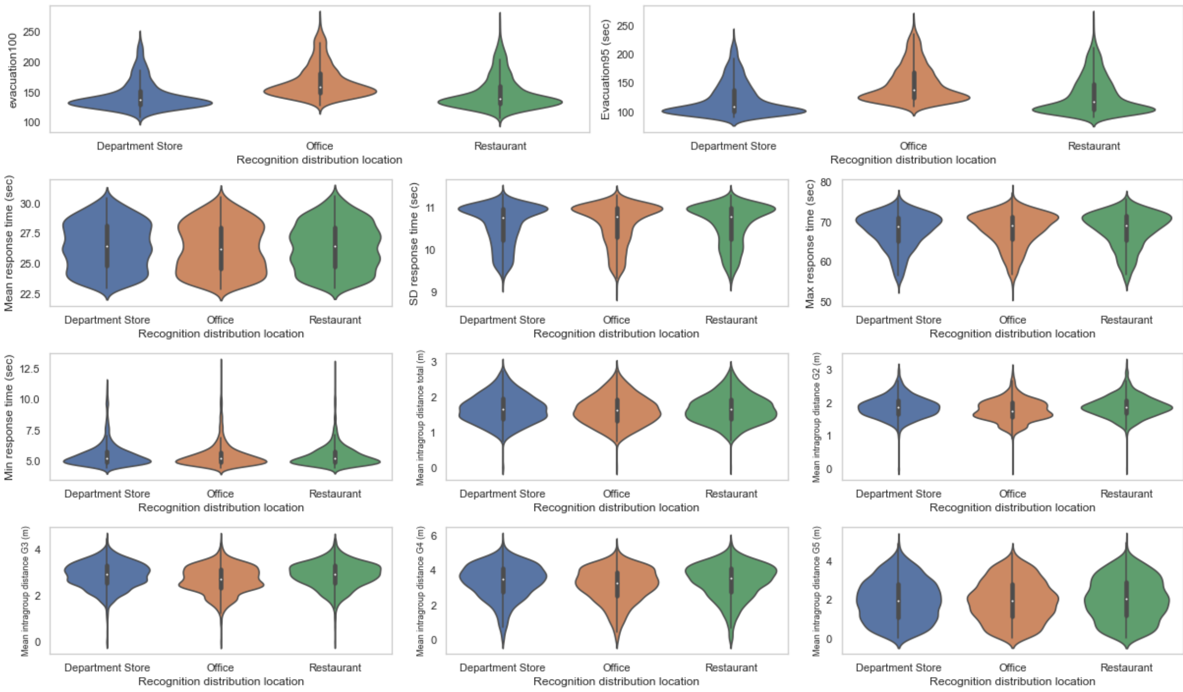

Figure B.7: The different locations for the recognition distribution plotted for each KPI

B.1.8. Max congestion

The value for the max congestion does not indicate any influence on the KPIs for the core leader-follower behavior, which is summarized in Figure B.8. The reason behind this observation is that the density of the population may not be as high in the building. Only if the density in one patch reaches the value of this uncertainty may this parameter influence the KPIs. The building has an area of 1766 square meters. With a maximum of 1600 people in the building, the average density may be only 0.91 people per square meter. Thus, this density may be too low for the influence of this parameter on the evacuation performance.

