The Influence of Socio-Technical Factors on Evacuation Performance of University Buildings

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The Influence of Socio-Technical Factors on Evacuation Performance of University Buildings

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An electronic version of this thesis is available at https://repository.tudelft.nl/.

The Netlogo model is available at https://github.com/roy-0/evacfactors/.

TU Delft

Preface

This work, The Influence of Socio-Technical Factors on Evacuation Performance of University Buildings, marks the official end of my academic journey. After several years at the Faculty of Technology, Policy and Management, all experiences, knowledge, and insights, come together in this document of 75 pages.

Studying at this faculty has provided me with multiple necessary skills and a multidisciplinary point of view. During the years, I could expand my knowledge on fields such as law, governance, information and communication technology, multi-actor systems, and the most interesting, modelling and simulation. With this skill set, I am sure that I have everything to succeed in my career.

I would like to express my gratitude to Dr. Van der Wal, my supervisor, for the excellence guidance during this project. Your enthusiasm, perspective and listening skills shaped this thesis to its current quality level. My sincere thanks also go to Dr. Kammouh, my second supervisor, whose supportive feedback and fresh perspective allowed me to upgrade weaker points of this thesis to a higher level. Also, I am immensely grateful to professor Dr. Ir. Verbraeck, the chair of this committee, for his great knowledge and the remarkable ability to explain complex ideas in a clear and accessible manner.

Finally, I want to thank family and friends, who provided me with adequate support throughout this journey. Deo gratias. I wish you, the reader, a pleasant reading.

Roy Dukker
Delft, June 2025

Summary

This research investigates the influence of socio-technical factors on the evacuation performance of university buildings. While prior studies have examined individual factors affecting evacuation, this thesis adopts a comprehensive socio-technical systems perspective, by considering the interactions of social, structural, and technical components within the complex context of university building evacuation systems.

To explore this, an agent-based simulation model was developed using NetLogo. The model simulates evacuation scenarios in two structurally different campus buildings at TU Delft: the Applied Sciences building and the Civil Engineering & Geosciences building. The key variables studied were familiarity with the building layout and exits, social influence behaviour, egress width, and signage. Evacuation performance was assessed using three metrics: 75% evacuation time, mean density, and exit choice.

Following a full factorial simulation experiment of 54 different scenarios per building totalling 10800 individual runs, a standardised ranking was created to equitably rank the scenarios based on their relative evacuation time, density, and exit choice, to determine the performance of the factors. A general linear model was created to determine the effect size of both the individual factors and all possible interactions.

The simulation results demonstrate that familiarity and egress width had the most significant impact on evacuation efficiency. In buildings with limited exits, egress width outweighed the effect of familiarity. While signage and social influence showed modest or statistically non-significant impacts overall, signage became more effective in low-familiarity contexts. The effect of social influence appeared to be sensitive to its level of formalisation in the model, underscoring its context-dependent nature.

Strengths of this study lie in the multi-metric perspective on evacuation performance, the use of multiple buildings to test effects in different structural environments, the possibility to include all possible interactions through a full factorial design, and the adaptability of the simulation model. Also, this study has several limitations, namely the balance between model correctness and performance, the difficulty to detect behavioural patterns, and software-based limitations.

From a policy perspective, the findings suggest that improving occupant familiarity with building layouts, through orientation, drills, or signage, can substantially improve evacuation performance. Furthermore, structural adjustments such as widening exits can mitigate congestion in critical zones, although its effect is dependent on hallway width. Although advanced signage technologies offer some improvements, their individual effectiveness is limited without complementary strategies.

The study highlights the importance of addressing evacuation preparedness as a multi-factorial challenge, especially in complex university settings where population heterogeneity and architectural diversity intersect. The model and methodology offer a flexible tool for future research and scenario testing.

Contents

List of Figures

List of Tables

List of Algorithms

Nomenclature

Abbreviations

Abbreviation	Definition
ABM	Agent-Based Model(ling)
AS	Applied Sciences
ASET	Available Safe Egress Time
CEG	Civil Engineering and Geosciences
CoSEM	Complex Systems Engineering and Management
GLM	General Linear Model
ICT	Information and Communication Technology
RSET	Required Safe Egress Time
TU Delft	Technische Universiteit Delft (or Delft University of Technology)

1
Introduction

Safety of individuals in buildings is an essential right. Every year, people die in buildings because of building fires, natural disasters, or other causes(Wu et al., 2015). In case of disasters, either man-made or natural, people rely immensely on the safety measures of the building they are in (Brulić & Dzidic, 2018). A lack of proper safety measures, during the design of buildings, can have huge impact on the physical health of occupants in case of emergencies (Colgate & Lee, 2012; Kobes et al., 2010). Examples of social, structural or technical defects in the evacuation system include social influence (Riad et al., 1999), narrow egress routes (Huang et al., 2013), or inadequate signage (Xie & Galea, 2022). In case of emergency, effective evacuation is key to reducing casualties (Hostetter et al., 2024). Therefore, it is necessary to research these factors that influence evacuation performance.

While there is research on individual factors that influence evacuation performance, there is little research that utilises the socio-technical systems perspective to regard an evacuation system. From a complex socio-technical perspective, there are multiple system characteristics that make it complex, such as path dependence, non-linearity and perhaps most interesting in this context, emergence (Mikulecky, 2001). A socio-technical perspective combines, as the name suggests, a view on both the social and technical aspects, crucial to understand the complex properties of evacuation systems.

Following the socio-technical view, the factors that impact evacuation performance can globally be categorised into three categories, namely social, structural, and technical (Kobes et al., 2010). The first category, social, can be defined as all influences individuals (non-safety staff members) have on the system. This can entail familiarity with the building layout (Kinateder et al., 2018; Sadri et al., 2014), physical location, number of visitors, or safety training level (Liu et al., 2021). The second category, physical, entails all structural aspects of the systems (Kobes et al., 2010). Apart from building layout and size, and egress width (G. Chu et al., 2006), also building-specific factors can play a role, such as special research activities which require extra care in case of evacuations. The third category, technical, covers all influences of information and communication technology on the system of building evacuation (Sudiarno et al., 2022). Provision of information, communication from safety staff, the type of alarm, or the presence of (dynamic) signage (Sudiarno et al., 2022) are aspects of this third category.

While numerous contributions are made towards evacuations of high-rise buildings or offices, there is little research on evacuation performance of university campuses (Ding et al., 2021; Liu et al., 2021; Van der Wal et al., 2021). Unlike conventional housing or office buildings, a university campus is a complicated environment with multiple purposes: educational activities, research activities, administrative activities, and student housing and recreation. This results in a diverse composition of people: students, researchers, teachers, campus and building personnel, and visitors. In case of emergency, evacuation can be hindered because of several aspects, like students taking exams, or special research activities which might be valuable and precious. Evacuation, in these cases, means retaking said exam, or the loss of years of intense research. These complexities make university campuses complex environments. It is interesting to explore the effect of these complexities on evacuation performance for university campus buildings. This results in the following research questions.

What is the influence of social, structural, and technical complexity on evacuation performance in university campus buildings?

The research question has the following four sub research questions:
SQ1: What is evacuation complexity in university campus buildings?
SQ2: What are the relevant evacuation performance metrics for evacuation in university campus buildings?
SQ3: Which combinations of socio-technical factors produce the most efficient outcomes for the evacuation metrics, and how do different factor levels interact to influence these outcomes?
SQ4: What are the main and interaction effects of familiarity, social influence, egress width, and signage on exit choice, density and total and 75% evacuation time in university campus buildings?

To answer sub research question 1 and 2, a literature review is performed. This method fits the exploratory nature of these sub research questions. The literature review follows a thematic structure, where evacuation systems are approached from a complex-sociotechnical perspective.

To answer sub research question 3 and 4, modelling and simulation are the used methods and techniques. Specifically, an agent-based model is built. In this model, two university campus buildings are modelled, together with agents and the necessary environment to answer the sub research questions. Model input is based on the real world buildings, as well as previous evacuation research.

The analysis of the simulation model output is twofold. To answer sub research question 3, runs are ranked based on the evacuation performance metrics. This provides insight into the relations between the factors. For example, it can show how factor levels differ, given that one other factor is constant. To answer sub research question 4, an analysis on partial eta-squared values is performed. These values give insight into each factor's contribution to each of the output metrics.

There are several methods to ultimately measure the performance of evacuations (Russo & Rindone, 2010; Zheng et al., 2009). Although regular evacuation drills can be performed, benefits of such drills are often disputed (Gwynne et al., 2020). Simulation models can provide a solution, since simulation models do not disrupt ongoing activities in the building (Gwynne et al., 2020; Ren et al., 2009; Rendón Rozo et al., 2019; Zheng et al., 2009), can be tested in a more efficient manner (Astudillo Muñoz et al., 2022; Marzouk & Mohamed, 2019). The benefits of using simulation modelling experimentation as a method are described in further detail below.

One of the biggest benefits of computer simulation and modelling is the minimisation of risk to participants. Real-life evacuation drills have the potential to be hazardous, possibly leading to injury or mental concerns (Ahmed et al., 2019). Simulations, however, are a zero-risk environment wherein evacuation situations may be tried without risking anyone. This is particularly important in an academic setting like a university, where the wellbeing and safety of students, lecturers, and staff is the most important.

Another benefit of computer simulation is the ability to create scenarios (Astudillo Muñoz et al., 2022). Conducting actual evacuation drills can be logistically complex and expensive. They require planning, coordination, and labour, and disturb ongoing activities in the buildings (Zhan & Chen, 2008). Computer simulations are inexpensive (Astudillo Muñoz et al., 2022). When the simulation environment is created, various scenarios can be run with little additional effort. Simulations are then a more sustainable choice for recurring research and continual refinement of evacuation plans.

The third advantage is that computer simulations provide unmatched scalability and flexibility (Astudillo Muñoz et al., 2022). Variables such as the number of participants, building configurations, and types of emergencies can easily be changed by researchers. This flexibility allows simulation of a very large variety of situations, even allowing simulation of extreme events that would be impractical or even impossible to test under real conditions. Moreover, simulations can be extended to cover entire university campuses or confined to specific buildings or floors and achieve a general view of evacuation behaviour at various levels.

Yet another of the significant advantages of simulation modelling experimentation is that it can have the capacity for collecting and handling large quantities of data with very high accuracy (Ahmed et al., 2019; Astudillo Muñoz et al., 2022). Displacements of individual people, reaction times, bottlenecks, and other key parameters can be tracked by simulations in real time. This kind of precision is hard to achieve in real-drills, with observation and data collection limited by human observation and recording capacity (Astudillo Muñoz et al., 2022). The information obtained from simulations can be used to identify weaknesses in current evacuation performance, improve evacuation routes, and improve overall safety measures.

Subsequently, simulation-based evacuation research provides steady results, where real-life drills can show abnormal results due to, e.g., participant behaviour, environmental, and time constraints variables (Ichinose & Takahashi, 2017). Computer simulation is done in a controlled environment where conditions are kept constant to ensure reproducibility and comparison of results. This constant environment is critical for scientists to draw conclusions and recommend evidence-based evacuating procedures.

Lastly, simulations allow for the testing of various emergency scenarios, including fires, earthquakes, and active shooter incidents (Astudillo Muñoz et al., 2022; Zambrano et al., 2020). This is difficult to do with real drills due to practical and ethical constraints. Simulations can also be used as training tools for emergency responders and university staff, providing interactive and immersive experiences that enhance preparedness without the need for disruptive and costly drills (Astudillo Muñoz et al., 2022; Zambrano et al., 2020).

This thesis is structured as follows: in chapter 2, a literature review is presented. In chapter 3, the conceptualisation of this research is described. In this chapter, sub questions 1 and 2 are answered. In chapter 4, the conceptualisation and formalisation of the agent-based model is described. In chapter 5, the results are displayed, and sub questions 3 and 4 are answered. In chapter 6, the discussion and conclusion is written.

2
Literature Review

In this chapter, a comprehensive exploration of the existing body of literature relevant to complexities in evacuations is provided.

This chapter follows a thematic structure. First, complex socio-technical systems are reviewed. Following, complexity science for evacuations is researched. Then, evacuation performance is described, with relevant evacuation phases and performance metrics. After, evacuation simulation practices are written. Last, evacuation performance specifically in university campuses is researched.

2.1. Complex Socio-Technical Systems

To understand the world around us, systems theory can be applied to define and organise systems (Adams et al., 2014; Sayin, 2016). Later, the field of systems thinking arose, which describes a holistic approach to analysing systems that are components of other systems (Engel, 2024). Systems thinking is the foundation in fields like engineering, environment, or economy (Engel, 2024). In the line of systems thinking lies the sub field socio-technical systems theory. In socio-technical systems theory, both the social aspects and the technical aspects of a systems are considered (Büscher, 2022). Social components of socio-technical systems can exist of actor relations, power dynamics, and behavioural aspects (Troyer, 2017). Technical components of socio-technical systems consist of the technical aspects of the systems, like the technologies and data used (Troyer, 2017).

In socio-technical systems theory, complexity is often described as a main characteristic (Troyer, 2017). There are several aspects or properties that make a socio-technical system a complex socio-technical system (Mikulecky, 2001; Nguyen, 2019). In the next section, each property will be briefly described.

- Non-linearity: Small changes in input can result in disproportionate and unpredictable changes in output.
- Context dependency: The behaviour and properties of the system can change depending on the surrounding environment and conditions. In socio-technical systems theory, aspects that influence the system from outside are called external factors.
- Observer dependency: Observations and interpretations of the system can vary significantly based on the observer's perspective and context.
- Path dependence: The system's current state and future possibilities are heavily influenced by its historical trajectory.
- Instability: The system tends to experience rapid and unpredictable changes.
- Adaptiveness: The system has the ability to change and evolve in response to internal and external pressures.
- Chaos: Sensitivity to initial conditions leads to seemingly random and unpredictable outcomes despite deterministic rules.

- Robustness: The system can maintain functionality despite disturbances or unexpected changes.
- Self-similarity: The system exhibits similar patterns at different scales.
- Diversity: The variety of components and interactions within the system contributes to its complexity and resilience.
- Self-organisation: The system can spontaneously form organised structures and patterns without external control.
- Intractability of evolution: It is difficult to predict the system's future evolution due to its complexity and the multitude of interacting factors.
- Emergence: Larger entities, patterns, and regularities arise through interactions among smaller or simpler entities that themselves do not exhibit such properties.

Having discussed the key features of complex socio-technical systems - like their intricate connections, dynamic interactions, and ability to adapt—it's now important to identify which systems are considered complex and which are not. This distinction helps in understanding the variety of socio-technical systems. Complex socio-technical systems combine technology and social elements in ways that are unpredictable and adaptable (Nguyen, 2019). On the other hand, non-complex socio-technical systems have simpler, more predictable interactions (Stojanov et al., 2020). To make this clearer, we will look at examples of both complex and non-complex socio-technical systems. This will show how these systems work differently depending on their level of complexity.

Now, three non-complex socio-technical systems are illustrated.
Traditional Library System: A library system that relies on physical books and manual cataloguing. It involves people (librarians, patrons) and basic technology (catalogues, shelves), but the interactions and dependencies are relatively straightforward and predictable.
Simple Manufacturing Assembly Line: An assembly line where workers and machines perform repetitive tasks to produce a product. While there is interaction between humans and technology, the process is linear and highly controlled, with minimal complexity compared to modern, flexible manufacturing systems.
Local Public Transportation System: A small city's bus network where buses run on fixed routes and schedules. The system involves drivers, passengers, and the transportation infrastructure, but operates in a relatively predictable and stable environment without the high-level dynamic interactions seen in larger, multi-modal transportation systems.

Subsequently, we look at three examples of complex socio-technical systems.
Air Traffic Control System: This system integrates sophisticated technology (radars, communication systems, aircraft) with human operators (air traffic controllers, pilots) and organisational structures (airlines, regulatory bodies). The interactions are highly dynamic and the system must respond to a wide range of unpredictable events, making it a prime example of a complex socio-technical system (Stojanov et al., 2020).
Healthcare System: The healthcare system involves advanced medical technologies (diagnostic machines, electronic health records), a diverse group of professionals (doctors, nurses, administrative staff), and organisational elements (hospitals, insurance companies, regulatory agencies). The interdependencies and variability in patient care, treatment protocols, and resource management contribute to its complexity (Nguyen, 2019).
Smart Grids: Modern power grids with smart technologies involve complex interactions between physical infrastructure (power plants, transmission lines), digital technologies (smart meters, sensors), and human actors (grid operators, consumers, regulatory bodies). The need for real-time adjustments and the integration of renewable energy sources add layers of complexity.

2.2. Complexity Science for Building Evacuation

Evacuation systems are a great example of socio-technical systems because they combine both human and technological elements to help people escape safely during emergencies (Kuligowski, 2009). These systems use technologies like alarms, information and communication networks, and sensors that work together with human actions, such as those of emergency responders and building occupants (Liu et al., 2021; Riad et al., 1999). The effectiveness of an evacuation relies on good coordination between these tools and people's responses. Training, practice drills, and clear communication are essential so that everyone knows what to do. The design of buildings, along with helpful technologies like exit signs and automated alerts, also guides people to safety (Sudiarno et al., 2022). This shows how evacuation systems depend on both technology and human behaviour to handle complex, stressful situations effectively.

Viewing an evacuation system from a complex socio-technical system perspective is crucial because traditional system thinking often overlooks the intricate and dynamic interactions involved (Baxter & Sommerville, 2010). Traditional approaches might focus solely on the technological components or the human aspects separately, failing to capture how these parts interact in real-time during an emergency. In contrast, a complex socio-technical viewpoint recognises that the success of an evacuation depends on the seamless integration of advanced technologies (e.g. alarms and sensors), human behaviours (e.g.) responders' actions and occupants' reactions), and organisational protocols (e.g. emergency procedures) (Baxter & Sommerville, 2010). This perspective takes into account the unpredictability, adaptability, and interdependencies within the system, ensuring a more comprehensive understanding and effective management of evacuation scenarios. By acknowledging these complexities, we can better design, implement, and improve evacuation systems to handle the nuanced challenges of real-world emergencies.

In recent years, the phenomena that influence evacuation performance have been identified and researched to great extent. Foundational work revealed multiple different factors that influence evacuations (Gwynne, Kuligowski, et al., 2019; Kobes et al., 2010; Kuligowski, 2009; Liu et al., 2021). Following the socio-technical system approach to evacuation systems, combined with the complex properties of socio-technical systems, we will divide these factors that influence evacuation performance into three categories: social factors, structural factors, and technical factors. Figure 2.1 displays the flow from a complex socio-technical systems perspective to the three categories. In the following subsections, the complexity properties, as well as individual factors that influence evacuation performance, are described for each of these categories.

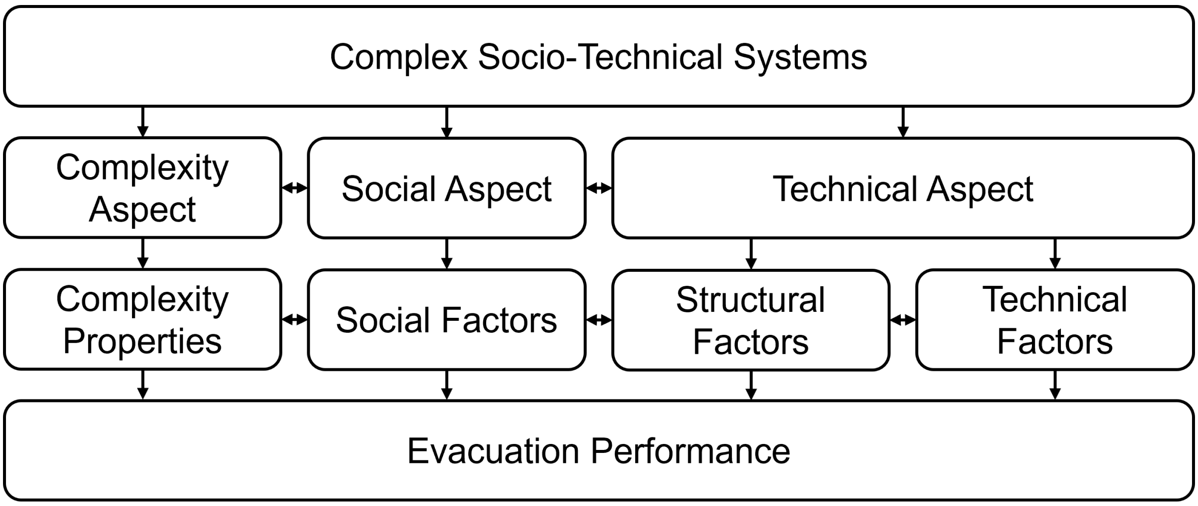

Figure 2.1: Complexity properties, social, structural and technical factors influencing evacuation performance, derived from a complex socio-technical perspective

2.2.1. Complexity Properties

Given all complexity properties, described in previous sections, there are several complexity properties that are most applicable to building evacuation systems, namely emergence, path dependency, and context dependency. Emergence in the context of building evacuation systems refers to the phenomenon that behaviour on the individual level can lead to unpredictable behaviour on higher levels. System-level patterns could form, in this context e.g. crowds or bottlenecks. It is hard to predict, based on individual behaviour, when or where these system patterns form. Path dependency, in the context of building evacuation systems, refers to the effects of initial decisions on the performance. In the case of building evacuation systems, these initial decisions predominantly entail exit selection and route choices. It is therefore interesting to investigate measures to positively influence these choices. Context dependency in this context predominantly refers to the effectiveness of certain strategies or scenarios based on the environment. To illustrate, a certain scenario with, for instance, dynamic signage might work in one building, while its effect might be less visible in another. The presence of context dependency in the building evacuation system is a fundamental assumption, because this research entails the influence of changes in this context.