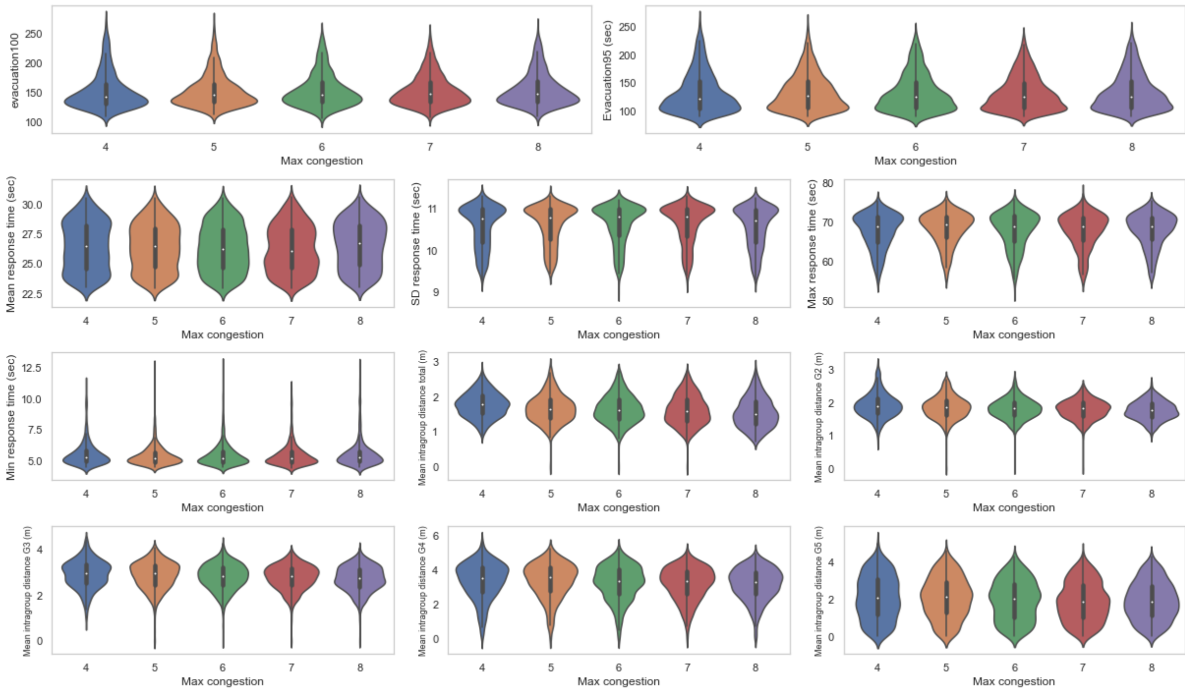

Figure B.8: The max congestion plotted for each KPI

B.1.9. Max age

Figure B.9 displays the influence on the maximum age on the KPIs. A clear pattern for any KPI cannot be observed. Also feature scoring confirmed this observation. The reason behind this result is that a higher age only minimally decreases the speed of agents. However, the behavior of agents may not differ in the developed model.

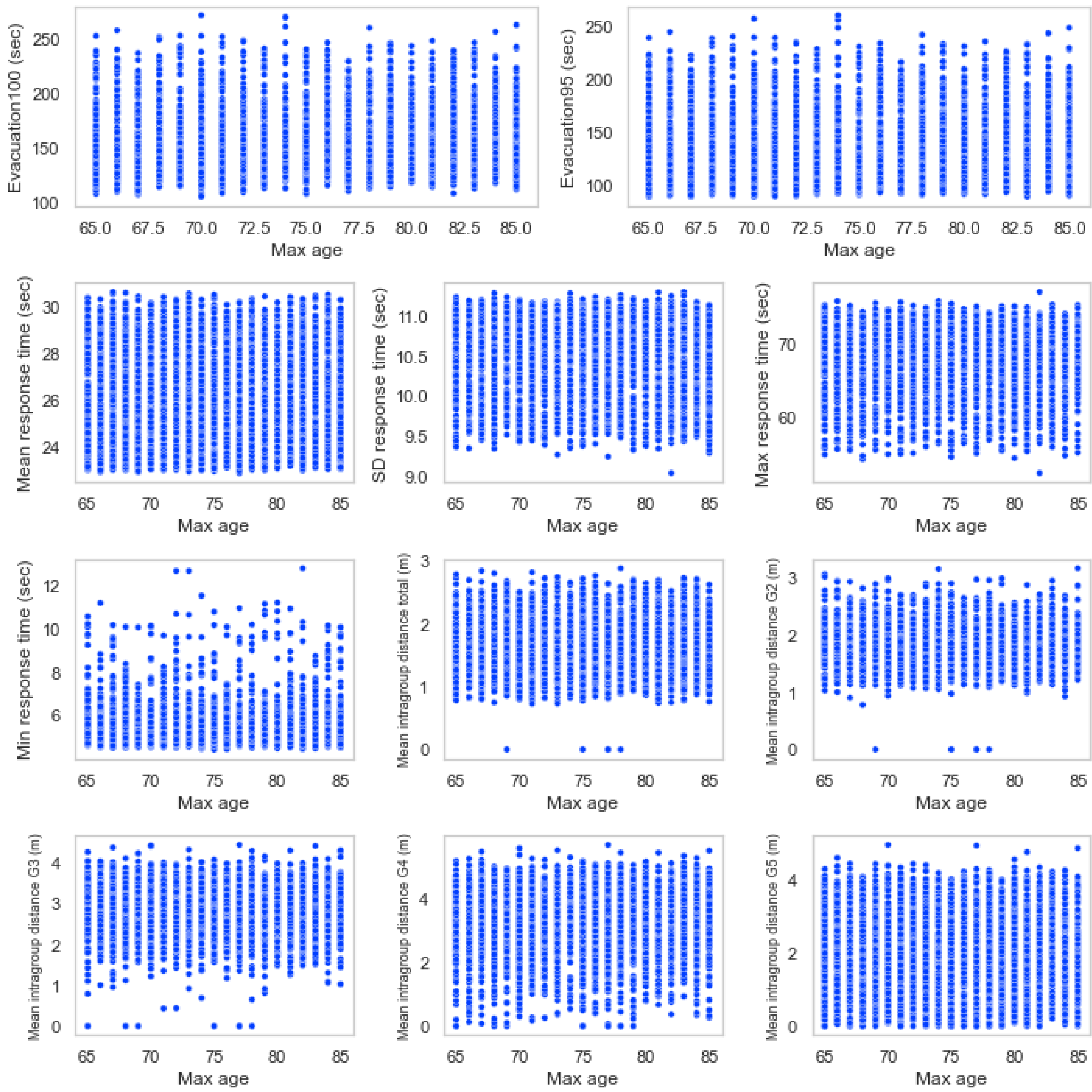

Figure B.9: The max age plotted for each KPI

B.1.10. Min age

The minimum age for agents has no influence on the evacuation and response time as well as intragroup distance. Figure B.10 depicts the results for each KPI with different values for the minimum age. It clearly indicates that no pattern may be observed regarding the variety of this uncertainty. This is logical as only the speed of agents increases only minimally with higher age.