2.2.2. Social Factors

The social aspect of the complex socio-technical system of building evacuation consists of multiple factors (Kuligowski, 2009). These factors, or dynamics, can be categorised into three categories: individual aspects, group aspects, and cultural aspects.

Individual Aspects

Response times during evacuations vary widely based on individual and environmental factors (Riad et al., 1999). Some people may react quickly due to personality traits like high anxiety or previous emergency experience, while others may take longer due to unfamiliarity with the environment or a calm disposition (Riad et al., 1999). According to Riad et al., agent decision-making in evacuation scenarios follows similar steps as the health belief model (Becker, 1974; Riad et al., 1999). In the health belief model, threats, costs, and benefits are considered at several steps, before ultimately deciding to, in this case, evacuate. Designing evacuation procedures that account for these differences, such as staggered evacuations, personalised emergency plans, or standard information protocols can help ensure that everyone evacuates safely and promptly (Riad et al., 1999).

During an evacuation, individuals tend to follow familiar paths, often using the routes they take daily, such as main hallways and exits (Sadri et al., 2014). This behaviour can create bottlenecks and slow down the evacuation process, as too many people may converge on the same exit points (Kinateder et al., 2018). Encouraging the use of alternative routes and clearly marking all exits can help distribute the flow of people more evenly, reducing congestion and speeding up the evacuation. However, researched also showed that evacuees are unlikely to follow alternative routes (Rendón Rozo et al., 2019). Also, just being familiar with the building layout has been proven to decrease the evacuation time (M. L. Chu & Law, 2019).

Evacuating individuals with mobility impairments, such as those who use wheelchairs, require specific considerations (Christensen, 2011; Hunt et al., 2020). Standard evacuation routes, like stairs, may not be accessible, necessitating alternative paths or the use of evacuation chairs or lifts. Ensuring that all areas of a building are accessible and that staff and students are trained to assist those with mobility issues is crucial for an inclusive and effective evacuation plan.

Cultural and Socio-demographical Aspects

Socio-demographical aspects also influence evacuation behaviour of agents. An example of these aspects in gender. Studies have shown that there is a difference in reaction time between men and woman (Mao et al., 2024). Also, in evacuations, men are more likely to include their physical environment in their decision-making, while women are more likely to follow groups (Mao et al., 2024). Both genders are more likely to follow groups of mainly their own gender in comparison to mixed groups or groups of mainly the opposing gender (Mao et al., 2024). Furthermore, the influence of visibility on evacuation efficiency seems to be gender specific, where women are more perceptible to visibility limitations compared to men (Chen et al., 2018; Shen et al., 2014). Lastly, (also) due to height differences, men and women have different walking speeds in evacuation, especially if building height is involved (Shen et al., 2014; Ye et al., 2012; Y. Zhang et al., 2020).

Diverse cognitive and cultural factors can affect how individuals respond to evacuation alarms and instructions. Multiple studies confirm a difference in predominantly pre-movement time for different cultures (Bergeron, 2015; Damme et al., 2023) Apart from culture, mental conditions can play a role. People with ADHD or autism might struggle with sudden changes in routine or sensory overload, requiring clear and calm instructions (Choi et al., 2020). Language barriers can hinder understanding of emergency announcements, while cultural differences might influence how people interpret authority or emergency cues (Purworini et al., 2021). Providing multilingual instructions, visual aids, and training staff to recognise and support individuals with different needs can enhance overall evacuation efficiency and safety.

Group Aspects

In evacuation, humans are proven to be subsequently to follow other groups of evacuees (Kinateder et al., 2018; Lin et al., 2020; Nilsson & Johansson, 2009). This behaviour, so-called social influence, is closely related to the desire to follow leaders, but is different to leader/follower behaviour. In the case of social influence behaviour, the cue to follow a group of evacuees is not the presence of an individual, the leader, but rather the presence of a group. Research has shown that the proximity and the degree of proximity of a group near an individual influences the decision-making of that individual (Kinateder et al., 2018; Nilsson & Johansson, 2009), where the closer the group to the individual, the more likely the individual is to follow the group (Nilsson & Johansson, 2009). Other studies also underline the influence of personal factors on the effectiveness of this social influence or herding behaviour (Lovreglio et al., 2016).

In emergency situations, the leader-follower dynamic can significantly influence evacuation efficiency (Y. Ma et al., 2016). People often look to those perceived as leaders—whether due to their authority, confidence, or familiarity with the environment—for cues on how to act (W. Li et al., 2016). Effective leaders can guide evacuees calmly and efficiently to safety, while the absence of clear leadership can lead to confusion and chaos (Y. Ma et al., 2016). Recognising and preparing designated leaders, such as staff or trained student volunteers, can improve evacuation outcomes by providing clear direction and reducing panic (Ding & Sun, 2020). The effect of leader-follower dynamics is increased when evacuees are less familiar with the building (Y. Ma et al., 2016).

The timing of an evacuation can coincide with peak periods, such as the start of classes or the workday, when buildings are densely populated. This expected crowding can significantly challenge evacuation efforts, as larger numbers of people attempt to exit simultaneously (Helbing et al., 2000; M. Zeng et al., 2021). This behaviour, known as queuing, is shown to impact evacuation times when compared to a more relaxed evacuation strategy (M. Zeng et al., 2021). Planning for these scenarios involves analysing typical occupancy patterns and designing evacuation drills that account for peak usage times, ensuring that evacuation procedures can handle maximum capacity efficiently.

2.2.3. Structural Factors

There are several structural factors that have been proven to influence evacuation performance. In short, these factors can be summarized as the presence and properties of different physical, structural elements.

The architectural design of a building can significantly impact the flow of evacuees during an emergency (Kodur et al., 2020). Narrow hallways, staircases, and exit points can create congestion, slowing down the evacuation process. These bottlenecks are especially problematic in older buildings not designed with modern evacuation needs in mind. Properly identifying and addressing these potential congestion points through structural modifications or improved evacuation planning can help streamline the evacuation process and reduce delays.

The width of exits is a critical factor in determining how quickly and efficiently people can evacuate a building (Kodur et al., 2020). Wider exits allow for a higher flow rate of people, reducing the time it takes for everyone to exit safely (G. Chu et al., 2006). Conversely, narrow exits can become choke points, causing significant delays and increasing the risk of injury due to crowding (Xiao et al., 2016). Ensuring that exits are wide enough to accommodate the maximum expected occupancy can greatly enhance evacuation efficiency (G. Chu et al., 2006).

The number of available exits directly affects the speed and safety of an evacuation (Kodur et al., 2020). Buildings with multiple exits provide alternative routes for evacuees, reducing the likelihood of congestion and allowing for a more distributed and orderly evacuation. In contrast, buildings with a limited number of exits can create dangerous situations, as large numbers of people converge on the same points (Kodur et al., 2020). Additionally, studies have shown that using parallel exit placement increases evacuation performance (G. Ma et al., 2021). Increasing the number of exits, where possible, and ensuring they are clearly marked and easily accessible, can significantly improve the evacuation process.

Also, there are other structural factors that are important for this research; not in terms of influence on evacuation performance, but in terms of implementation efficiency. These factors can be described as architectural complexity. Architectural complexity can be divided into horizontal and vertical architectural complexity. Horizontal architectural complexity, not to be mistaken with complexity for a systems perspective, refers to the complication of the horizontal layout of the building. For instance, a traditional office building has a more rectangular layout compared to a modern artistic airport terminal. Buildings with less complicated horizontal layouts are more efficient to implement in a simulation model. Vertical architectural complexity refers to the degree in layout changes across multiple floors. For instance, again, a traditional office building is likely to consists of layers with the same outer dimensions and inside layout, compared to a modern artistic airport terminal, where the area of the ground floor is less likely to be the same as the area on upper floors. When selecting buildings to use in a computer simulation model, it is wise to consider the architectural complexity of the building, since less complicated buildings are easier to implement, while still preserving realism of the actual layouts.

2.2.4. Technical Factors

The presence of exit signs, evacuation signs, or just signage for short, can impact evacuation performance (Hui et al., 2014). Conventional signage usually consists of green and white signs with an arrow pointing towards the nearest exit. Often these signs are lit, and connected to an emergency circuit, to prevent shutting off during power outlets. These signs are typically placed near exits, or at interval points on longer hallways. Studies show that people follow signage once they see them, but that the detection rate of these signs is crucial. Conventional signage is observed to have relatively low detection rates, often set at 38% (Filippidis et al., 2021). Therefore, researchers have experimented with so-called dynamic signage systems. A first experiment is performed with signs with flashing LEDs, improving the detection rate to 77% (Hui et al., 2014). Another experiment is performed with an Intelligent Active Dynamic Signage System, a system which display routing information on the sign (Galea et al., 2017). Such systems can be helpful in situations where routes are obstructed or closed, to successfully reroute evacuees to safer routes.

Effective communication with evacuation coordinators is essential for a smooth and organised evacuation process (Q.-A. Zeng et al., 2008). Coordinators need to be informed promptly about the nature and location of the emergency to direct evacuees appropriately. This can be achieved through integrated communication systems, such as radios or dedicated communication apps, that provide real-time updates and instructions. Ensuring that all coordinators are equipped with reliable communication tools and have clear protocols to follow can greatly enhance coordination and response times during an evacuation (Q.-A. Zeng et al., 2008).

Communicating efficiently with evacuees is critical to ensuring their safety and facilitating a calm and orderly evacuation. Clear, concise, and timely information helps prevent panic and confusion. Traditional methods, such as public address systems and visual alarms, should be complemented by modern technologies to reach a broader audience. For instance, multilingual announcements and visual cues can aid those with language barriers or hearing impairments.

Leveraging technology, such as SMS alerts, can significantly enhance the communication process during evacuations. SMS alerts can quickly disseminate critical information to a large number of people, providing instructions on evacuation routes, assembly points, and safety tips. This technology can be particularly useful in reaching individuals who may not hear alarms or public announcements, such as those in remote areas of the building or wearing headphones. Additionally, mobile apps can offer interactive features, such as real-time updates and GPS-based directions to the nearest exits, further aiding in a safe and efficient evacuation.

Figure 2.2 displays an overview to all influences to evacuation performance that have been covered in this section. Please note that this is not an exhaustive list. A selection of aspects is made, to fit the duration of a Master's Thesis Project.

2.3. Evacuation Performance

This section is about the different evacuation phases and metrics, which together form the evacuation performance.

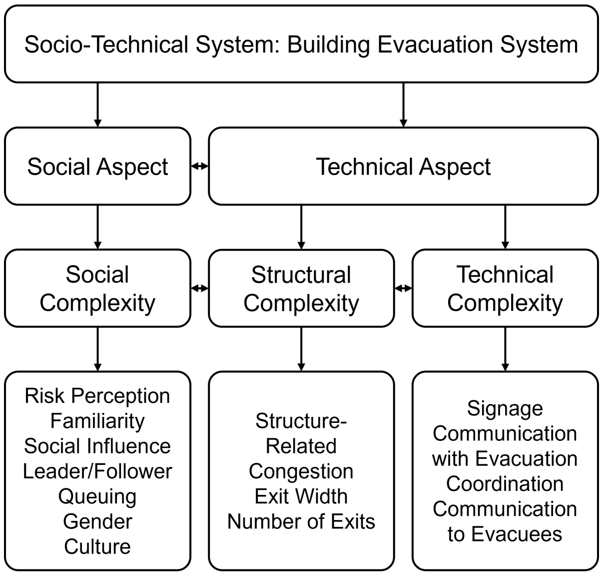

Figure 2.2: Socio-technical factors influencing evacuation performance mentioned

2.3.1. Evacuation Phases

In fire evacuation literature, two variables are of importance: ASET and RSET. ASET, Available Safe Egress Time, is the time from the moment a disaster is started, i.e. the ignition of a fire, until the time the disaster forms a safety risk, i.e. the moment smoke, gas, or heat create deadly conditions (Babrauskas et al., 2010; Gwynne, Galea, et al., 2019; Lovreglio et al., 2015). RSET, Required Safe Egress Time, on the other hand, is defined as the time from the start of the disaster, until full evacuation (Babrauskas et al., 2010; Gwynne, Galea, et al., 2019). A building is perceived safe if the ASET is greater than the RSET (ASET>RSET), implying evacuation time is less than the time until deadly conditions arise (Babrauskas et al., 2010; Gwynne, Galea, et al., 2019).

For understanding and categorising different steps in evacuation processes, concerning the RSET, evacuation timelines can be created (Galea et al., 2010; Wang et al., 2021). Galea et al. define two main evacuation phases, namely the response phase and evacuation movement phase (Galea et al., 2010; Gwynne, Galea, et al., 2019). The first phase, the response phase, can be further divided into three phases, namely notification, cognition, and activity (Galea et al., 2010). The notification stage begins after the incident is started, at the time the first cues are presented. Following, once the incident is perceived, the cognition stage starts, in which evacuees process their observations. Often closely followed or in parallel (Galea et al., 2010; Gwynne, Kuligowski, et al., 2019), the activity phase starts. In the activity phase, information is gathered and/or actions prior to evacuation movement are performed, like packing belongings or retrieving items. Wang et al. also divides evacuation time in two main phases, namely pre-travel phase and travel phase (Wang et al., 2021). However, unlike Galea et al., Wang et al. further divides the pre-travel or response phase, into two phases, namely recognition and validation, and evaluation and preparation (Wang et al., 2021). The next phase following the three phases in the response phase, is the evacuation movement phase (Gwynne, Galea, et al., 2019). Wang et al. also includes reentry time in this phase, while in Galea et al., re-entry time is not mentioned (Wang et al., 2021) (Galea et al., 2010). In relation to RSET, reentry does not apply, since in scenarios where the situation becomes unsafe or even deadly, immediate return is impossible. In section 2.1, the factors that influence the pre-travel phase and travel phase are explored.

2.3.2. Evacuation Metrics

In literature and national safety regulations, the objective of building evacuation (drills) is to perform evacuations while regarding safety of occupants and to perform the evacuations orderly (Gwynne, Kuligowski, et al., 2019). In Baig et al. (2024), an evacuation template is presented (Baig et al., 2024). This template is developed to provide a standard method of reporting evacuation drills. In evacuation templates, information about the incident, number and properties of occupants, and challenges of

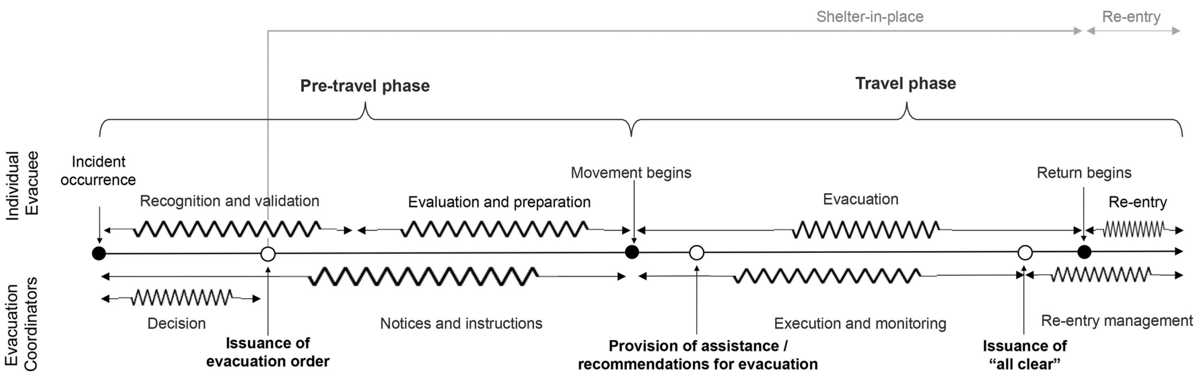

Figure 2.3: Evacuation timeline (Wang et al., 2021)

evacuations are noted (Baig et al., 2024). Here, we cover three different metrics, important to building evacuation.

Evacuation Time

The first important evacuation performance metric is evacuation time. Evacuation time is perhaps the most predominant metric to track, and often the only metric that is tracked (Van der Wal et al., 2021). Evacuation time is an important measure to consider, since it indicates if the current evacuation performance is sufficient enough to minimise casualties. That is, an evacuation time longer than the Required Safe Egress Time, the time needed to safely evacuate, means evacuation is not safe enough. Evacuation time therefore, is often the first metric that can show improvements in the evacuation system are necessary. Variations of evacuation time can be collected, like total evacuation time, and percentages, such as the time when 75% of occupants were evacuated.

Exit Choice

The second important evacuation performance metric is exit choice. Exit choice refers to the amount of occupants which select or exit through a specific exit. It is interesting to track the exit choice of evacuees, since it gives insight in their decision-making process. After all, the exit an evacuee might consider as their target exit at first might not be the exit they exit through. Also, insights in exit choice can be used to, for example, spread traffic across multiple exits, and therefore reducing evacuation time and lowering density. Research showed that exit choice is heavily influenced by the aspects we discovered in this chapter (Kinateder et al., 2018; Sagun et al., 2013; Xie & Galea, 2022). Therefore, exit choice is an important evacuation performance metric.

Density

The third important evacuation performance metric is density. Density refers to the amount of people present in a specific location, over a given time. Density gives insight in 'hot-spots' during evacuation, where many people might travel at a certain moment. With the information that density provides, measures can be taken to spread or redirect large crowds and traffic. Also, high density situations lead to lower visibility amongst evacuees, increasing the social influence behaviour and lowering the effectiveness of signage (Cao et al., 2021; Y. Ma et al., 2017).

3
Case Study: Complexity Science for University Campuses

In this research on building evacuation, we specifically look at university campuses. The research is focused on university campuses because of their diverse populations, differences in building familiarity, and architectural layouts. The research includes four influencing factors: building familiarity, social influence behaviour, egress width, and signage. Two buildings are selected: the Applied Sciences building, and the Civil Engineering and Geosciences building, both TU Delft campus buildings, because of their similar population distributions but different structural components. The complete motivation for the building selection, as well as the conceptualisation of the influencing factors, is described in this chapter.

3.1. Influencing Factors

3.1.1. Familiarity

Following the literature review, familiarity is shown to influence evacuation performance in building evacuation. Mainly, familiarity influences exit choice, and pre-movement time. In the conceptual model, this behaviour is included.

In the conceptual model, if an evacuee is familiar (enough) with the building, it is assumed that the evacuee selects the closest available exit. If the evacuee is not familiar, there are two possible scenarios. The evacuee entered the building through one of the building's entrances. Since the evacuee is not familiar with the building, it is assumed that it has limited knowledge about the presence of nearby (emergency) exits. Unfamiliar evacuees then select their entrance as the target exit. However, if they passed another main entrance underway to their room location, it is assumed that they remember that entrance, and therefore set their targeted exit to the nearest entrance.