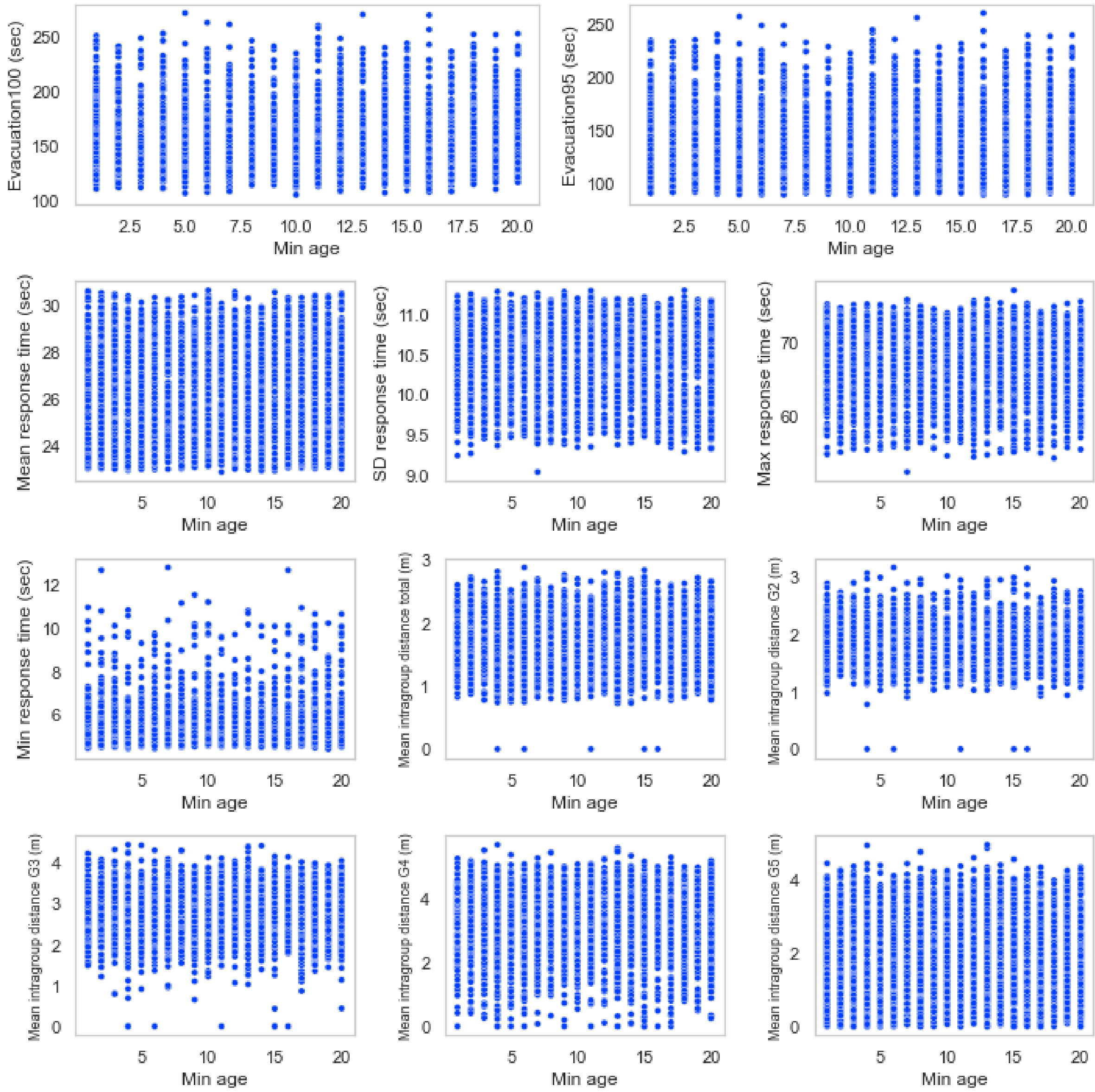

Figure B.10: The min age plotted for each KPI

B.2. Three unique leader-follower behavior

This section provides additional results regarding the three unique leader-follower behaviors and shows box plots for all KPIs in Figure B.11. In addition, the feature scores to investigate the influence of uncertainties for each behavior are summarized.