- Familiar evacuees: select the nearest exit
- Unfamiliar evacuees: select the nearest entrance

3.1.2. Social Influence

Another phenomena that is included in the model is social influence behaviour, since it is proven to have an effect on evacuation performance in building evacuations. To conceptualise social influence behaviour, we create multiple scenarios.

If an evacuee is familiar with the building, the evacuee is less susceptible to social influence behaviour, since that evacuee possesses knowledge on the building (Haghani et al., 2019; Nilsson & Johansson, 2009). Also, proximity to groups has been described to influence the effect of the social influence behaviour. Next, the size of the groups also play a role. The bigger the group, the more likely to walk in the correct direction, at least it is perceived that way. Last, the gender distribution of groups is also important, since it is proven that people tend to get influenced by presence of persons of the same gender (Mao et al., 2024). Ultimately, the social influence behaviour influences evacuees routing behaviour, and exit choice.

Factors determining the social influence behaviour:

- Familiarity
- Proximity to group
- Group size
- Group gender distribution

3.1.3. Egress Width

In the conceptual model, we include egress width as a factor. Literature has shown that the width of exits plays a part in evacuation performance (Xiao et al., 2016). In this research, we will model existing university campus buildings. Egress width will vary in increments allowed in the simulation model.

3.1.4. Signage

Researched has shown that signage has an influence on evacuation performance (Filippidis et al., 2021; Galea et al., 2017; Hui et al., 2014). However, the detection rate of signage plays a crucial part in the efficiency of the signage (Galea et al., 2017), and that conventional signage does not produce optimal effects (Xie & Galea, 2022). Therefore, this phenomena is included in the conceptual model.

We conceptualise signage in the model with three different levels. The first level of signage is none. In this case, there is no signage present, and therefore no influence on the evacuee. The next level of signage is basic. This translates to the conventional signage that is present in most modern university campus buildings. This conventional signage has a detection rate of 38% (Galea et al., 2017). The third level of signage we conceptualise is advanced level. This entails conventional signage systems, but equipped with flashing LEDs. This extension increases its detection rate to 77% (Galea et al., 2017). Another implemented, but unused level, is the advanced level. Here, an Intelligent Active Dynamic Signage System is used (Hui et al., 2014). This signage systems consists of the benefits of the above, the flashing LEDs, but extended with the routing mechanic of the Intelligent Active Dynamic Signage System. This signage level will provide evacuees with actual routing information. Such intelligent, adaptive systems can be used to redirect evacuees, not only because of possible obstructions, but also to regulate traffic flow. An overview of the conceptualised signage levels, their working, detection rates, and influence on the evacuees is displayed in Table 3.1.

Level	Working	Detection rate	Influence on agent
None	None	N/A	None
Basic	Points to nearest exit	38%	Routes in sign direction
Intermediate	As basic, but with flashing lights	77%	As basic
Advanced	Displays routing	77%	Routes as sign provides

Table 3.1: Conceptualisation of signage

3.2. Performance Metrics

In the previous chapter, multiple metrics to measure the performance of evacuations were described. In this section, the three selected performance metrics are described, namely 75% evacuation time, mean density, and exit choice.

3.2.1. 75% Evacuation Time

The first metric that is included in the conceptualisation is 75% evacuation time. The evacuation time is important in the context of university campuses for two reasons: evacuation times much larger than the response time of emergency services conflict with existing law (Ministry of Internal Affairs and Kingdom Relations, 2011), and evacuation time is a frequently used metric in evacuation research (Astudillo Muñoz et al., 2022; Cao et al., 2021; Kobes et al., 2010). Conversations with building management in different TU Delft buildings, and earlier TU Delft evacuation research revealed that total evacuation time is often one of the few metrics tracked (Van der Wal et al., 2021).

There are several possible variations of evacuation time to use as a metric. Previous research has used 100% or total evacuation time, 95%, 90%, and 75% evacuation time (Astudillo Muñoz et al., 2022; Cuesta et al., 2014). For this research, 75% evacuation time is selected. The 75% evacuation time is selected over 95% or 100% evacuation time to eliminate outliers, and to capture the influence of the four included factors equitably. After the 75% evacuation time, the buildings can be mostly empty, leading to an over-representation of the effects of familiarity and signage, compared to an under-representation of the effects of social influence and wider egress, since the former two are independent of agent density, while the latter two are dependent of agent density.

3.2.2. Mean Density

The second metric that is included in the conceptualisation is mean density. Density, in general, refers to the number of people in a given space at a given time (Y. Ma et al., 2017). In this research, density is defined as the number of people in the exits and hallways on the main floor. Because of this definition, people in rooms, or on upper floors are not included in this metric. This allows abstractions and simplifications in agent behaviour in rooms and on upper floors.

Since there are no specific areas of interest in both buildings to determine the influence of the socio-technical factors, the density is determined for the entire main floor as a whole. Also, since there are no specific interesting thresholds, the mean density is selected as the performance metric in this research, instead of, e.g., maximum density.

3.2.3. Exit Choice

The third metric that is included in the conceptualisation is exit choice. In the context of university buildings and this particular research, it is interesting to track the exit choice of agents, because it can help to understand emergent behaviour of the system. Earlier in this chapter, the distinction on familiar exits and unfamiliar exits was made. Given that the number of exits per buildings is 19 for the Applied Sciences building and 7 for the Civil Engineering and Geosciences building, tracking each exit individually makes interpreting all data a challenge. Therefore, the data are combined into two categories: the number of agents who exited through an unknown exit, and the number of agents who exited through a known exit. Here, unknown exit are all exits that are not marked as main entrance, and known exits are all exits which are entrances. For this research, exit choice is described as the proportion of agents that exited through a known exit, their entrance, compared to the number of total agents.

3.2.4. Relations between Metrics

While traditional evacuation research focusses on evacuation time, we present three metrics in this conceptualisation. These three metrics are selected over only evacuation time to get a more clear understanding of the performance of each combination of factors. I.e., a scenario with a relatively low evacuation time could have a relatively high density. In this case, this high density could lead to bottlenecks and dangerous situations. The addition of exit choice in the conceptualisation allows for simple insight in agents decision-making. In case of scenarios with similar evacuation times, the exit choice can aid to determine the influence of the factors. Therefore, three metrics are selected.

3.3. Building Selection

The research focusses on evacuation in university campus buildings. For practical reasons, the output of this research consists of a computer model of multiple TU Delft campus buildings. Because of the time constraint on the duration of a Master's Thesis Project, two different TU Delft campus buildings are modelled.

Figure 3.1 displays the different campus buildings on the TU Delft campus, with the buildings under TU Delft's control in violet. A field visit provides first insights in the structure and dynamics of the buildings, to make an informed choice on building selection. Buildings on the TU Delft campus can have different purposes, which are mainly divided into three categories: education, research, and (campus) management. Section 2.1 illustrated that familiarity has influence on evacuation performance. Of

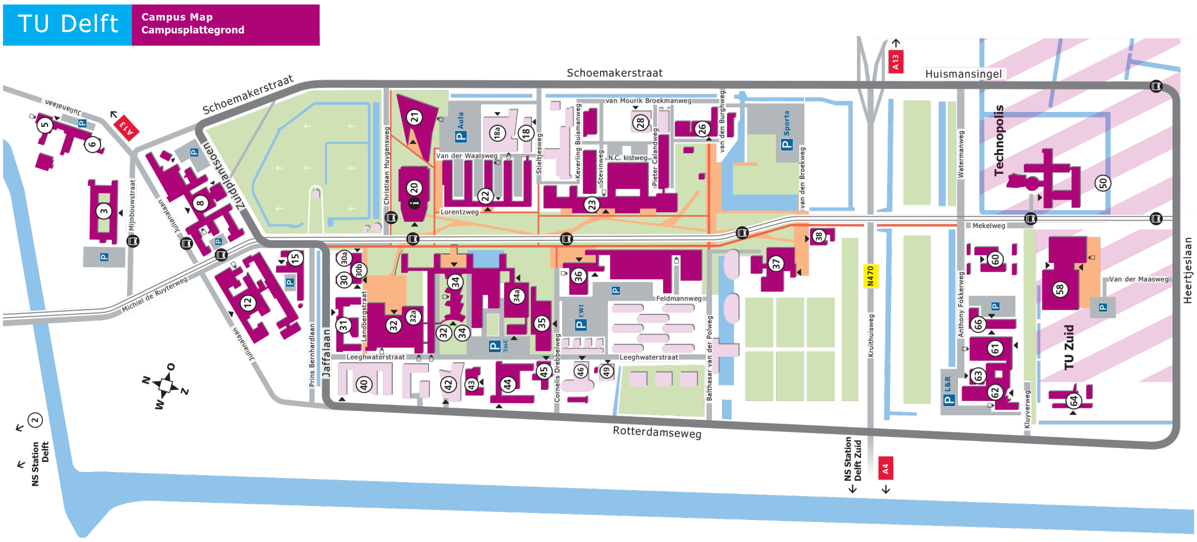

Figure 3.1: TU Delft campus map.

the three categories of building purposes, education attracts the most interesting mix of familiar and unfamiliar population, because lectures often take place at other faculties. Since occupants for research or management purposes are often employees of that faculty or building, they are likely to visit the building multiple times compared to e.g. students who visit a building for lectures, it is assumed that (sections of) buildings with research or management buildings have a higher percentage of familiar occupants. Therefore, it is most interesting to study buildings with education purposes.

Another selection criteria lies in angular and regular forms in the building layout. In simulation software, the environment is often made up of square patches in a grid structure. This square grid structure poses challenges for building layouts with more creative hall and room layouts. Therefore, it is preferred to select a building with a squared layout. Also, since all of the TU Delft education buildings, with an exception in the Flux buildings, are multi-level buildings, a building with a layered structure is desirable. An example of a TU Delft campus building with no easy layered structure is the Aula building. Furthermore, the presence of uneven floors, mezzanines et cetera, creates for a difficult modelling experience. Conventional simulation software is often a two-dimensional application. It is more difficult to model a level with a built-in stairway, a mezzanine, because the horizontal speeds of human differs on a stairway compared to a level floor. Examples of TU Delft campus buildings with a difficult level structure are the lower part of the Aerospace building, with pits, and walkways one meter above others, or the Pulse building, with rooms touching multiple levels.

3.3.1. Applied Sciences building

Following the requirements described above, there are two TU Delft campus buildings selected to include in the model. The first building that is modelled is Technische Natuurkunde (22). This building is also known under the names Technische Natuurwetenschappen (TNW), the name of the faculty the building belongs to, or Applied Sciences, the English name. Also, in recent years, the faculty has shifted its research activities to a newer building in the south of the campus, conveniently named Applied Sciences (58) (TU Delft Campus, 2023). For the remainder of this research, this building is referred to as the Applied Sciences (AS) building.

There are several reasons why the Applied Sciences building is selected as the first case to implement in the model. The first reason is the horizontal architectural complexity of the building. The building outline reveals a relatively simple structure, with five wings connected by a larger wing. The wings can be simplified to five rectangles equal in size, connected by another rectangle. The second reason is the vertical architectural complexity. In the Applied Sciences building, there is a total of six floors including the basement. Observing the floor plans, reveals that all floors build up from the ground floor (or even basement floor, for that matter) in the same layout (see figure 3.2). Meaning, there are no new layouts presented after the ground floor. The wing A-D all are three stories high, with the E-wing


Figure 3.2: Aerial photo of the Applied Sciences building (left), plan of the Applied Sciences building with overlay, highlighting the simple structure (right).

four stories and the F-wing being five stories tall, all without including the basement. This stacked, layered layout makes it more efficient to model multiple floors, since their layout is closely equal. The third reason is the absence of mezzanines or level changes. The Applied Sciences building consists of floors with no changes in level. This creates a level environment without abrupt interruptions. The fourth reason to select the Applied Sciences building is the presence of spacial constraints. One predominant spacial constraint in the building is the hallway width; being approximately two metres around most of the building, also in sections with education rooms, which can produce up to 132 in case of the first education room on the ground floor, in the A-wing (TU Delft, 2024). In case of evacuation, all these evacuees have to manoeuvre in this narrow halls, which makes it interesting to observe in the simulation model. The fifth and last reason is varying occupancy levels. The Applied Sciences building offers a range of education rooms, mostly housed in the A- and F-wing, topped by an exam room with a 200 person capacity all the way on the fifth floor, stretching across the F-wing (TU Delft, 2024). The interesting mix of education and research spaces in the building can display differences in evacuation performance, for example when comparing wings.

3.3.2. Civil Engineering and Geosciences building

The second building selected to be implemented in the simulation model is the Civil Engineering and Geosciences building, also known as its abbreviation CEG, or its building number, 23. This building houses, as in the name, the civil engineering studies, as well as a section for the geosciences studies.

Like the Applied Sciences building, there are also several reasons why the Civil Engineering and Geosciences building is selected as a case for the simulation model. The first reason to select this building is its horizontal architectural complexity. The main part of the building (from the first floor onwards) consists of a 260+ metre long rectangle, with notches for lecture halls. This differs completely from the Applied Sciences building, which consists of multiple wings. The second reason is the vertical architectural complexity. In this case, just like the Applied Sciences building, the building levels follow the same outline structure, meaning the building consists effectively of layers stacked upon each other. This is more efficient for implementation, since the layout can be reused. The third reason is the absence of mezzanines or level changes. In this building, in contrast to the Applied Sciences building, there is a mezzanine present, at the right end of the building. The stairway connects the narrow hallway at the right end of the main hall of the first floor with instruction rooms and the upper entrance of the lecture hall. In the building plans, this mezzanine is regarded as level 1. The fourth reason to select the Civil Engineering and Geosciences building, is the presence of spacial constraints. As lightly described before, there are multiple instances of (presence or lack of) spacial constraints, when comparing to the other building. In this building, the main hall changes width multiple times, with narrow halls in the geosciences section at the left end, broad halls in the middle left, and narrow walkways from the middle right onwards. It is interesting to observe the effect of these spatial constraints on the evacuation performance. The fifth reason to select this building is varying occupancy levels. In contrast to the Applied Sciences building, the Civil Engineering and Geosciences building's main floor has access points to multiple lecture halls, spread evenly along its hallway. Also, there are no research activity rooms on the main floor, apart from the geosciences section. In this building, the research activities occur in the

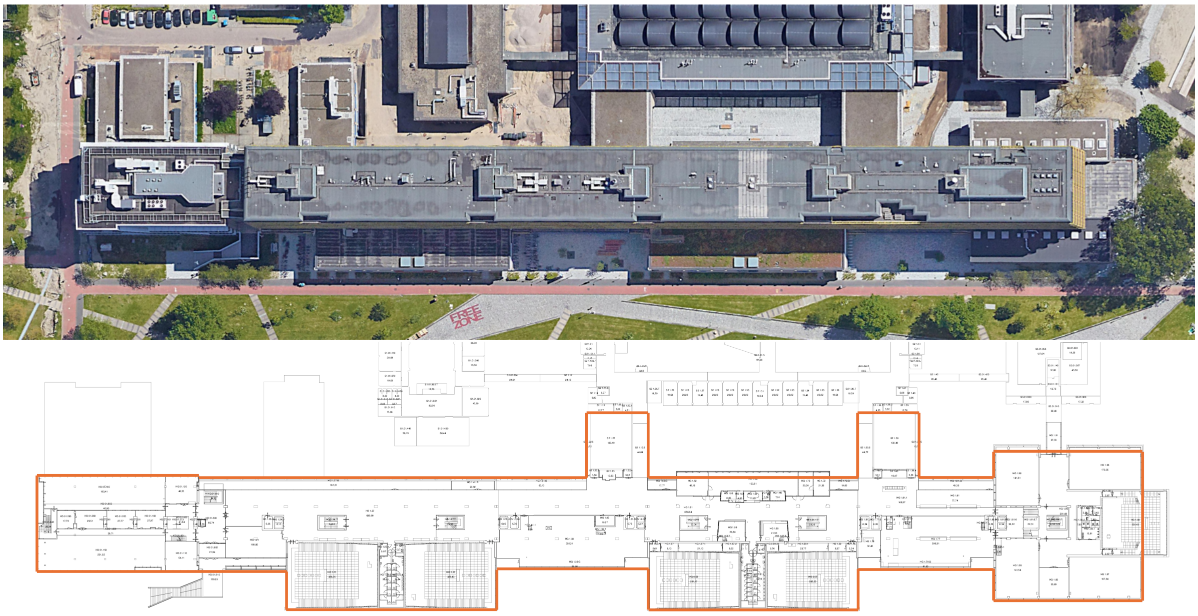

Figure 3.3: Aerial photo of the Civil Engineering and Geosciences building (upper), plan of the Civil Engineering and Geosciences building with overlay, highlighting the simple structure (lower).

side buildings, which will not be regarded in this research, and in the office rooms on the higher floors. In case of evacuation, this means a stream of mostly familiar research personnel from all stairways.

4
Agent-Based Model

Following the literature review and the conceptualisation, the conceptual model will be formalised in this chapter. This formalisation entails the translation from formal concepts and relations to in-practice agent behaviour. The agent-based model has to be formalised using modelling and simulation software. There are multiple modelling and simulation tools to model and simulate agent-based models. Among others, Repast, GradABM, FlameGPU and Netlogo are popular simulation tools (Chopra et al., 2023; Niazi & Hussain, 2009; North et al., 2008; Richmond et al., 2023; Taylor et al., 2015; Thiele et al., 2012; Umlauft et al., 2022). Because of its relatively lower model development effort combined with its medium/high computational modelling strength, Netlogo is selected as the modelling and simulation tool (Abar et al., 2017). An overview of the model interface is shown in Figure 4.1.

4.1. Sub-models

The model is built through ten sub-models: environment setup, pre-evacuation time, moving, upper floors, exit selection, path finding, familiarity, social influence, wider egress, and signage. In this section, the implementation of these sub-models are described in detail.

4.1.1. Setup of the Environment

In Netlogo, there are three main entities that can interact with each other, namely agents, patches, and links. In this model, the environment of the agents is formalised by the patches, which together represent the TU Delft campus buildings. In the Netlogo model, there are eight procedures called by the main setup procedure to setup the environment.

The setup starts first, after clearing all data from previous runs, by setting up the values of global variables. This entails colour values for patches, as well as declaring lists and output variables. Next, the outline of the chosen building is drawn. This is performed by a temporal agent, a non-evacuee, which follows a serpentine pattern to the coordinates of corner patches. After, the room and hall patches are coloured. Because of the layered layout of the Applied Sciences building (halls in the middle layer, almost completely surrounded by rooms, the second layer, which are almost completely surrounded by the building outline, the outer layer), the rooms and halls are created with this serpentine pattern again, going in layer towards the centre. Because there are some exceptions to this layered layout, such as at the end of wings, or at connection points between wings, manual changes are made afterwards. In the Civil Engineering and Geosciences building, there are a lot of islands of rooms, encapsulated by halls and the outer wall. Therefore, a flooding or ripple effect function is used (Wiberg & Harris, 1994). Because this function is highly similar to the Breadth-First Search, the procedure can switch modes, to serve both needs. On the main floor in the Civil Engineering and Geosciences building, all rooms are connected by the central path, without obstructions (apart from several doors near the ends in real life, but this is not in scope). Therefore, the central hall is also drawn by flooding.

Next, the exits are simulated. This is performed by declaring each exit as a list of patch coordinates, to allow for easy manipulation. This way, exits can be of multiple shapes, especially for the Applied

Figure 4.1: Overview of the model interface in Netlogo, with AS as the chosen building

Sciences building, where some stairs are part of the exit. For such exits, the entrance point of the exit is not considered the same as with a straight exit. Therefore, an outline is needed, to prevent agents from entering an exit through a fence for example. All exits are collected in a list of exits. This makes enabling or disabling exits possible, since its name can be removed from the list, resulting in that exit not appearing. The exits are provided with labels displaying their name.

All room or hall patches in the model store, among others, two pieces of important data. These data is the closest patch of the (entrance of the) nearest exit, and the nearest main entrance of that patch. This is done to increase performance of the model. Now, instead of each agent calculating the nearest exit or entrance by itself, it can simply retrieve this information at the patch. This is especially helpful in scenarios where there are more agents calculating routes from the same starting point (the nearest hall patch). A downside of this method is when the environment changes over time, for example in case of routes getting obstructed or inaccessible. In this project, there are no such instances.

After the exits, the assembly point and the upper floors are set up. The assembly point, the place where the agents who have evacuated stay to keep them in the model, is nothing more but a coloured square. This is the same for the upper floors. This formalisation is selected to keep agents in the model for monitoring and graphing purposes. By keeping agents in an environment, but in a physical space outside of the building, it is easy to isolate them in agent code.

The signage is set up as a label attribute of the patch. The locations of the signage is replicated from the actual signage locations in the buildings. The signage patches use the Breadth-First Search algorithm to determine the direction to point in. This is different from using the general distance function in Netlogo, since signage is to point in the direction from that point to

Lastly, the agents are set up. Agents get assigned random values, such as a random position inside the building, as well as values for familiarity, attentiveness, and persuasibility. The agents have a chance to spawn on an upper floor, which can be altered by the user.

4.1.2. Pre-Evacuation Time

As described in subsection 2.3.1, evacuations are predominantly the sum of the pre-movement phase and the movement phase. In this model, the pre-movement phase is included. Studies showed the pre-movement time is dependent on the type of cue the evacuees receive. For instance, a spoken alarm text yielded longer pre-movement times than a siren alarm (Forssberg et al., 2019). In case of evacuation in TU delft buildings, the broadcasted alarm is always a siren. In the model, these properties are taken into account. However, the scope of the research entails the influence of the socio-technical factors on the movement phase of evacuation. Therefore, we include the pre-movement time as part of the evacuation model, but we do not vary it based on other properties, such as character traits, familiarity, or the selected building.

4.1.3. Moving

The procedure that is most visible in the model is the agent moving procedure. This procedure handles the actual, physical movement of the agents. Since the main floor is displayed only, moving on upper floor is simulated with a time delay only. The movements on upper floors will be described later in this section.

A large proportion of the code in the moving procedure is dedicated to the position of the agent. For each of the different possible patch types, i.e. a hall patch, a room patch, an exit patch, etcetera, the agent will perform differently. If the agent is on a patch belonging to the assembly point, it has to stay in the model, but not perform any more tasks. If an agent is on an outside patch, it is regarded as outside of the building. Therefore, it is regarded as evacuated, and will be teleported to the assembly point. This is also done to keep them in the model, for statistical purposes, and to keep the outside of the model neat.

The moving algorithm makes use of multiple stages, which are completed in a set order. Upon setup, all agents are considered to be in rooms, either on the main floor or on other floors. Agents in rooms are facing the nearest hallway by default, and move towards that hall. When arrived on a hall patch, the next stage, the agent is never able to return to a room patch. This eliminates returns or movement to other rooms. In the halls, agent follow their predetermined path towards their selected exit. Their paths can however be altered due to social influence or signage, which are included in other sub models. Agents face the next patch, and step forward with a determined stride length until arrived at the next patch. Then, that patch get popped from the path. The agent follows its path, which ultimately leads to an exit patch. Arrived at the exit, the agents face the outside patch, and step forward until out of the building. This stage-oriented implementation eliminates the possibility to move away from progressing to the next stage, for example from a hall back into a room. In real life, such instances can occur when people go to retrieve personal belongings, or to help others who might be disabled (Koshiba & Suzuki, 2018).

Agent use a spreading mechanic to be able to spread around, and pass other agents. If not implemented, long queues would form. To realise this, agents compare the number of agents on their patch to the patches directly left and right to them, given their heading. If there is a patch that has much fewer agents on it compared to the agent's own patch, the agent moves there. In reality, people look forward to determine the presence of a faster path (Zou et al., 2018). Implementing this phenomenon requires the agent to be able to consider the future density values of the patches in front of it. This method is computationally very inefficient, since the future density values have to be calculated of each walkable patch in every time step.

The walking speed of agents is influenced by the agents close to itself and its gender. Following literature, walking speed is decreased based on a higher number of agents near the agent (Ibrahim et al., 2016; H. Kim et al., 2019; Yugendar & Ravishankar, 2018). Also following literature, female agents have a decreased stride speed compared to men (Yugendar & Ravishankar, 2018).

4.1.4. Upper Floors

Almost all TU Delft campus buildings are multi-level buildings, with the temporary Flux building as an exception. In the model, we need to account for the upper floors, and include them in the formalisation. There are several ways to implement these upper floors. Perhaps the most obvious way to implement upper floors in the model is by creating physical levels, with their own rooms, halls, and exit points, and displaying them all in one view. The layouts would be highly similar and therefore reusable, allowing for a quick implementation time. However, this method of implementation also brings downsides. The chosen simulation environment, Netlogo, is two-dimensional by default. Since connection points in-between floors (the stairs) cannot be connected in a two-dimensional environment, we have to implement a way of connecting the floors. A relatively simple way to connect the floors, through the stairs,

Algorithm 1 Agent Moving Procedure

```
if not at the assembly point then
    if on an outside patch then
        move to the assembly point
    else                                                        ▷ if in the building
        if in a hall then                  ▷ agents in a room are already facing the hall
            if on the next patch of route then
                remove patch from route
                face next patch on route
            end if
        else
            if in an exit then
                face the outside patch
            else
                if on an upper floor then
                    move to the set location on the main floor
                end if
            end if
        end if
        if there are less evacuees left or right than here then
            move there
        else
            if there are more evacuees close-by then
                decrease moving speed
            end if
            move forward
        end if
    end if
end if
```

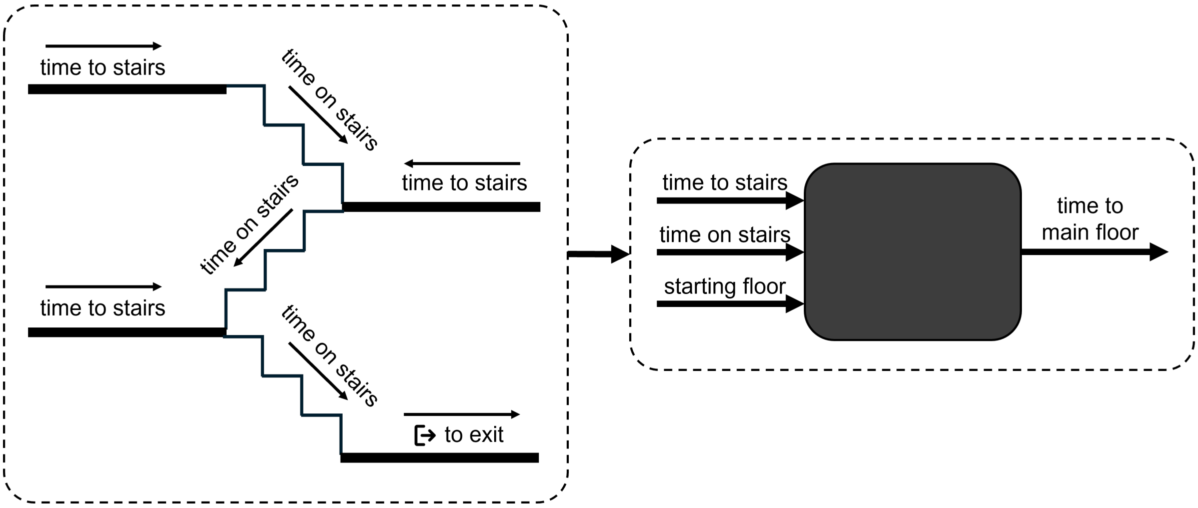

Figure 4.2: Formalisation of Upper Floors: Visualisation of the situation (left), implementation through "black box" (right)

would be to teleport agents from one level to the other on the same two-dimensional plane. With larger numbers of agents, tracking agents would be more difficult, because agents move large distances on the view when moving to another floor. Also, every stair needs to be linked to its next part on the floors going downwards. This would be an extensive task when linked manually or automatically, but would also be challenging for applying density limits. Lastly, since the upper floors in both the selected buildings are extremely similar per building, it is not likely that we observe different challenges or behaviour comparing one upper floors to another.

Following the described method of visually implementing upper floors, another option is to implement the upper floors computationally, which is the selected method in the model. Instead of visually displaying the upper floors, the floors are solely represented by a blue square, located outside of the building. On this square, all agents which are to be on all upper floors are located. This square asks as a source, from which the agents get teleported to their destination on the main floor once their simulation is completed.

In the real world situation, the agent performs multiple steps before it arrives on the main floor. First, it has a pre-evacuation time, then it moves from their room to the hall, from the hall to the stairs, and descends until it arrives on the main floor, where it follows the same procedures as the other agents on the main floor. This behaviour is independent of the floor number the agent is on, apart from the number of stairs the agent has to descend.

In the simulation model, this behaviour is included, by simulating the described processes as a time delay. An agent get assigned a position on the main floor, and uses the pathfinding algorithm to assign their route to the nearest exit. Since most exits have stairs above them or very close to them, that route can be interpreted as the route from a position on an upper floor to the stairs. It uses that route, combined with a set average walking speed on upper floors, to calculate the time it takes to move from that position on the upper floors to the stairs. Then, once "arrived" at the stairs, it calculates the descend time with the number of floors it needs to descend, multiplied by the average time to descend one level (Norén et al., 2014). The combination of these times together forms the duration an agent takes from a random position on a random floor to (close to) its target exit on the main floor. The formalisation using this method is visualised in Figure 4.2.

Once the time delay of upper agents is expired, the simulation model checks for any available patch in a 6-8 metre radius where the number of agents present is not higher than the physical maximum. In real life, most exits are positioned directly under a staircase, but not all exits. This means that the distance from the entrance patch from the staircases to the main floor and the exit patch would differ with each combination of stairs and exit. In addition, for instances with stairs directly above exits, an additional mechanism has to be implemented to determine which agent (an agent from the upper floors versus an agent from the main floor) can enter that patch if its density is below the maximum.

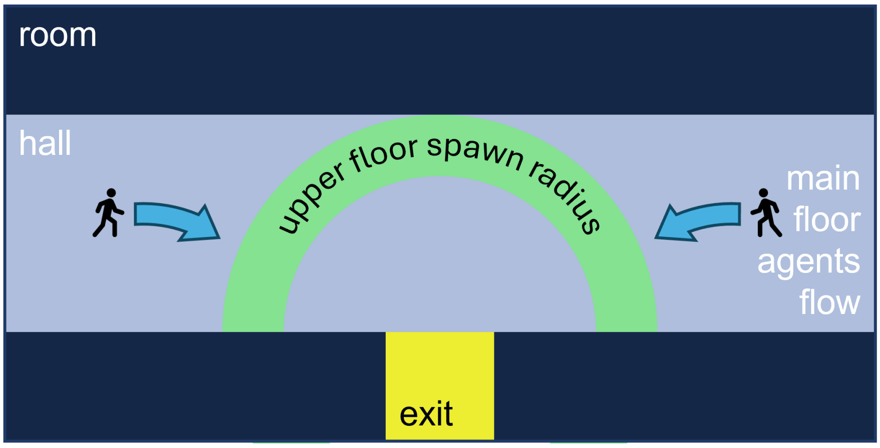

Figure 4.3: Spawn radius of upper floor agents

Previous research revealed that evacuees show an arc shape around exits once they become more crowded (Cao et al., 2021). To allow agents from upper floors to enter the main floor without the need for advanced queueing and priority algorithms, we can spawn the agents on, or slightly behind, that arc. This way, agents still can get stuck in the congestion near the exits, but do have an opportunity to get on the main floor. For efficiency purposes, this simplification is made, and agents from upper floors enter the main floor from a set radius, equal for all exits. A visual representation of this mechanic is shown in Figure 4.3.

4.1.5. Exit Selection

Exit selection is another sub-model of this model, and controls the initial target exit of the agents. The exit selection procedure is called during the setup of the model. During the model run, agents' target exit can get changed, either through social influence or through signage.

During initial exit selection, there are two possible exits: the closest **exit** to the agent, or the closest **entrance** to the agent. The choice of one or the other depends on the agent's familiarity value: if the agent is considered familiar with the building layout, it is assumed to know the closest exit from its position. If the agent is considered not familiar, it is therefore assumed to not know the closest exit from its position. In that case, the agent selects its entrance point as its target exit (Sadri et al., 2014). Since those agents are unfamiliar with the building, their entrance might not be the entrance that is closest to their position. The algorithmic view of the exit selection procedure is shown in Algorithm 2.

Algorithm 2 Exit Selection Procedure

```
if not at the assembly point then
    if familiarity of agent higher than threshold then
        agent is familiar
        find a path to the closest exit
    else
        agent is not familiar
        if chance to enter through the nearest entrance is higher than threshold then
            find a path to the closest entrance
        else
            find a path to another entrance
        end if
    end if
end if
```

4.1.6. Path Finding

Path finding in the model is based on two similar algorithms, namely Breadth-First Search and A. The Breadth-First Search algorithm is used by the agent to determine the nearest exit. The Breadth-First Search Algorithm is needed by the A* algorithm, since the A* algorithm requires the target as an input. Netlogo, the programming environment, comes with a built-in distance function, and combined with other built-in Netlogo selection functions, like *with-min*, the closest exit to the agent can be found. However, this distance is the great circle distance from start to goal. This poses difficulties in modelling the environment realistically, since this closest great circle distance might select an exit which has no or at least a longer actual route from the starting point. An example of a scenario like this is Figure 4.12 (right), where the nearest exit as the crow flies is the exit left of the start, but cannot be accessed as easily as the other exit. The algorithmic view of the working of the Breadth-First Search algorithm is displayed in Algorithm 3.

Algorithm 3 Breadth-First Search Algorithm

```
ask-next = current-patch of the caller
while not found? do
    if one of the neighbours of one of the ask-next patches, that is not visited yet, is a target then
        report the location of the target-patch
        exit the while loop
    else
        Add the visited patches to a list
        Add the visited patches to a list with patches that have been visited this round
    end if
    set the ask-next list to the list of patches that have been visited this round
    empty the visited this round list to use in the next loop
end while
```

The second algorithm that is used in the model is the A* algorithm. The A* algorithm is used to find the shortest possible path from a start to a destination (Yang et al., 2017). The A* algorithm is a commonly used path finding algorithm, in agent-based models (Yang et al., 2017). In this model specifically, the A* algorithm is selected over other link algorithms like Dijkstra, because of the differentiation in patches. I.e., paths in this model should only exit of hall patches, since the simplification is made to not regard re-entry of rooms. Therefore, the algorithm has to include possibilities to detect if patches are allowed, hence using A*. The A* algorithm works with a heuristic function, by checking the actual cost to travel to a patch, combined with the estimated costs. It keeps exploring the patches with the lowest combined costs, until it reaches its destination (Yang et al., 2017). The A* algorithm is also programmed to handle exceptions, when there is no possible route. As mentioned in other sections, we assume there are no obstructions in this model. The algorithmic view of the working of the A* algorithm is displayed in Algorithm 4.

4.1.7. Familiarity

Modelling familiarity is a topic that has been researched by previous researchers and proven to be a large influencing factor in evacuation performance (Kinateder et al., 2018). Literature shows people are likely to follow routes that are familiar to them during evacuation (Rendón Rozo et al., 2019; Sadri et al., 2014). Therefore, we formalise familiarity as a factor in exit selection decision making, as described in previous sections. If an agent is familiar, the agent will route towards its nearest exit. If an agent is not familiar, it will route to the entrance it entered through, that may or may not be the entrance that is closest to them. Also, the presence of familiarity has an effect on social influence behaviour (Haghani et al., 2019). Literature showed that familiar agents can function as an example for unfamiliar or less familiar agents (Nilsson & Johansson, 2009), and that unfamiliar agents can change their route and target exit when familiar agents are present (Haghani et al., 2019). In the model, we let these familiar agents perform as leaders or examples by making them insusceptible to social influence of neighbouring agents, while making unfamiliar agents susceptible to social influence behaviour. The mechanics of social influence behaviour is described in the next subsection. An overview of the influence of familiarity is displayed in Table 4.1.

Algorithm 4 A* Algorithm

```
function AStar(start, goal)
    Add start to open list
    while open list is not empty do
        Choose node with lowest cost (f) from open list
        if node is goal then
            return path
        end if
        Move node to closed list
        for each neighbour of node do
            if neighbour is not in closed list and not an obstacle then
                if neighbour is not in open list then
                    Add neighbour to open list
                    Set neighbour's parent to node
                    Calculate cost for neighbour (f = g + h)
                end if
            end if
        end for
    end while
    return no path found
end function
```

Table 4.1: Formalisation of familiarity

	Familiar	Not Familiar
Exit Selection	Nearest exit	Nearest or random entrance
Effect of Social Influence	No influence	Susceptible to social influence

4.1.8. Social Influence

To formalise social influence, the discovered subfactors, discussed in the previous chapter, are considered: persuasability, presence of nearby groups, and group size. As social influence behaviour is linked to leader-follower behaviour, there needs to be a way to describe leaders, or individuals, or simply determined agents. This is performed by marking agents who are familiar as such, therefore those agents get no chance to be influenced by others. The social influence algorithm consists of 5 checks any agent has to pass. Checking familiarity is the first step of the social influence algorithm. If not familiar, the algorithm checks if the agent is on a hall patch, since any behaviour is only allowed there. If true, the algorithms checks if the agent is persuaded before. This is done to prevent agents from executing the algorithm every time step. If this is not the case, the algorithm checks if there are any groups in sight of the agent. These groups need to be greater than a set size, because literature showed agents are more likely to follow bigger groups (Nilsson & Johansson, 2009). Also, the distance to the group is important (Haghani et al., 2019; Kinateder et al., 2018). Lastly, the persuasability, how susceptible the agent is, needs to be above the set threshold. If all those conditions are passed, the agent selects one member of the group, and copies its target exit. Since that agent is most likely not at the same exact position as the caller agent, the caller agent itself needs to find a new path to its new exit. A flowchart of the mechanic is displayed in Figure 4.4.

4.1.9. Wider Egress

The formalisation of wider egress might seen straightforward, just increasing the width of the exits. An important detail is that Netlogo works with patches, squares that can represent a physical space. In this model, one patch represents one square metre. Physically widening the exits in the simulation model means that exits can only increase per metre in width.