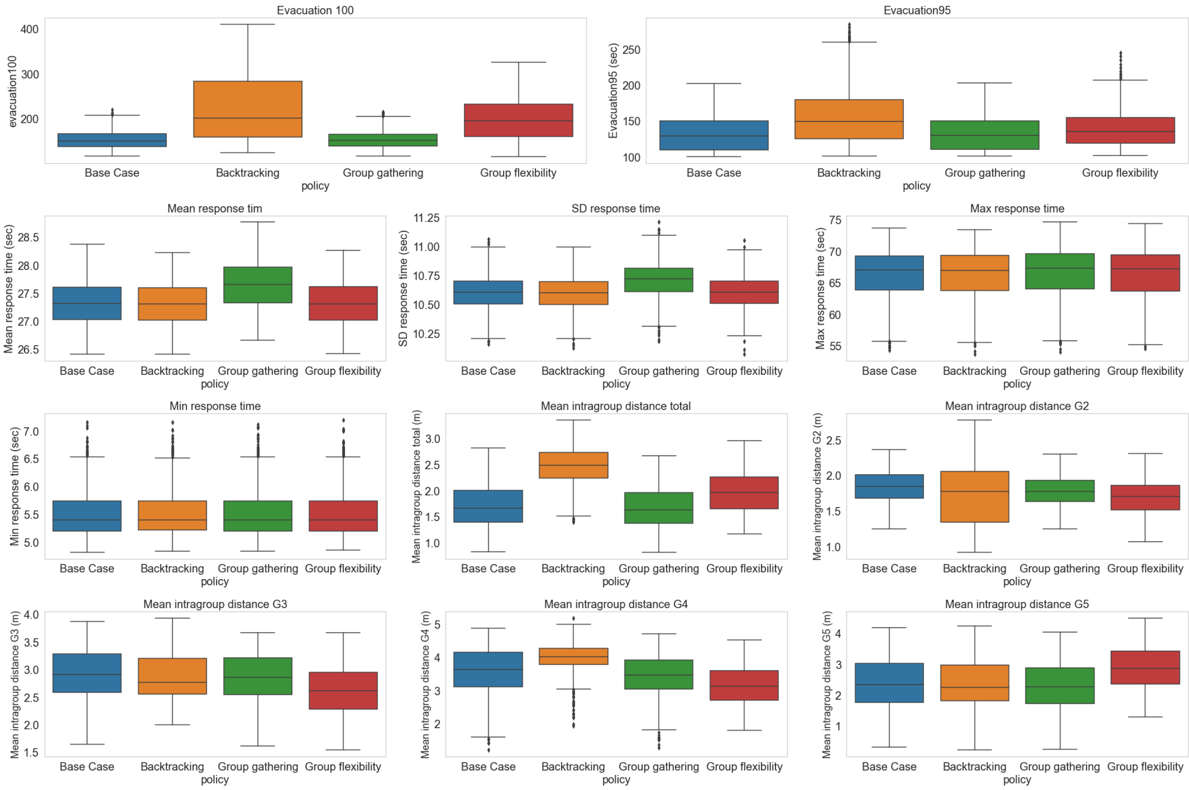

Figure B.11: Plots for all KPIs for different leader-follower behaviors

B.2.1. Feature scoring for Backtracking

Figure B.12 summarizes the feature scores for scenarios with backtracking. A higher value for the uncertainty indicates a greater influence on the KPI. It indicates the strong influence of the uncertainty "distance of group members" at the beginning of the evacuation, as already explained in Chapter 5. The population and the familiarity may not be as influential if this behavior is activated. For the other KPIs, the influential parameters do not change.

Figure B.12: Feature scoring for the scenarios with backtracking

B.2.2. Feature scoring for group gathering

The influence of uncertainties on the group gathering scenarios was identified with the help of feature scoring. A higher value for the uncertainty indicates a stronger impact on the KPI in Figure B.13. It clearly indicates a stronger influence of the parameter "mean poisson distribution" for the group gathering scenario compared to the base case. Other uncertainties do not indicate a difference.

Figure B.13: Feature scoring for the scenarios with group gathering

B.2.3. Feature scoring for flexibility of the group

Finally, feature scoring was utilized for the flexibility of the group behavior. The results may be observed in Figure B.14. It indicates a strong influence of the parameter "max congestion" compared to the base case. The reason behind it is that followers may find more leaders in their vision, leading to more group changes. In addition, bigger groups may emerge in the model in this scenario. These groups demonstrate a longer evacuation time in contrast to smaller groups. This also implies the lower impact of this parameter for the 95 percentile of the evacuation time.

Figure B.14: Feature scoring for the scenarios with flexibility of the group

B.3. Multivariate behavior testing results

This section provides deeper insight into the results of multivariate behavior testing. First, box plots for all KPIs with different scenarios are shown and analyzed in more detail, then feature scoring for the ”All behavior” scenario is illustrated.

B.3.1. Visual analysis

Visualization aids in finding patterns in the model (van Dam et al., 2013) and thus is utilized for Multivariate behavior testing. Thus, this chapter complements Chapter 5.3 and provides a visual analysis of the results observed.

Evacuation time

Figure B.15 clearly indicates the influence of combinations of behaviors on the evacuation time. Especially for combinations with backtracking and flexibility of the group, the growth is the highest. Additionally, it exhibits a higher variance with the activation of the behaviors, indicating that for some parameter combinations, the difference between the base case and the scenarios with behavior is higher compared to other combinations. This indicates a higher sensibility regarding changing uncertainties.

For the 95 percentile of the evacuation time, the difference between the combinations is lower compared to the total evacuation time. This indicates that only the evacuation time is determined by a few big groups that emerge due to the possibility of changing to another leader. Thus, these groups need a longer time to evacuate as leaders waiting time increases due to a higher chance of losing a member.

Response time

Figure B.15 displays that only scenarios with group gathering show an increase in the mean response time. At the same time, the response time variance increases. The reason is that the gap between the response times of individuals and group members growths, leading to a more significant response time variance. However, no difference may be encountered with combinations compared to the behavior itself. Scenarios with Group gathering slightly increase the maximum response time, while no clear pattern may be observed for the minimum response time.

Intragroup distance

The graph displays the highest growth with backtracking activated for the mean intragroup distance. Although, the combination with other behaviors reduces this effect. The reason behind this phenomenon is that followers may change to another leader in case the distance between the leader and follower increases. For smaller groups, all additional behaviors lead to lower intragroup distance as the leader waits for the followers, or the follower may change to other leaders in case the distance is too high. Figure B.15 also displays a higher variance for the intragroup distance of groups with two members with combinations including backtracking, indicating that some scenarios may lead to higher intragroup distances while others reduce this KPI. This variance results from the changing threshold for backtracking, which determines the parameter ”Distance group member setup”. In particular, a lower value leads to a decreased intragroup distance for groups with a size of 2 people. While a higher threshold leads to higher intragroup distances, increasing the variance. Only for bigger groups with four or more members the intragroup distance increases, especially for combinations with backtracking. The reason is the model implementation that group members avoid the patch of other members.