Exits are widened on each side to preserve symmetry. This poses challenges to certain exits, because multiple exit possibilities exist. The first exit possibility is one that is most common in the Applied Sciences building: exits with one side to the outside, two sides touching room patches, and one side to

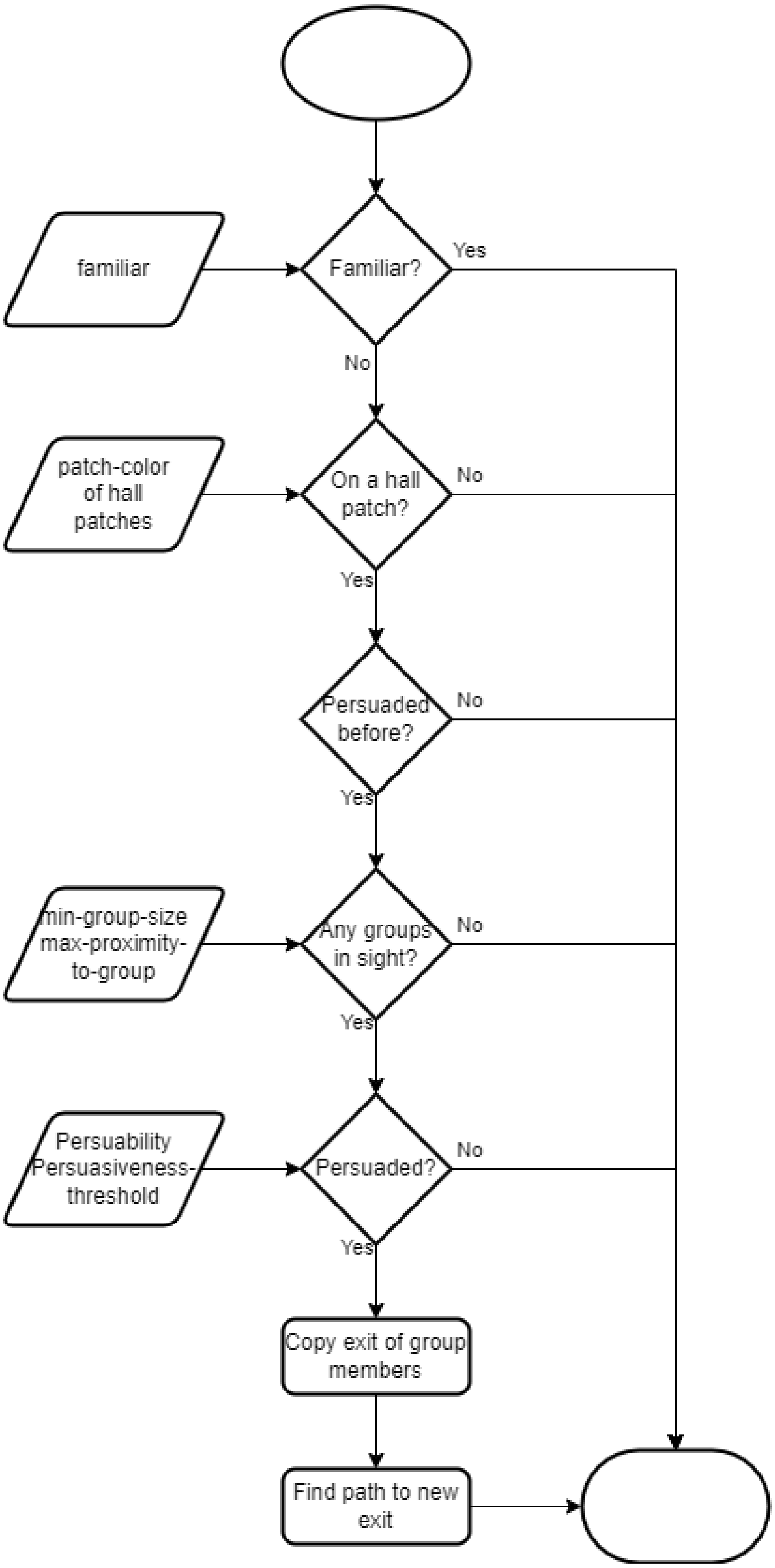

Figure 4.4: Flowchart of social influence

Figure 4.5: Example of widely used exit signage

the halls. Because of the movement phases (from rooms to halls to exits), agents are unable to enter an exit through a room, since they first need to path-find to a hall patch. This type of exits are widened by selecting the patches that have at least one room-patch neighbour in the eight patches surrounding them. The second exit type is mostly found in the Civil Engineering and Geosciences building: the stairways in the middle of the halls, surrounded by glass, with one opening on one side. To model this type of exit, an outline is placed around the exit patches, to prevent agents entering from all sides. To widen these exits, the top and bottom row of patches ask their neighbouring hall patches to copy the caller's patch type, and those callers in turn become exit patches.

4.1.10. Signage

Signage is the last of the sub-models included in the simulation models. In the conceptualisation, four possible levels of signage were introduced: no signage, basic signage, intermediate signage, and advanced signage. Now, three levels are implemented: no signage, basic signage, and intermediate signage (now named advanced).

The locations of the exit signs in the simulation model are placed in the same locations as in the building in real life. To achieve this, a field visit has been performed, and the exit signs have been drawn on the building map. The coordinates were visually matched with the map to determine the locations in the simulation model.

Conventional exit signs consist of an arrow combined with either a door or a man running through a door, as shown in Figure 4.5. According to previous research, there are no strict rules in determining the direction of the arrow of the signs (C. Kim et al., 2016). In the real-life situation, in the two buildings, signage is mostly placed close to exits or stairs, or in the middle of longer hallways where the distance towards exit is larger. The signs are placed so that a network of signs exists which, when followed, always leads towards an exit. In the buildings, signs point in the direction towards the exit or stairs. In the simulation model, the direction of the sign arrow is determined by reusing the exit routing algorithm to determine the closest exit, and then determines the direction of the first path in route compared to the patch of the signage.

An assumption of this simulation model is that agents always have an executable route. When an agent would detect one sign, but not the next, this would leave the agent in a state of wandering, conflicting with this assumption. To prevent this, one solution might be to force the route to the next sign ahead to the agent. With this method, signs would have to calculate where the next sign is, given their shown

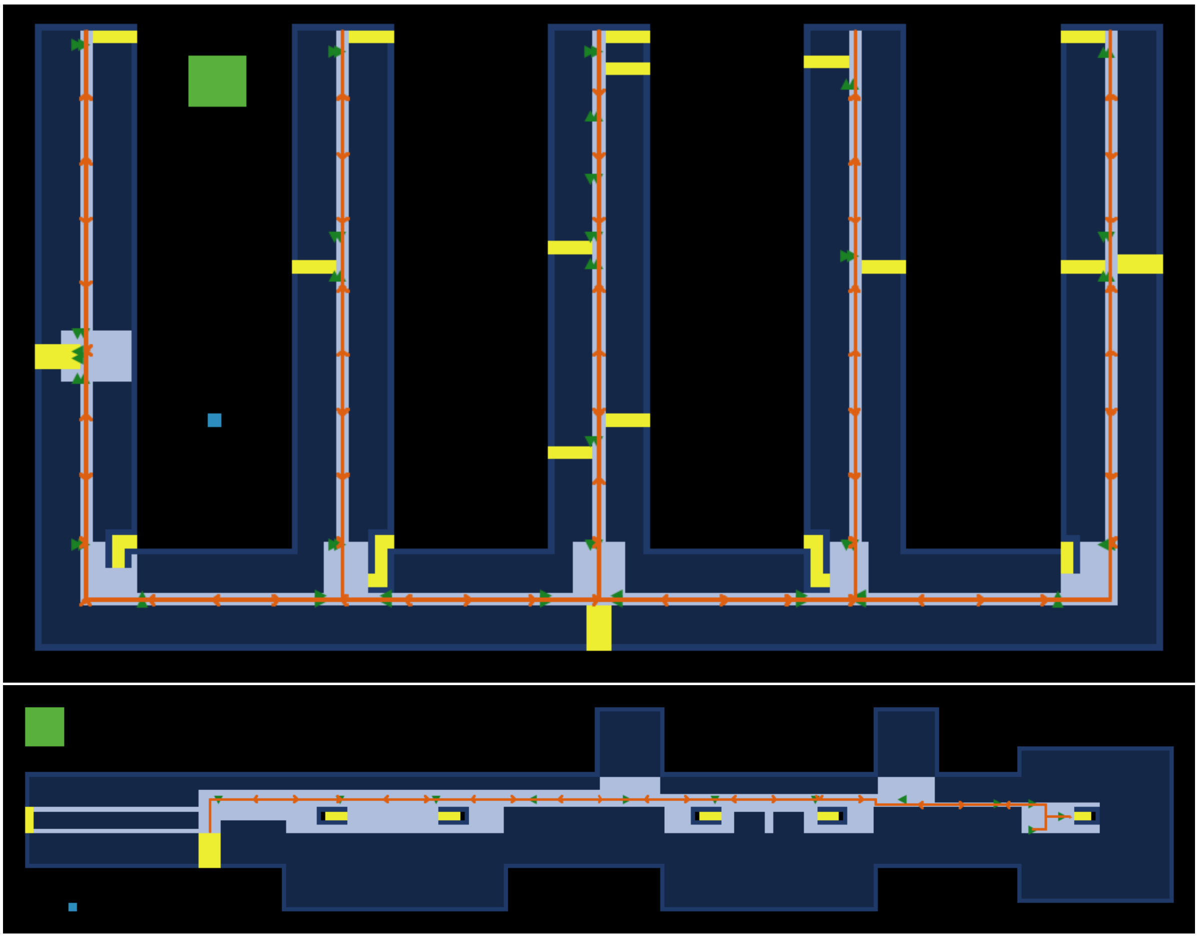

Figure 4.6: Model view displaying the direction (orange) to each sign (green) from hall patches, for both buildings.

direction and the direction the agent comes from. This process is computationally extremely inefficient and greatly increases run times.

The implemented signage solution honours simplicity, as described in Ockham's razor (Lazar, 2010). In reality, the signs are placed in a network-like configuration, as shown in Figure 4.6. This prevents agents from wandering or looping if the signs are followed. Also, scenarios are created as normal situations, without obstructions. Therefore, if an agent detects a sign, it is assumed that it can detect all signs. If an agents sees a sign and the agent's attentiveness value is above the set detection rate, it will follow those signs by setting its route towards the nearest exit. The detection rate of conventional signage and advanced signage are based on previous research (Filippidis et al., 2021). The flowchart of signage is displayed in Figure 4.7.

4.2. Verification and Validation

Verification and validation tests are performed for five different elements of the model. The selection and design of these tests is based on previous research (Gwynne et al., 2012). Tests are performed for pre-evacuation time, density and walking speed, familiarity and exit choice, the routing algorithm, and face validations.

4.2.1. Pre-evacuation Time

To verify that the model correctly implements pre-evacuation time, we conduct an experiment within the normal simulation environment. In this test, we systematically vary the number of agents from 100 to 2000, increasing in steps every 100 runs, and measure the average pre-evacuation time in each scenario. Since pre-evacuation time an always included piece of behaviour that adds directly to

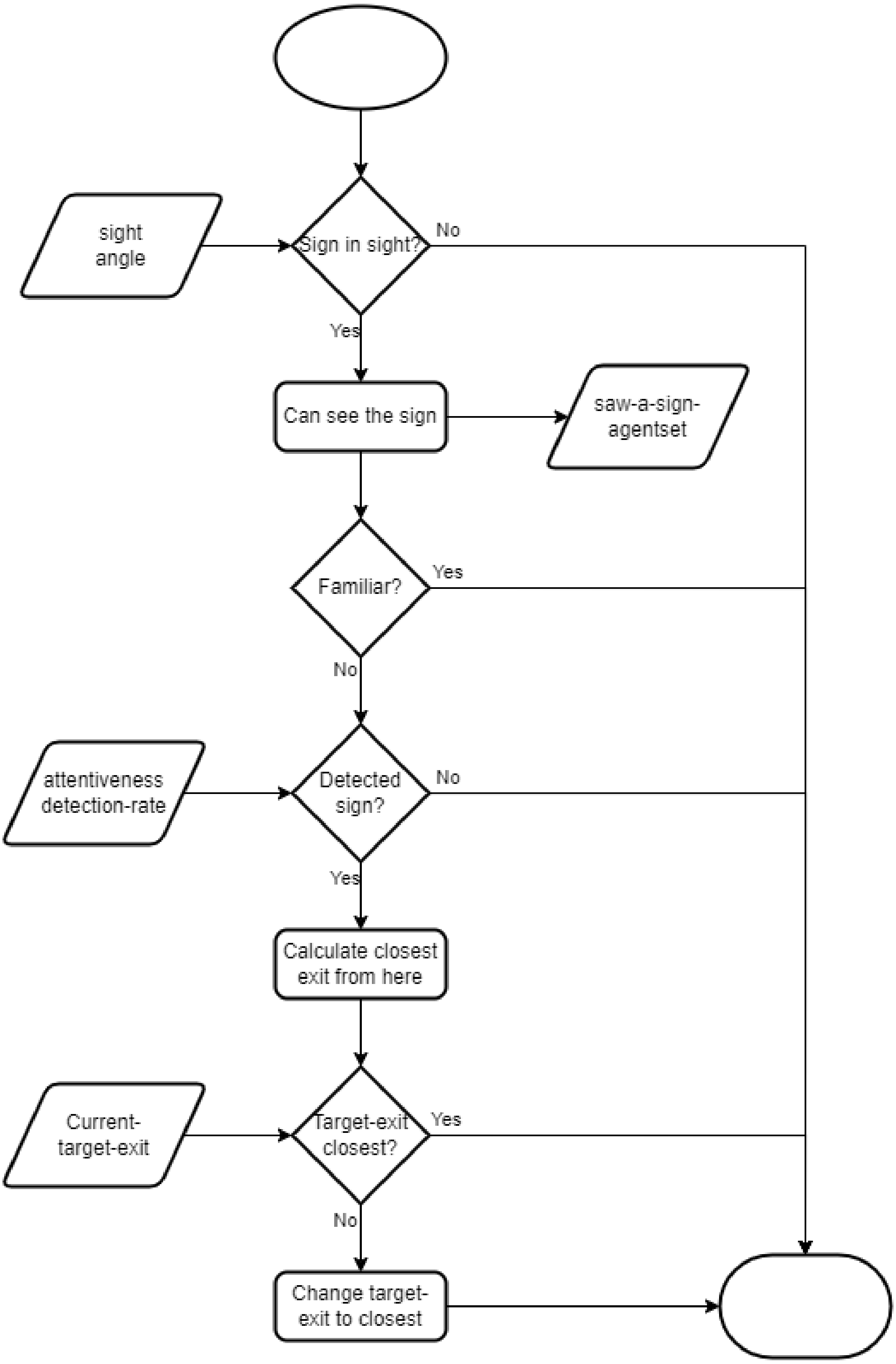

Figure 4.7: Flowchart of signage

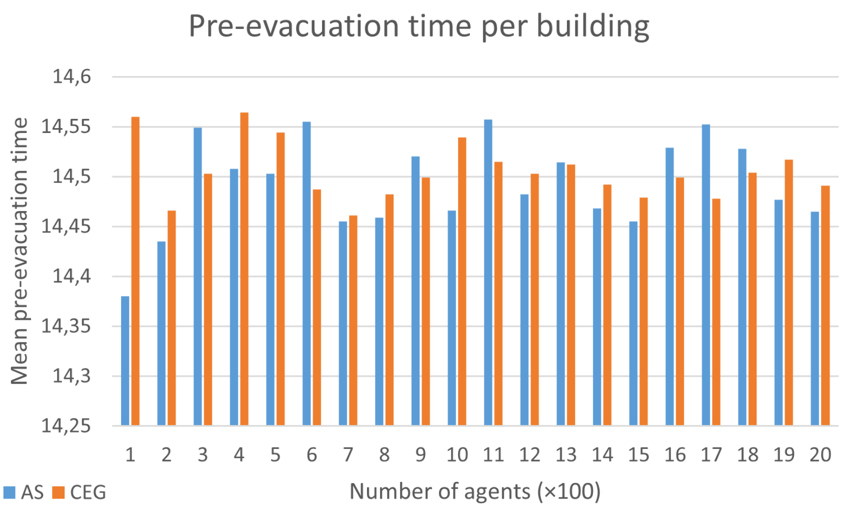

Figure 4.8: Pre-evacuation time per building

Figure 4.9: Test environment for walking speed verification

evacuation time, it is essential to confirm that its implementation is implemented correctly and according to literature.

For each simulation run, agents experience pre-evacuation delays based on the model's parameters, reflecting realistic variations in response times before movement begins. After completing multiple runs at each agent count, we calculate the average pre-evacuation time and compare it against the expected range.

The results confirm that the implementation functions as intended, as shown in Figure 4.8. Despite fluctuations due to randomness, the average pre-evacuation time consistently falls within the defined range when altering the number of agents in the model. This verification ensures that the model correctly applies pre-evacuation delays regardless of the number of agents in the simulation, maintaining realistic variability in evacuation behaviour.

4.2.2. Density and Walking Speed

To verify and validate that walking speed in the model is correctly influenced by density, we create a controlled experiment in a simple test environment. In this scenario, the agents have to move along a straight hallway that is one patch wide and ten patches long. This restricted space ensures that agents can only move unidirectional. This environment is displayed in Figure 4.9 This allows to isolate the effect of density on walking speed.

The experiment begins with a single agent, who moves through the hallway at their normal speed. We then gradually increase the number of agents from one to ten, adding one agent every one hundred runs. Here, an increase in density should lead to reduced movement speeds due to the limited space available. By measuring the time it takes for all agents to reach the end of the hallway, we can observe whether walking speed correctly decreases as the density increases.

The results confirm that the model displays a decrease in walking speed when density is increased. When only one agent is present, it moves at its maximum speed, reaching the end in the shortest possible time. As more agents are added, their movement becomes increasingly constrained, and the time required to traverse the hallway increases accordingly. In Netlogo, the environment is built

Table 4.2: Observed walking speed based on number of agents

Number of agents	1	2	3	4	5	6	7	8	9	10
Observed walking speed	0.96	0.84	0.73	0.67	0.64	0.56	0.52	0.37	0.34	0.32

from patches. The function to calculate the density is calculated based on the number of agent on the same patch as the agent. In several instances, agent can be nearby, but not on the same patch, causing the actual walking speed to be slightly higher compared to the inputted walking speed. In the normal simulation model, the total agent count is much higher compared to this test environment. Therefore, in the normal environment, there would be relatively fewer instances where agents can move to patches with far less agents compared to its current. This density calculation based on the current patch of the agent is favourable over other methods. Another method could be to use the in-radius function to calculate the number of agents in a specific distance around the agent. However, with the latter, the method has to verify the patch its surrounding agent are on is a hall patch. Therefore, every time this method using in-radius is called, the patch type of the surrounding agents has to be requested, decreasing computational performance of the model. With the current method based on the calculation of agents on the same patch, we ensure that only nearby agents on the same type of patch are considered, eliminating the possibility to ”look behind walls”.

This experiment demonstrates that the model correctly implements density-dependent speed reduction, verifying that pedestrian flow behaviour aligns with theoretical expectations (Ibrahim et al., 2016; H. Kim et al., 2019). The observed deviation caused by the Netlogo limitations is considered acceptable. The average walking speed based on the number of agents in the model is displayed in Table 4.2.

4.2.3. Familiarity and Exit Choice

To verify that familiarity influences exit choice as expected, we conduct an experiment, in the normal simulation environment. In this test, we systematically vary the share of familiar agents in increments of 10% every one hundred runs. Familiar agents are aware of all exits, while unfamiliar agents tend to head toward the exit they entered through. Increasing familiarity should lead to a higher proportion of agents exiting through the nearest available exit rather than the nearest entrance.

For each scenario, we record the share of agents who evacuate through the closest exit and compare it to those who leave via the closest entrance. If the model correctly implements familiarity effects, we expect that as familiarity increases, more agents will use the closest exit rather than retracing their steps to their entrance.

The results confirm this expected behaviour. As the proportion of familiar agents rises, a greater number of evacuees choose the nearest exit. In Figure 4.10, the share of unfamiliar agents compared to familiar agents and its influence on exit choice is displayed. In the Civil Engineering and Geosciences building, the share of the number of agents exiting through known entrances is higher compared to the Applied Sciences building. This increase is explained by the number of exits in the buildings. In the Applied Sciences building, there are 19 exits, of which 2 entrances. In the Civil Engineering and Geosciences building, there are 7 exits, of which 2 entrances. Therefore, the chance that the closest exit is an entrance is greater in the latter compared to the former. However, the trend is similar for both buildings.

The verification confirms that the model correctly implements familiarity-based exit choices, aligning with theoretical expectations of evacuation behaviour.

4.2.4. Face Validation

To further verify the correctness of the model, we perform a face validation by directly observing individual agents during simulation runs. This qualitative check ensures that all programmed behaviours, like movement, decision-making, and response to the factors, are executed as intended.