B.3.2. Feature scoring for the all behavior scenario

In order to identify the relevant uncertainties for the scenario where all behaviors are turned on, feature scoring was utilized. Figure B.16 summarizes the results. It indicates a greater influence of the parameter ”distance group members setup” for the evacuation time. The reason behind this observation is the strong influence of the backtracking behavior as it determines the threshold when backtracking is activated.

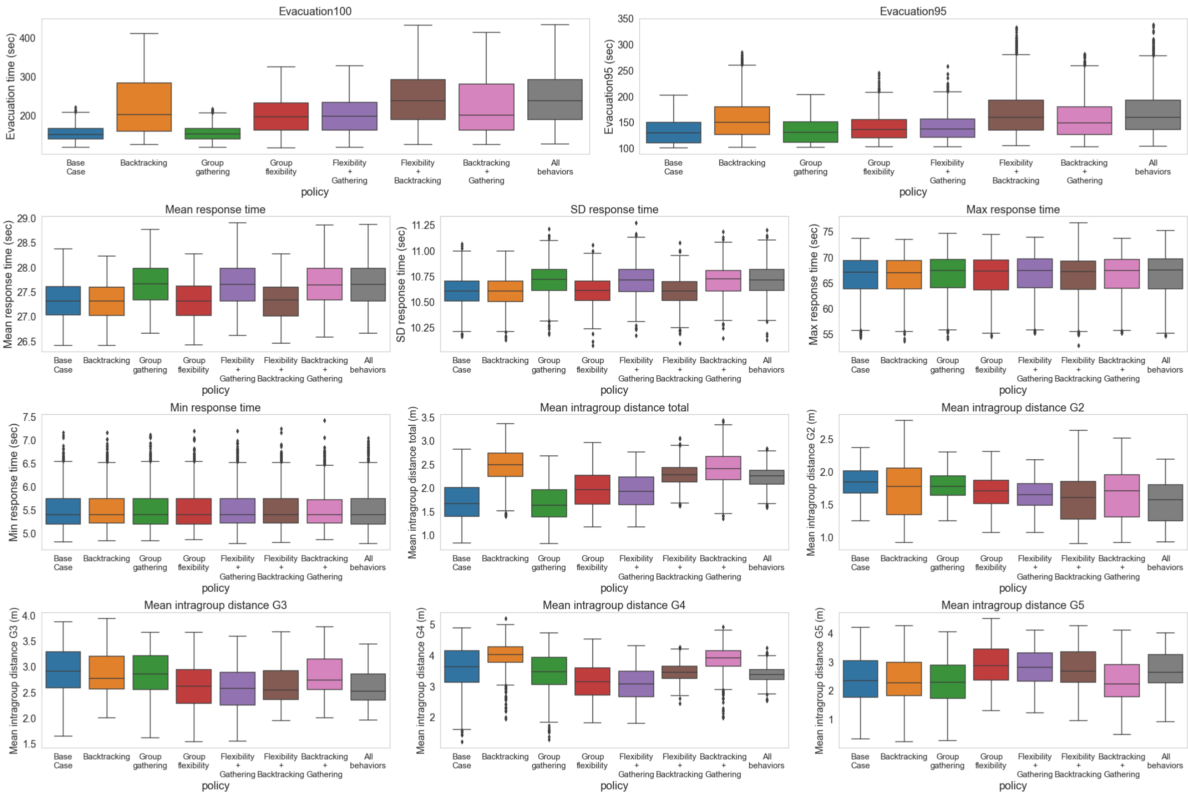

Figure B.15: Multivariate behavior testing for all KPIs

Figure B.16: Feature scoring for the scenario with all behaviors

B.4. Multivariate behavior testing results in an empty room

Finally, box plots for all KPIs for the experiment of multivariate behavior testing in an empty room are shown. The goal of the experiment was to test the pure behavior and reduce the interaction with the environment. Thus, visual analysis is utilized to complement the statistical analysis in Chapter 5.4.

B.4.1. Evacuation time

Of course, the evacuation time in an empty room is overall lower compared to a room with obstacles and walls. Figure B.17 indicates the same pattern for an empty room as in the layout with obstacles. Combinations with backtracking demonstrate the highest evacuation time. However, the group flexibility scenario's evacuation time clearly indicates a lower growth compared to the scenario in the original layout in Figure B.15. The reason behind this decrease is the lower influence of bottlenecks, which boosts the congestion and leads to a higher distribution of leaders in an area. This results in more changes in leaders and bigger groups that need a longer time to evacuate. Finally, the 95 percentile of the evacuation time does not exhibit any difference compared to the original layout, leading to a higher trust in the received results.