In this validation, we observe both familiar and unfamiliar agents. Their pen-mode is set to down so that their path is highlighted. In Figure 4.11, these paths are displayed. Here, different situations are displayed. Several agents take the route to the nearest exits, other agents proceed to the nearest entrance, some agents get influenced by signage or social influence, and other agents walk by an exit to walk to their target exit. Also, the phenomenon of stepping to the side to find a faster route is

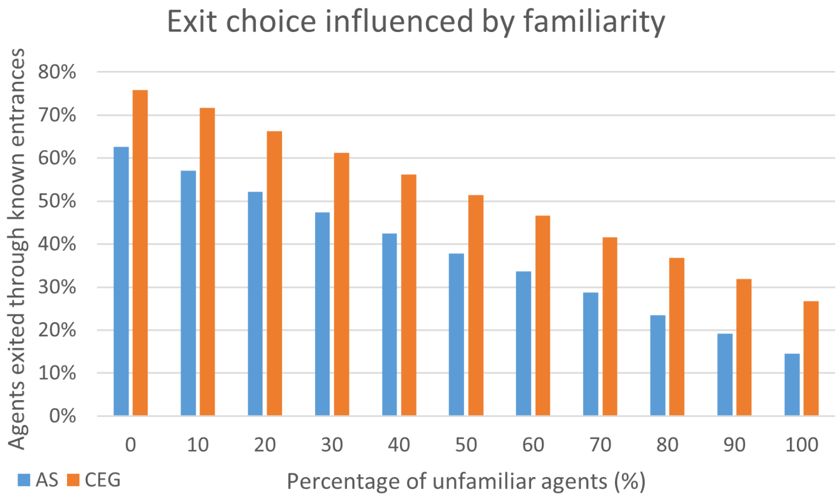

Figure 4.10: Exit choice influenced by familiarity

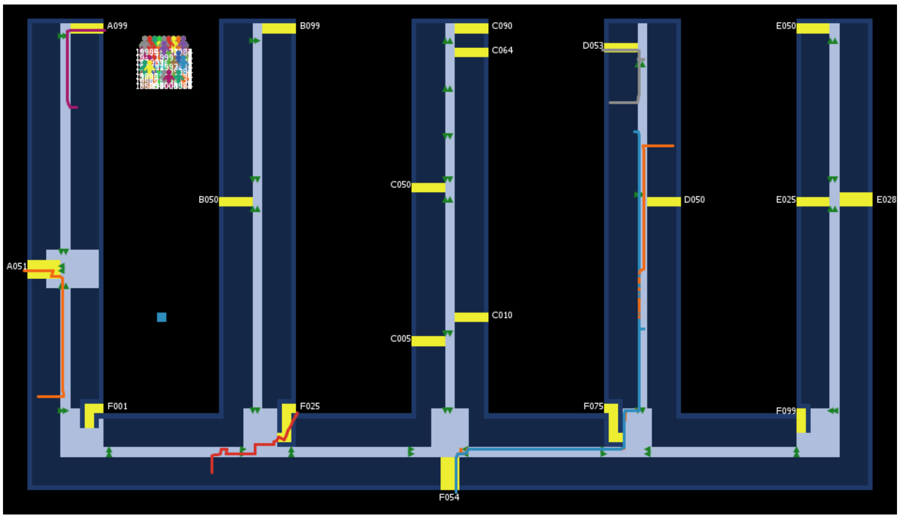

Figure 4.11: Face validation with coloured lines displaying the agents' route

observed, predominantly seen in the red line at the bottom of the figure.

The observed behaviours align with the expected agent logic, confirming that the model correctly implements movement, decision-making, and response to the implemented factors. Agents follow different evacuation strategies based on their familiarity, social influence and signage, with some choosing the nearest exit, some changing their exit while walking, and others moving toward their initial entrance.

4.2.5. Routing Algorithms

Breadth-First Search

The Breadth-First Search algorithm is an important algorithm in this model, since it finds the closest exit from a destination, which therefore forms the basis for the exit routing logic. Breadth-First Search works, as described in section 4.1, by checking if the neighbours of the start patch satisfy the criteria and repeating to ask those neighbours until the criteria are satisfied.

The algorithm is tested in three different scenarios. The first scenario is a world with obstacles and destinations in random locations. This scenario displays the algorithms ability to find the nearest destination, while not including obstacles in its way. Figure 4.12 (left) shows the algorithm that finds the closest destination in green, with the distances from the start displayed in the yellow patches. The

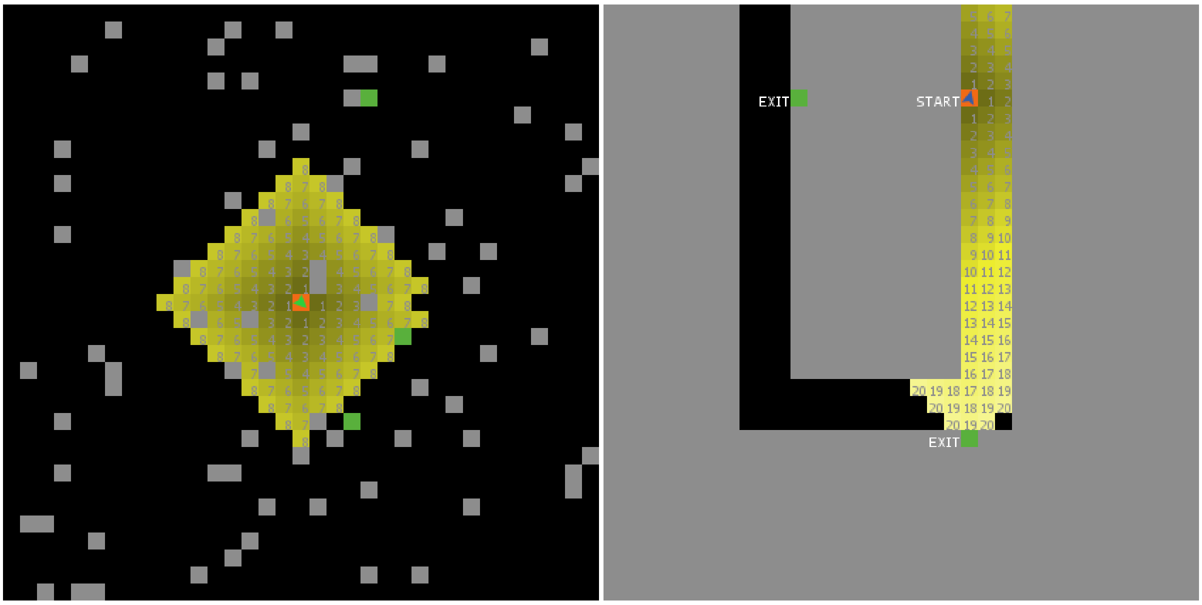

Figure 4.12: Testing scenarios of the Breadth-First Search algorithm: random obstacles and targets (left), hallway example (right)

second scenario highlights the main reason to implement the Breadth-First Search algorithm in the simulation model. Figure 4.12 (right) displays an example of a U-shaped hallway, where the nearest exit as the crow flies is not the nearest exit when regarding patches as obstacles. Using the built-in Netlogo distance function would provide the left exit as the closest exit from the start, disregarding the obstacle in-between them. The figure shows the algorithm is able to only reach for the accessible patches, and therefore find the closest accessible exit. The third scenario to test the algorithm is in the normal environment of the campus building. Here, the working of the algorithm is tested through face validation by placing agents in such locations where the closest exit as the crow flies is not the closest accessible exit. Again, we observe that the algorithm selects the closest exit given the obstacles.

A*

The A algorithm is responsible for generating the shortest possible route from hall patches to exit patches in the model. The correctness of the implementation of the A algorithm is tested first in a test environment. This test environment consists of a random start and destination, with an obstacle in between. In Figure 4.13, the test scenario is displayed. Here, it is shown that the algorithm works as expected. The benefit to using the A algorithm instead of the Breadth-First Search algorithm is that the A algorithm also calculates the cost of each patch to the destination. This phenomenon is nicely illustrated in Figure 4.13, where the patches in the bottom left corner are not visited, since the algorithm knows any path going through that corner is less efficient as through the other directions. After the test environment, the algorithm is tested through face validation in the normal environment, where this same behaviour occurs.

4.3. Sensitivity Analysis

To test the effects of variations in values for the input variables, a sensitivity analysis is performed. A sensitivity analysis helps to explore how input changes affect output changes in the model (Carroll, 2016). Also, it can uncover potential bugs in the model which have not been discovered since.

In this sensitivity analysis, the variables that belong to the factors are changed as a group. An example of this is with social influence, where the maximum distance to the group, as well as the minimum group size, et cetera, as changed together. However, if in this example the value for social influence is increased, the underlying variables are changed in the direction so that the effect is increased. That is, if social influence gets increased, the threshold for persuasiveness is lowered, while the maximum distance to a group is increased.

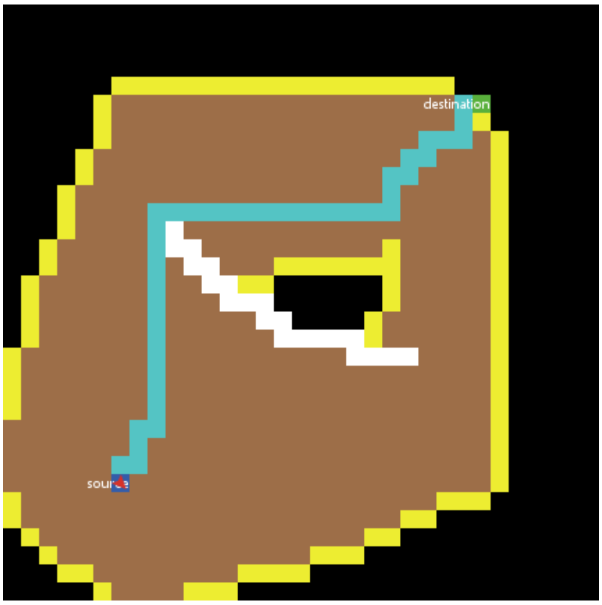

Figure 4.13: An example of a testing scenario of the A* algorithm, with obstacles (white), earlier visited patches (brown) and new visited patches (yellow)

There are 11 different scenario's in the sensitivity analysis. Starting with a base case, the input variables are altered, by -10 percent and +10 percent. The scenarios are the following: base case, familiarity low, familiarity high, social influence low, social influence high, wider egress on, signage none, signage basic, signage advanced. The full design of the sensitivity analysis is stated in Appendix A. The input values for the base case are shown in Appendix A.

Figure 4.14 shows 75% evacuation time varied most for changes in the egress width in the model in the Civil Engineering and Geosciences building 24.8 percent ($p < 0.001$) compared to the base case. The 75% evacuation time for the Applied Sciences building showed the largest difference compared to the base case when using advanced signage (-6.5%, $p < 0.001$), followed by changes in familiarity (3.5% and -5.1%, $p < 0.001$ and $p < 0.001$ respectively). No scenarios in which social influence was altered showed a significant difference in mean value compared to the base case.

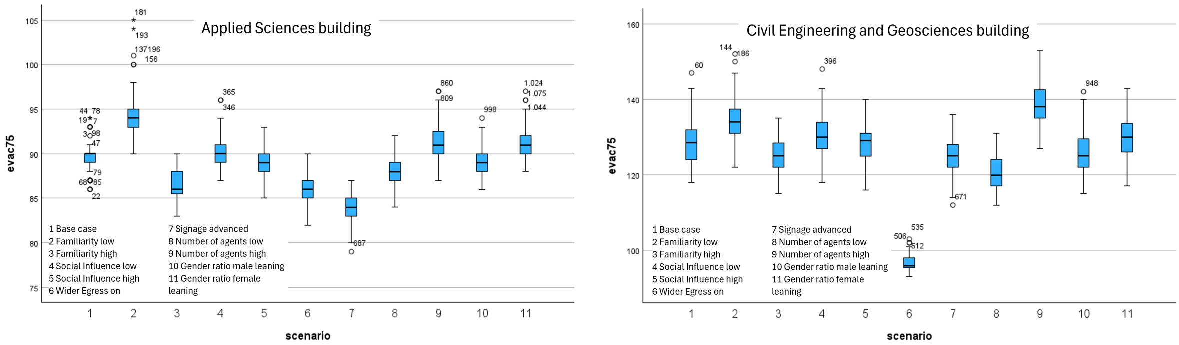

Figure 4.14: Box-plot of 75% evacuation time per scenario, AS building (left), CEG building (right)

Density in the Civil Engineering and Geosciences building was only statistically significant different in scenarios where wider egress was on (-42.4% , $p < 0.001$). In the Applied Sciences and Geosciences building, egress width also had the highest chance in density value (-17%, $p < 0.001$), followed by higher numbers of agents (13.8%, $p < 0.001$). Again, changes in social influences did not yield significant differences compared to the base case.

For the third metric, exit selection, the largest change was observed for the Applied Sciences building in scenarios with wider egress on (-13.5%, $p < 0.001$). For the Civil Engineering and Geosciences building, the only significant changes were in scenarios with familiarity +10% ($p < 0.001$) and familiarity 10% ($p = 0.037$).

4.4. Experimental Setup

The main research question of this thesis is the following: What is the influence of social, structural, and technical complexity on evacuation performance in university campus buildings? Continuing on the conceptualisation and formalisation, the question can be specified further to this: What is the effect of familiarity, social influence, egress width, and signage on exit choice, density and total and 75% evacuation time in university campus buildings? With the help of an experimental design, we can provide a contribution.

The aim of this experiment is to explore the impact of familiarity, social influence, egress width, and signage detection rate on exit choice, density, and evacuation time in university campus buildings. To achieve this, an agent-based model will be implemented using the NetLogo simulation environment.

There are four independent variables that are varied through the experiments. Familiarity: Represents the evacuees' knowledge of the building layout, which can affect their ability to choose exits effectively. Social Influence: Models the tendency of evacuees to follow others or make independent decisions when choosing an exit. Egress Width: Reflects the variation in the width of exits, impacting how quickly evacuees can pass through. Signage Detection Rate: Refers to the likelihood of evacuees noticing and using emergency signage to guide their exit choice.

There are three dependent variables. Exit Choice: The selected exit chosen by each agent in the simulation. Density: The number of agents on each hall patch with agents during the evacuation process. 75% Evacuation Time: The time taken for 75% of the agents to exit the building.

The simulation will be conducted in NetLogo, a platform suited for agent-based modelling. Agents (representing evacuees) will be programmed to make decisions based on the independent variables. The environment consists of the Applied Sciences building and the Civil Engineering and Geosciences building, university buildings on the TU Delft campus, focussing on the dynamics of evacuation under different conditions of familiarity, social behaviour, exit width and signage. The built-in BehaviorSpace feature is used to execute the experiments in an automatic manner.

The number of runs for each scenario has to be determined. It is important to select a number that is high enough to eliminate the effects of randomness. It is also important to select a number that is low enough to achieve manageable run-times when performing experiments.

Figure 4.15 shows the cumulative mean evacuation time for both buildings. Here, the running average is calculated each added run, up to 400 runs. The graphs show that the cumulative mean time is fluctuating at the first runs, but quickly evens out. After one hundred runs, the running average differs only 0,5% from the population average for the Applied Sciences building, and only 0,3% for the Civil Engineering and Geosciences building. Therefore, the standard run size for the experiments in the experimental design and sensitivity analysis is one hundred runs.

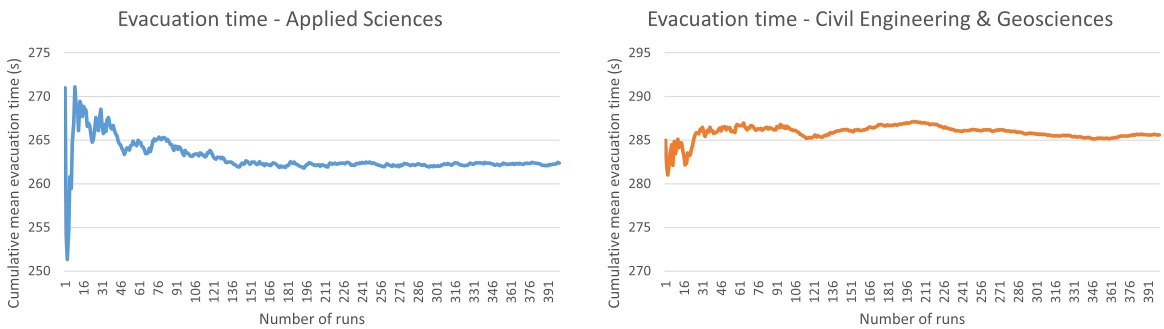

Figure 4.15: Cumulative mean evacuation time

This experiment is performed with a full factorial design. For familiarity, three levels are selected: 0%, 50% and 100% of familiar agents. For social influence, three levels are selected: standard, -25% compared to standard, and +25% compared to standard. This difference with the familiar levels is because while real life scenarios with 0% or 100% of familiar agents can be created, while social influence behaviour cannot be shut down. Wider egress is two levels: on or off. For signage, there are again three levels: no signage, basic signage, and advanced signage. Lastly, there are two buildings in the simulation model: the Applied Sciences building and the Civil Engineering and Geosciences building. This combination gives a full factorial design of $3 \cdot 3 \cdot 2 \cdot 3 \cdot 2 = 108$ scenarios of each 100 runs, 10800 runs in total.

Table 4.3: Variable variation

Building	**Familiarity**	**Social Influence**	**Wider Egress**	**Signage**
Applied Sciences	0%	-25%	On	None
Civil Engineering & Geosciences	50%	Standard	Off	Basic
	100%	+25%		Advanced

For each run, the 25%, 50%, 75% and 100% evacuation time, the minimum, average, maximum, median, and mode density, the number of agents exited through each exit, the total number agent saw signs, and the number of agents who got influenced by other agents, are tracked. This data is output to comma-separated values files. After collection, the data is transformed. The main transformation lies in the creation of the exit ratio variable. This ratio consists of the number of agents who exited through an entrance, divided by the number of agents who exited through non-entrance exits. This ratio is a float between 0 and 1. Through this ratio, we can compare different scenarios between buildings, or if we were to alter the number of agents in the model.

The data analysis is performed in SPSS. After explorative and descriptive analytics, a general linear model (GLM) is created. After tests of heteroscedasticity, an overview of tests of between-elements effects shows the contributions of each main effect and interaction effect on the dependent variables through the partial eta-squared. In addition, scenarios are ranked based on their output value, to discover patterns of influencing variable levels.

4.4.1. Expectations

There are two expectations made before executing the experiments. The first expectation is that familiarity will have a greater effect on evacuation time in the Applied Sciences building compared to the Civil Engineering and Geosciences building. Familiarity directly influences exit choice, and since the first building has more exits, increasing the number of (familiar) agents who exit through the nearest exit will decrease the evacuation time more in the Applied Sciences building compared to the Civil Engineering and Geosciences building. Another expectation is that egress width will have a larger effect on the output metrics in the Civil Engineering and Geosciences building compared to the Applied Sciences buildings. This expectation is also linked to the number of exits: in CEG, there are relatively fewer exits, which means that given an equal population size, the number of agents per exit will be higher.

5
Results

To investigate the influence of social, structural, and technical factors on evacuation time, density, and exit selection, two distinct analyses were performed. The first analysis, a standardised ranking, gave insight into the relative performance of specific scenarios. The second analysis, a general linear model, gave insight into the effect size of each factor and the interactions between them. To achieve this, a full factorial experiment was performed, totalling 10800 individual runs. The minimum and maximum values of all runs, as well as the base case values, are shown in Table 5.1.

5.1. Most Efficient Combinations of Socio-Technical Factors

Sub question 3 was: Which combinations of factors produce the most efficient outcomes for the evacuation metrics, and how do different factor levels interact to influence these outcomes? To equitably rank the scenarios of the full factorial design, the mean value for the three output variables was standardised. The standardised output value was based on the relative position of the value in the range. To illustrate, a 75% evacuation time value of 89.65 seconds is standardised to $(89.65 - 69.38)/(241.03 - 69.38) = 0.118$, where 69.38 is the minimum value for that metric, and 241.03 is the maximum value for that metric, as displayed in Table 5.1. The standardised output values were ranked, and combined to a weighted average rank value. The weight of each of the three metrics is set equal, since each of the three metrics are of equal importance. That is, a scenario with a relatively low evacuation time but a relatively high density is arguably less desirable than a scenario that scores average for both metrics. The average rank value determined the total rank of the scenarios.

5.1.1. Applied Sciences building

Figure 5.1 shows the output values for the 75% evacuation time, the mean density, and the exit choice. Here, the vertical position of each value is determined by the total rank of that scenario, which is determined by ranking the standardised values of each metric.

Figure 5.2 shows the standardised ranked value per output variable, for the Applied Sciences building. Each value is standardised in the range (0,1), where zero represents optimal values (lowest evacuation time, lowest mean density, lowest exit ratio) and one represents the least optimal values (highest evacuation time, highest mean density, highest exit ratio). These number values of these minimums

Table 5.1: Minimum, base case, maximum output values for all simulation scenarios

Building	Applied Sciences			Civil Engineering and Geosciences		
Metric	Min	Base	Max	Min	Base	Max
75% evacuation time (s)	69.38	89.65	241.03	82.56	128.50	347.78
Mean density (persons/m^2)	2.18	2.40	5.68	3.35	6.16	7.20
Exit ratio (% nearest exit)	0.14	0.48	1.00	0.27	0.55	1.00

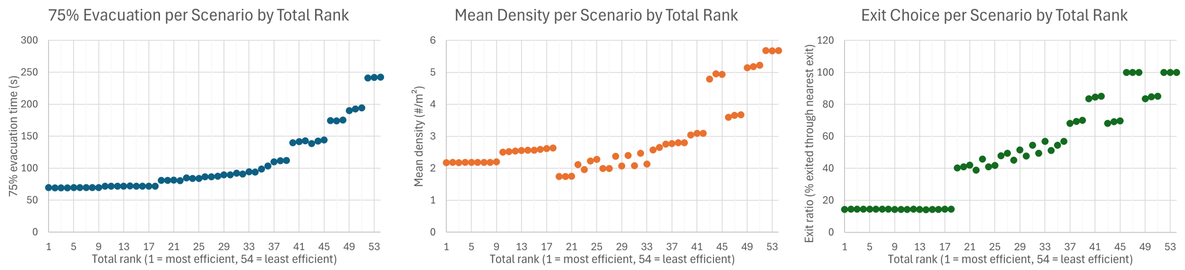

Figure 5.1: Ranked output values, Applied Sciences building

and maximums are displayed in Table 5.1.

The graph in Figure 5.2 seems to show multiple groups of ranked scenarios with similar output values for one or more metrics, namely ranks 1 to 9, 10 to 18, 19 to 20, 46 to 48, and 52 to 54. The pairwise comparisons showed non-significant mean differences for all metrics for four groups of ranks. Specifically, from rank one to nine, from rank 10 to 18, from rank 19 to 20, from rank 46 to 48, and from rank 52 to 54 (all $p > 0.05$). Furthermore, all scenarios ranked from one to nine showed non-significant mean differences in exit ratio compared to ranks 10 to 18 ($p > 0.05$). Additionally, in 64 of the 81 comparisons of ranks one to nine with 10 to 18, a non-significant mean difference in evacuation time was observed ($p > 0.05$).

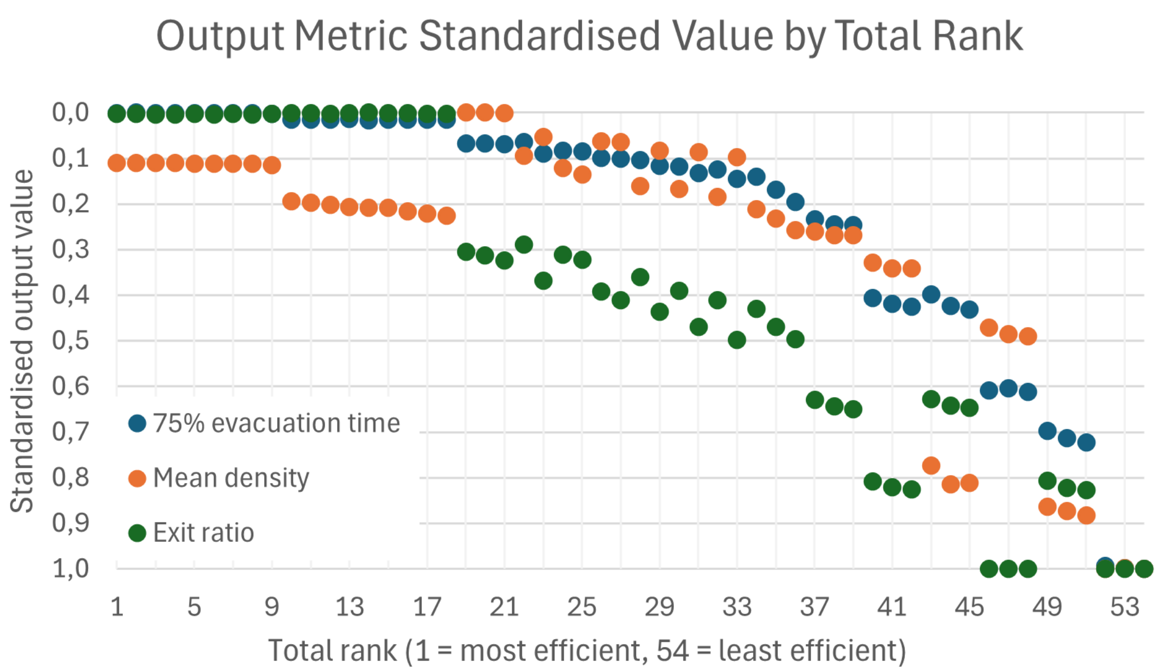

Figure 5.2: Standardised output value by rank, Applied Sciences building

Figure 5.3 shows the factor levels sorted by total rank for the Applied Sciences building. Each combination of four vertically aligned points represents one scenario, where the level of each point represents the level of its corresponding factor. These scenarios were ranked according to the standardised output values, as shown in Figure 5.2. To illustrate, the scenario ranked first based on evacuation time, density and exit ratio, had a value of 100% for familiarity, -25% for social influence, wider egress on, and no signage.

In Figure 5.3, the factor familiarity shows a stepwise pattern. Here, all scenarios with 100% familiarity ranked one to eighteen, followed by all scenarios with 50% familiarity, ranking nineteen to thirty-six, ending with all scenarios with 0% familiarity. Furthermore, the wider egress values for the 100% famil-

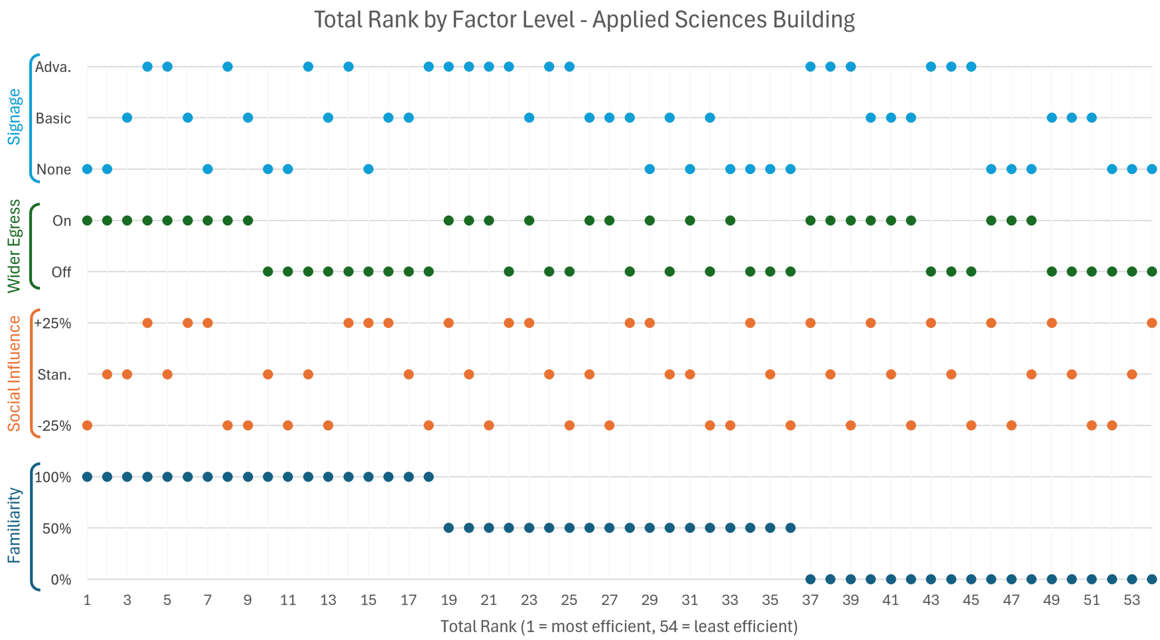

Figure 5.3: Total rank by factor level, Applied Sciences building

iarity scenarios were in order from on to off. This pattern continues for the other values of familiarity: scenarios with wider egress on ranked lower, although there was more variability. The signage ranking was less straightforward when familiarity was high, but also showed stepwise patterns when familiarity is 50%, with advanced signage ranking lower, followed by basic signage, and no signage ranking the highest. For scenarios with familiarity 0%, the scenarios with advanced signage ranked lower than the scenarios with basic signage. However, for 0% familiarity, the combination of no signage with wider egress ranked lower than basic signage without wider egress. Lastly, for maximum familiarity, social influence did not show a clear pattern. When familiarity was not maximised, patterns in social influence were observed. Here, a pattern where +25% social influence ranked lowest, followed directly by standard social influence, followed by -25% social influence, repeated multiple times. This social influence pattern was most notable when the other three factors were constant, for example for ranks 34-36, 37-39, 40-42.

By synthesising the standardised output values, factor levels, and given the non-significant differences in mean output values across (groups of) scenarios, various assertions may be posited. The familiarity values are arranged in a precise, stepwise pattern, whereby scenarios with the highest familiarity scores perform the best, followed by those with average familiarity scores, and lastly those with the lowest familiarity scores. This indicates that familiarity serves as the strongest predictor. If familiarity was 100%, the only other influencing factor was wider egress (rank one to nine and 10 to 18). In this case, the difference in the egress width mainly influenced the mean density. In 79,0% of the pairwise comparisons between these groups of ranks, no notable mean variation was observed in evacuation time. In scenarios where familiarity was not maximised, wider egress became relatively less influential. Here, scenarios with advanced signage ranked relatively lower. Given that the other factors were constant, the social influence showed stepwise patterns. Higher effect of social influence, ranks lower. If familiarity was minimised, the significance of wider egress increased once more. The influence of signage was observed to be similar to that of wider egress. Social influence again showed a stepwise pattern when other factors were constant. This indicates that social influence serves as the weakest predictor of total rank.

5.1.2. Civil Engineering and Geosciences building

Figure 5.4 shows the output values for the 75% evacuation time, the mean density, and the exit choice. Here, the vertical position of each value is determined by the total rank of that scenario, which is determined by ranking the standardised values of each metric.

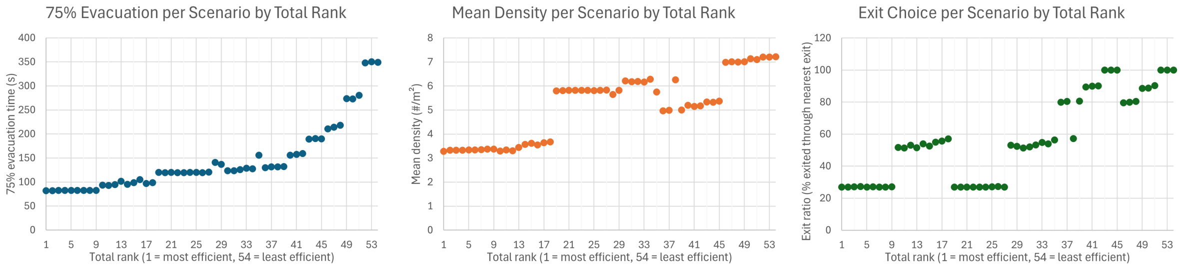

Figure 5.4: Ranked output values, Civil Engineering and Geosciences building

Figure 5.5 shows the standardised value per output variable, sorted by total rank, for the Civil Engineering and Geosciences building. Compared to the Applied Sciences building, this figure shows more differences between groups of ranks. Also, the difference in range for each rank was higher compared to the Applied Sciences building. This showed that the Civil Engineering and Geosciences building was relatively more sensitive to changes in input.

The graph in Figure 5.5 shows multiple groups of ranked scenarios with similar output values for one or more metrics. A pairwise comparison showed non-significant mean differences for all metrics for four groups of ranks. Specifically, from rank one to nine, from rank 10 to 12, from rank 19 to 27, from rank 43 to 45 (all $p > 0.05$). Furthermore, all scenarios ranked from one to nine showed non-significant mean differences in exit ratio compared to ranks 19 to 27 ($p > 0.05$). Additionally, a non-significant mean difference in mean density was observed ($p > 0.05$) for ranks one to nine with ranks 10 to 13.

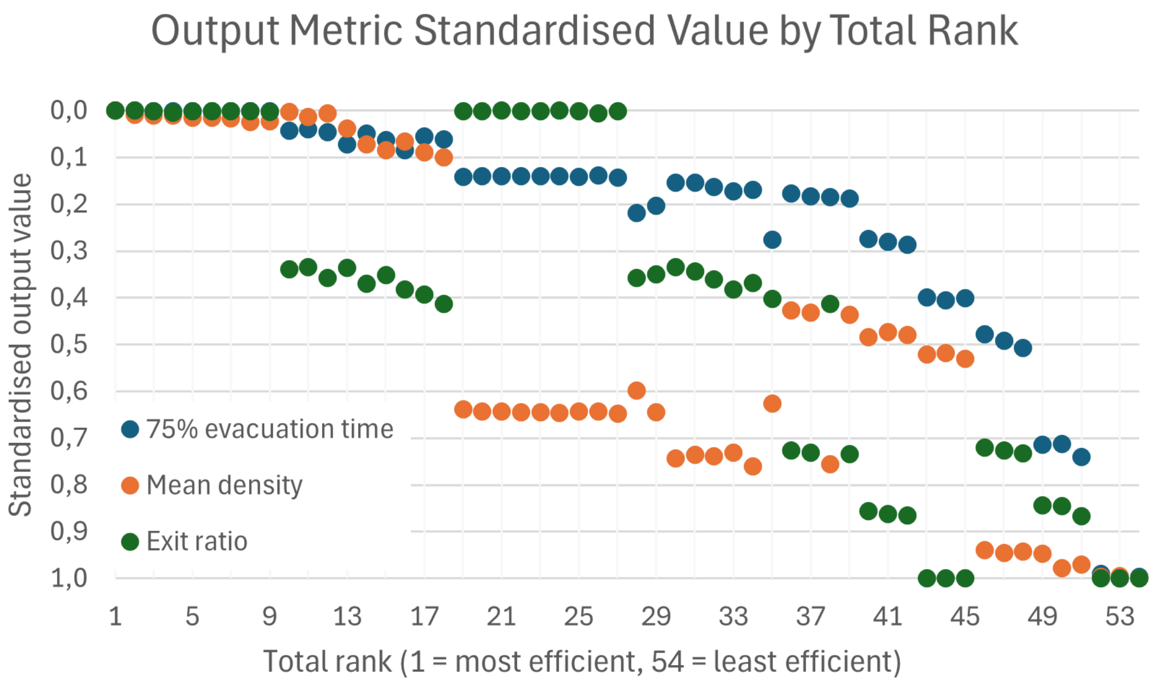

Figure 5.5: Standardised output value by rank, Civil Engineering and Geosciences building

Figure 5.6 shows the factor levels sorted by total rank for the Civil Engineering and Geosciences building. These scenarios were ranked according to the standardised output values, as shown in Figure 5.5. The graph showed a long series of ranks where wider egress is constant. In this circumstance, familiarity showed stepwise patterns, where all scenarios with 100% familiarity were ranked lower than scenarios where familiarity was 50%. In scenarios where familiarity was minimised, signage showed stepwise patterns, specifically in the highest ranks. Social influence did not show clear patterns, except for two stepwise patterns when the other factors were constant, namely in ranks 40 to 42 and 46 to 48.

The graph shows the presence of wider egress as an influencing factor, since it shows long streaks of the same level. For this building, wider egress showed more influence on total rank compared to familiarity. Given the non-significant mean differences on all metrics for scenarios one to nine and 19 to 27, wider egress was again the only contributing factor to changes in output when familiarity was maximised. In scenarios where familiarity was 50%, signage and social influence became relatively more influential, but did not show clear patterns. For scenarios where familiarity was minimised, signage showed stepwise patterns, where scenario with advanced signage ranked lower, followed by scenarios with basic signage, and ending with scenarios without signage.

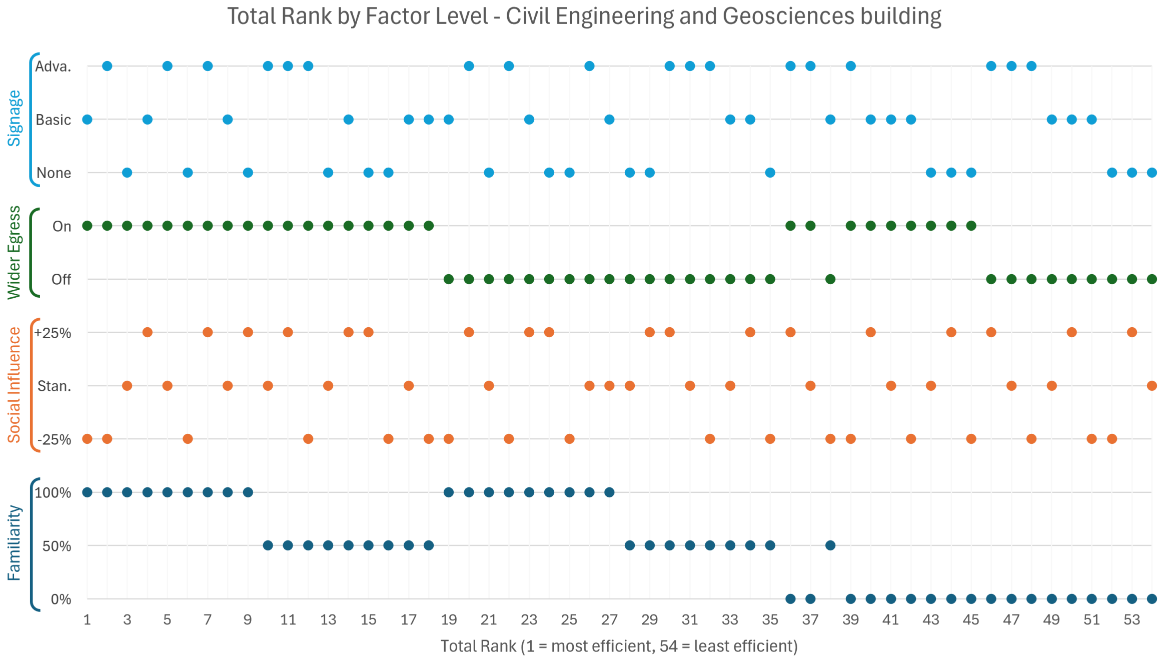

Figure 5.6: Total rank by factor level, Civil Engineering and Geosciences building

5.2. Main and Interaction Effects of Socio-Technical Factors

Sub question 4 was: What are the main and interaction effects of familiarity, social influence, egress width, and signage on exit choice, density and total and 75% evacuation time in university campus buildings? To further describe the effect and effect size of the factors and interactions on the metrics, a tests of between-subjects effects analysis was performed, using a general linear model. This analysis, an F-test with alpha 0.05, provided F-values and partial eta-squared values for all factors and all possible interactions on all metrics. In this analysis, only values with a p-value > 0.05 and partial eta-squared > 0.05 were considered. In this way, only scientifically significant and practically significant outcomes were evaluated.

5.2.1. Applied Sciences building

Table 5.2 shows the F-value and the partial eta squared for all relevant factors on the relevant metrics for the Applied Sciences building. In the Applied Sciences building, several factors and interactions had a relevant impact on the evacuation process. The degrees of freedom of the error was 5346. The p-values were all < 0.001. Familiarity was a very important factor, since it showed several of the highest partial eta-squared values ($F(2,5346) = 246417.3$, $\eta^2 = 0.989$, $p < 0.001$; $F(2,5346) = 41251.5$, $p < 0.001$, $\eta^2 = 0.939$; $F(2,5346) = 1121866.8$, $p < 0.001$, $\eta^2 = 0.998$). Social influence was the lowest influencing factor, only significantly influencing the exit ratio ($F(2,5346) = 648.5$, $p < 0.001$, $\eta^2 = 0.195$). Wider egress had a strong effect on evacuation time ($F(1,5346) = 24275.6$, $p < 0.001$, $\eta^2 = 0.820$) and mean density (F(1,5346) = 23988.2, p < 0.001, η² = 0.818). Signage also played an important role, with a strong effect on evacuation time (F(2,5346) = 23482.8, p < 0.001, η² = 0.898) and exit ratio (F(2,5346) = 49619.6, p < 0.001, η² = 0.949). Furthermore, signage moderately affected mean density (F(2,5346) = 1318.8, p < 0.001, η² = 0.330).

Several interactions between factors also showed substantial effects. The interaction between familiarity and social influence affected exit ratio (F(4,5346) = 314.9, p < 0.001, η² = 0.191). The interaction between familiarity and wider egress had a strong influence on evacuation time (F(2,5346) = 16789.3, p < 0.001, η² = 0.863) and mean density (F(2,5346) = 7490.5, p < 0.001, η² = 0.737). The interaction between familiarity and signage strongly impacted evacuation time (F(4,5346) = 15020.2, p < 0.001, η² = 0.918) and exit ratio (F(4,5346) = 18282.8, p < 0.001, η² = 0.932), while also affecting mean density (F(4,5346) = 513.7, p < 0.001, η² = 0.278). The combination of wider egress and signage influenced evacuation time (F(2,5346) = 1115.2, p < 0.001, η² = 0.294). Finally, the three-way interaction between familiarity, signage, and wider egress had an effect on evacuation time (F(4,5346) = 785.0, p < 0.001, η² = 0.370).