B.4.2. Response time

The response time in an empty room does not show any deviation compared to the implemented layout in the model. This is logical as the response time is not affected by the layout. Also, in the implemented layout with obstacles, people are already situated in the same room and next to each other. Thus, no interaction with the environment occurs, even for the group gathering scenario where group members move close to the leader.

B.4.3. Intragroup distance

Overall, the intragroup distance is lower compared to the original layout. The reason is that fewer bottlenecks are present, leading to higher congestion. This results in the observed pattern that groups remain close to each other without getting lost in traffic. Most scenarios indicate the same pattern as in the original layout for the mean intragroup distance. However, for the scenarios with group flexibility, the increase is not as significant. The reason here is also the missing bottlenecks. Bigger groups with an increasing intragroup distance may not emerge due to the missing bottleneck decreasing the intragroup distance. Finally, no pattern change may be observed with the layout modification for the different group sizes.

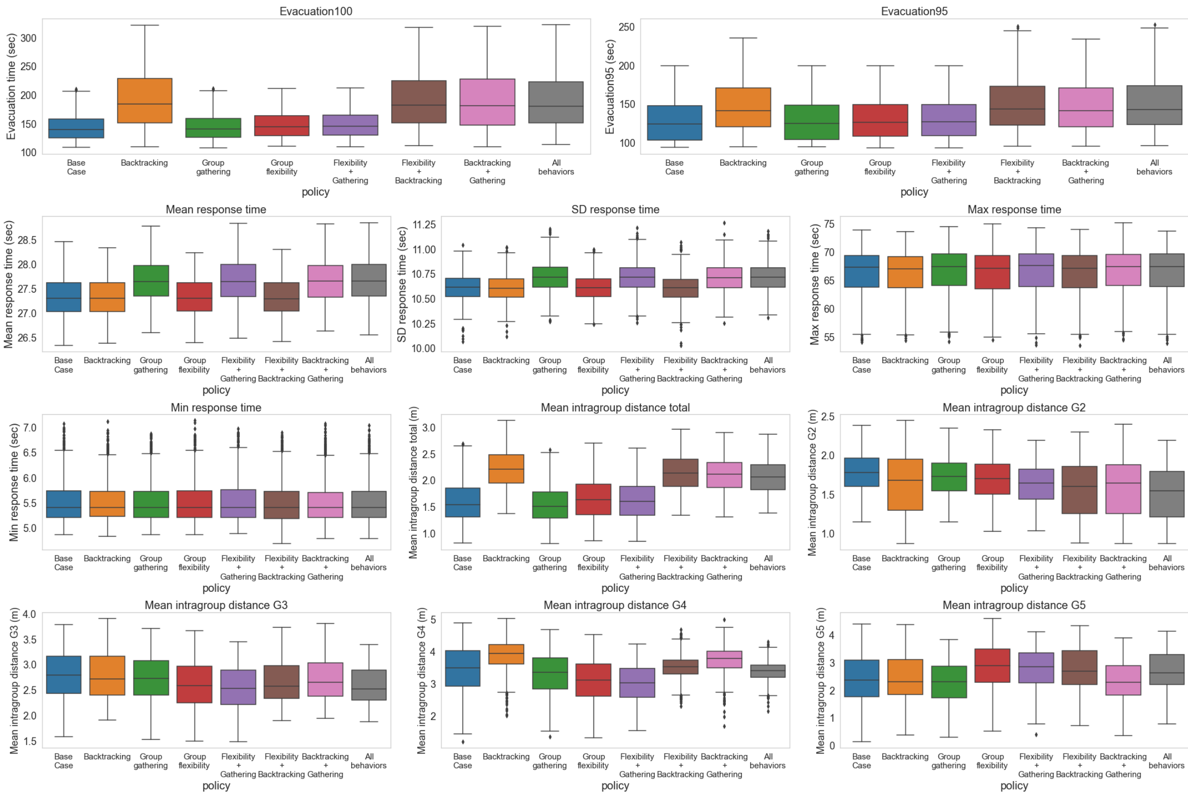

Figure B.17: Multivariate behavior testing for all KPIs in an empty room