Table 5.2: Tests of Between-Subjects Effects and Effect Sizes, Applied Sciences building

Factor(s)	Metric	F	Partial Eta Squared
Familiarity	evac75	246417.3*	0.989
	mean-density	41251.5*	0.939
	exit-ratio	1121866.8*	0.999
Social Influence	exit-ratio	648.5*	0.195
Wider Egress	evac75	24275.6*	0.820
	mean-density	23988.2*	0.818
Signage	evac75	23482.8*	0.815
	mean-density	1318.8*	0.370
	exit-ratio	49619.6*	0.949
Familiarity × Social Influence	exit-ratio	314.9*	0.191
Familiarity × Wider Egress	evac75	16776.9*	0.863
	mean-density	7490.5*	0.737
Familiarity × Signage	evac75	15020.2*	0.918
	mean-density	513.7*	0.278
	exit-ratio	18282.8*	0.932
Wider Egress × Signage	evac75	1115.2*	0.294
Familiarity × Social Influence × Signage	exit-ratio	41.4*	0.058
Familiarity × Wider Egress × Signage	evac75	785.0*	0.370

Note. $* = p < 0.001$

5.2.2. Civil Engineering and Geosciences building

In the Civil Engineering and Geosciences building, familiarity had a strong effect on all three metrics. The degrees of freedom of the error was 5346. The p-values were all < 0.001. Its influence on evacuation time was high (F(2,5346) = 211137.7, p < 0.001, η² = 0.987). The impact on mean density (F(2,5346) = 3889.9, p < 0.001, η² = 0.593) suggests that familiarity affects how evacuees spread throughout the building, although to a lesser extent than its effect on evacuation time. Exit ratio was also strongly influenced by familiarity (F(2,5346) = 46224.7, p < 0.001, η² = 0.945). Wider egress had a considerable effect on both evacuation time (F(1,5346) = 156132.8, p < 0.001, η² = 0.967) and mean density (F(1,5346) = 22053.3, p < 0.001, η² = 0.805). Signage played a role in guiding evacuees, with a notable effect on evacuation time (F(2,5346) = 17357.4, p < 0.001, η² = 0.867), indicating that the presence of signage helped evacuees navigate toward exits more efficiently. However, signage had a weaker effect on exit ratio (F(2,5346) = 587.8, p < 0.001, η² = 0.180).

Several interactions between factors also showed substantial effects. The interaction between familiarity and wider egress had a strong influence on evacuation time (F(2,5346) = 29540.4, p < 0.001, η² = 0.917), suggesting that the effectiveness of wider exits depends on evacuees' familiarity with the building. The effect on mean density was smaller (F(2,5346) = 161.8, p < 0.001, η² = 0.057). The interaction between familiarity and signage impacted evacuation time (F(4,5346) = 11466.8, p < 0.001,

η^2 = 0.896) and exit ratio (F(2,5346) = 490.4, p < 0.001, η^2 = 0.268). The combination of wider egress and signage also had an impact on evacuation time (F(2,5346) = 2762.4, p < 0.001, p < 0.001, η^2 = 0.508), indicating that signage helps evacuees make better use of the increased exit capacity. Additionally, the three-way interaction between familiarity, signage, and wider egress affected evacuation time (F(2,5346) = 1750.8, p < 0.001, η^2 = 0.567), meaning that these factors together contribute to shaping the overall evacuation process.

Table 5.3: Tests of Between-Subjects Effects and Effect Sizes, Civil Engineering and Geosciences building

Factor(s)	Metric	F	Partial Eta Squared
Familiarity	evac75	211137.7*	0.987
	mean-density	3889.9*	0.593
	exit-ratio	46224.7*	0.945
Wider Egress	evac75	156132.8*	0.967
	mean-density	22053.3*	0.805
Signage	evac75	17357.4*	0.867
	exit-ratio	587.8*	0.180
Familiarity × Wider Egress	evac75	29540.4*	0.917
	mean-density	161.8*	0.057
Familiarity × Signage	evac75	11466.8*	0.896
	exit-ratio	490.4*	0.268
Social Influence × Signage	evac75	2762.4*	0.508
Familiarity × Wider Egress × Signage	evac75	1750.8*	0.567

Note. $* = p < 0.001$

5.3. Differences and Similarities between Buildings

Following the standardised ranking analysis and the general linear model analysis, it was evident that the four factors and their interactions influenced the two buildings differently. In Figure 5.7, the factor levels by total rank are shown for both buildings, where the levels of the Civil Engineering and Geosciences buildings are visualised above the levels of the Applied Sciences building. The figure shows a different dominant factor in the first ranks. For the Applied Sciences building, familiarity was dominant in the first ranks. For the Civil Engineering building, wider egress was dominant in the first ranks.

Familiarity had a strong effect on all three metrics in both buildings, with high partial eta squared values for evacuation time and exit ratio. However, the effect of familiarity on mean density was greater in the Applied Sciences building (F(2,5346) = 41251.5, p < 0.001, η^2 = 0.939) compared to the Civil Engineering and Geosciences building (F(2,5346) = 3889.9, p < 0.001, η^2 = 0.593). Wider egress strongly influenced both evacuation time and mean density in both buildings, with partial eta squared values above 0.8 for these metrics in both cases (Applied Sciences: F(1,5346) = 24275.6, p < 0.001, η^2 = 0.820 for evacuation time, F(1,5346) = 23988.2, p < 0.001, η^2 = 0.818 for mean density; Civil Engineering: F(1,5346) = 156132.8, p < 0.001, η^2 = 0.967 for evacuation time, F(1,5346) = 22053.3, η^2 = 0.805 for mean density). The influence of signage on exit ratio was high in the Applied Sciences building (F(2,5346) = 49619.6, p < 0.001, η^2 = 0.949), while in the Civil Engineering and Geosciences building, this effect was lower (F(2,5346) = 587.8, p < 0.001, η^2 = 0.180), but still large.

The interaction between familiarity and wider egress affected evacuation time in both buildings, with a higher partial eta squared in the Civil Engineering and Geosciences building (F(2,5346) = 29540.4, p < 0.001, η^2 = 0.917) compared to the Applied Sciences building (F(2,5346) = 16789.3, p < 0.001, η^2 = 0.863). This interaction also influenced mean density in both buildings, with a stronger effect in the Applied Sciences building (F(2,5346) = 7490.5, p < 0.001, η^2 = 0.737) than in the Civil Engineering and Geosciences building (F(2,5346) = 161.8, p < 0.001, η^2 = 0.057). The interaction between wider egress and signage on evacuation time was present in both buildings but was stronger in the Civil Engineering and Geosciences building (F(2,5346) = 2762.4, p < 0.001, η^2 = 0.508) compared to the Applied Sciences building (F(2,5346) = 1115.2, p < 0.001, η^2 = 0.294).

Some interactions were present in one building but not in the other. The interaction between familiarity and social influence was relevant for exit ratio in the Applied Sciences building (F(4,5346) = 314.9, p <

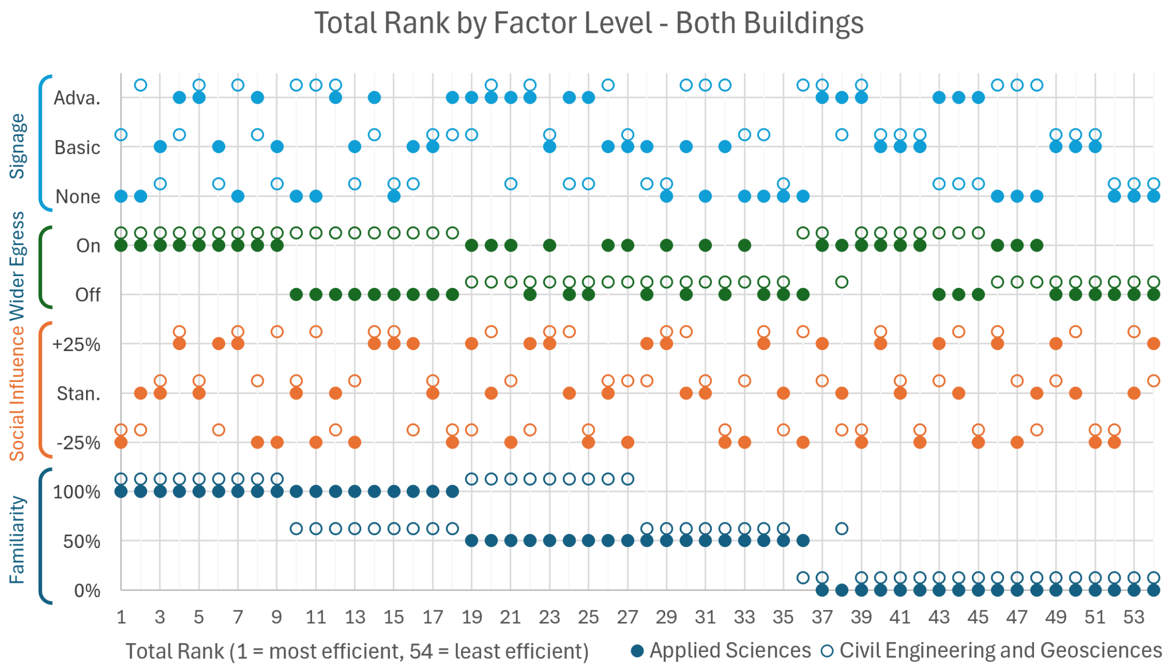

Figure 5.7: Total rank by factor level, both buildings

0.001, $\eta^2 = 0.191$) but not in the Civil Engineering and Geosciences building. The interaction between familiarity and signage was strong for exit ratio in the Applied Sciences building ($F(4{,}5346) = 18282.8$, $p < 0.001$, $\eta^2 = 0.932$) but lower in the Civil Engineering and Geosciences building ($F(2{,}5346) = 490.4$, $p < 0.001$, $\eta^2 = 0.268$). The three-way interaction between familiarity, signage, and wider egress affected evacuation time in both buildings, with a higher effect in the Civil Engineering and Geosciences building ($F(2{,}5346) = 1750.8$, $p < 0.001$, $\eta^2 = 0.567$) compared to the Applied Sciences building ($F(4{,}5346) = 785.0$, $p < 0.001$, $\eta^2 = 0.370$). The interaction between wider egress and signage on exit ratio was relevant in the Civil Engineering and Geosciences building ($F(2{,}5346) = 41.4$, $p < 0.001$, $\eta^2 = 0.058$) but did not appear in the Applied Sciences building. The three-way interaction between familiarity, social influence, and signage was present for exit ratio in the Civil Engineering and Geosciences building ($F(2{,}5346) = 41.4$, $p < 0.001$, $\eta^2 = 0.058$) but not in the Applied Sciences building.

Table 5.4: Comparison of metrics across different factors in Applied Sciences and Civil Engineering & Geosciences

Factor(s)	Metric	Applied Sciences F	Applied Sciences $\delta\eta^2$	Civil Engineering & Geosciences F	Civil Engineering & Geosciences $\delta\eta^2$	$\Delta\delta\eta^2$
Familiarity	evac75	246417.3*	0.989	211137.7*	0.987	0.002
	mean-density	41251.5*	0.939	3889.9*	0.593	0.346
	exit-ratio	1121866.8*	0.998	46224.7*	0.945	0.052
Social Influence	exit-ratio	648.5*	0.195	15.7*	0.006	0.189
Wider Egress	evac75	24275.6*	0.820	156132.8*	0.967	-0.147
	mean-density	23988.2*	0.818	22053.3*	0.805	0.013
Signage	evac75	23482.8*	0.898	17357.4*	0.867	0.031
	mean-density	1318.8*	0.330	14.7*	0.005	0.325
	exit-ratio	49619.6*	0.949	587.8*	0.180	0.769
Familiarity × Social Influence	exit-ratio	314.9*	0.191	8.9*	0.007	0.184
Familiarity × Wider Egress	evac75	16789.3*	0.863	29540.4*	0.917	-0.054
	mean-density	7490.5*	0.737	161.8*	0.057	0.680
Familiarity × Signage	evac75	15020.2*	0.918	11466.8*	0.896	0.023
	mean-density	513.7*	0.278	31.6*	0.023	0.255
	exit-ratio	18282.8*	0.932	490.4*	0.268	0.663
Wider Egress × Signage	evac75	1115.2*	0.294	2762.4*	0.508	-0.214
Familiarity × Social Influence × Signage	exit-ratio	41.4*	0.058	p > 0.05		0.058
Familiarity × Wider Egress × Signage	evac75	785.0*	0.370	1750.8*	0.567	-0.197

Note. $* = p < 0.001$

6
Discussion

6.1. Main Results

This research aims to contribute to the research question: What is the influence of social, structural, and technical complexity on evacuation performance in university campus buildings? For this purpose, a standardised ranking of a full factorial experiment design, as well as a generalised linear model, were designed and analysed. An agent-based model was created to generate evacuation data.

Sub question 1 was: What is evacuation complexity in university campus buildings? Through a literature review, a framework was proposed, where university building evacuations were viewed from a complex socio-technical perspective. This perspective resulted in the classification of complexity properties, social factors, structural factors, and technical factors. Emergence, path dependency, and context dependency were the complexity properties most applicable to university building evacuation systems. Familiarity, social influence, egress width, and signage were the selected socio-technical factors to investigate in this research.

Sub question 2 was: What are the relevant evacuation performance metrics for evacuation in university campus buildings? A literature review, combined with real-life insights, revealed that the traditional evacuation metric is the total evacuation time. In this research, three metrics were used, namely 75% evacuation time, the time 75% of the agents have exited the buildings, mean density, the average density in all hallways and exits during the evacuation, and exit choice, expressed in the ratio of agents who exited through a known exit, the entrance, compared to an unknown exit, the emergency exits. The 75% evacuation time is selected instead of the total evacuation time to evaluate the effect of density-based factors, familiarity and social influence, to the effect of density-independent factors, egress width and signage, in a balanced way. The selection of three metrics allows for a relatively more complete understanding of the emergent behaviour of the evacuation system.

Sub question 3 was: Which combinations of socio-technical factors produce the most efficient outcomes for the evacuation metrics, and how do different factor levels interact to influence these outcomes? A standardised ranking of 54 distinct scenarios for the Applied Sciences building and the Civil Engineering and Geosciences building was performed. The most efficient scenarios in both buildings are scenarios with 100% familiarity and wider egress. The factor levels of social influence and signage were insignificant in these scenarios.

Sub question 4 was: What are the main and interaction effects of familiarity, social influence, egress width, and signage on exit choice, density and total and 75% evacuation time in university campus buildings? The results revealed that the four included factors, familiarity, social influence, egress width, and signage, had different levels of impact on the two buildings. In the Applied Sciences building, the strongest influencing factor was familiarity. For this building, familiarity significantly affected all three metrics. For the Civil Engineering and Geosciences building, familiarity also had a significant impact, but relatively less on density. For this building, egress width was the strongest influencing factor, with scenarios with wider egress ranking lower than scenarios with high familiarity. For both buildings, in scenarios with maximum familiarity values, the only other significant factor was egress width.

Signage and social influence had a noticeably smaller impact on evacuation performance for the two campus buildings. Signage showed a large difference in effect size on exit selection: for the Applied Sciences building, the effect size for exit selection ($\delta\eta^2 = 0.949$) was greater than the effect size for exit selection for the Civil Engineering and Geosciences building ($\delta\eta^2 = 0.180$). Of the three metrics, signage had the largest impact on evacuation time and exit selection. Social influence had the least visible impact on evacuation performance, with no repeated streaks of ranks with the same level, and only a significant effect on exit selection.

Differences in interactions were also observed. The interaction familiarity $\times$ wider egress had a large effect on the density of the Applied Sciences building, but a moderate effect on the density of the Civil Engineering and Geosciences building. This observation was the same for the interaction familiarity $\times$ signage, where the effect sizes of the Applied Sciences building were higher than those of the Civil Engineering and Geosciences building.

6.2. Discussion of Main Results

Familiarity had a large effect on the evacuation time, density, and exit ratio in the Applied Sciences building, as shown through the standardised ranking, supported by the very high partial eta-squared values. This is in line with previous research (M. L. Chu & Law, 2019; Kinateder et al., 2018), which showed that increasing familiarity leads to a decrease in evacuation time (D. Li & Han, 2015). It showed that for the Applied Sciences building, familiarity was the strongest influencing factor, followed by wider egress, then signage, and lastly social influence. For the Civil Engineering and Geosciences building, wider egress was the strongest influencing factor, followed by familiarity, then signage, and lastly social influence. The order of influencing factors per building is shown in Table 6.1.

Table 6.1: Order of strongest influencing factor per building

Building / Influence	Strongest		Weakest	
Applied Sciences	Familiarity	Egress Width	Signage	Social Influence
Civil Engineering and Geosciences	Egress Width	Familiarity	Signage	Social Influence

The difference in the strongest influencing factor is likely caused by the difference in number of exits. In the Applied Sciences building, there are 19 exits, evenly spread across the six wings. The Civil Engineering and Geosciences building houses seven exits, a difference of 12 exits. This difference in exits means a larger number of people per exit in the Civil Engineering and Geosciences building compared to the Applied Sciences building.

For the Civil Engineering and Geosciences building, egress width is the most influencing factor of the four, instead of familiarity for the Applied Sciences building. A possible explanation is that while increasing familiarity changes the distribution of people over the exit, it does not increase the exit flow rate, which widening exits does. Therefore, since the number of people per exit is already higher for the Civil Engineering and Geosciences building compared to the Applied Sciences building, increasing the exit flow rate by employing wider egress results in more optimal evacuation compared to a more even exit distribution.

For the Applied Sciences building, familiarity is the most influencing factor, instead of egress width. A possible explanation is the relatively larger number of exits and the relatively longer distance to the entrances, the known exits. The large number of exits in the Applied Sciences building allows for a smaller number of people per exit, and a greater exit flow rate. If the people are routed to their nearest exit, the benefit is twofold: the number of people per exit is lower compared to standard scenarios, and the people have shorter paths to their exit, ultimately lowering their time in the system. Although the hallways in the Applied Sciences building are relatively narrow, two metres, these narrow hallways are not critical when people are spread more evenly through the building. This confirms previous research, which indicated the effect of egress width is dependent on the building layout, and the current egress width (J. Zhang et al., 2024).

Previous work also stated that the effect of exit width is dependent on the hallway width in the building

(Zhao et al., 2008). In reality, the standard hallway width in Applied Sciences is 2 metres, for all wings and floors. In the simulation model, most exits, with the entrances as exceptions, are 2 metres wide. Given that the hallway width is equal to the standard egress width, widening exits to more than the hallway width can speed up the actual exiting process and reduce congestion around the exits. However, since hallway flow rates remain the same, in buildings with small hallway widths, spreading agents over the hallways is a more effective strategy than widening exits.

Surprisingly, there was not one scenario with 100% familiarity and normal egress width for the Civil Engineering and Geosciences building that ranked lower (more optimal performance) than scenarios with 100% familiarity and wider egress. In contrast, for the Applied Sciences building, there was not one scenario with 50% familiarity and wider egress that ranked lower than the scenarios with 100% familiarity and normal egress width. This dominance of the strongest influencing factor, familiarity for Applied Sciences versus egress width for Civil Engineering and Geosciences is an example of context dependency, a complexity inherent to complex systems: one or more scenarios might be effective in one building, but ineffective in another building.

In scenarios in which familiarity was maximised, wider egress was the only other factor with significant impact on both buildings. This effect is predominantly caused by the definition of familiarity in the simulation model. In the model, familiar agents will target the nearest exit. If a familiar agent were to pass a sign, the direction in which the sign points is probably the direction to that nearest exit. Similarly, if all agents are destined towards the nearest exit, getting influenced by social influence behaviour will output the the same exit in most cases.

In scenarios in which familiarity was minimised, an increase in the influence of signage was observed. This effect was observed to be larger in the Applied Sciences building compared to the Civil Engineering and Geosciences building. This difference was likely caused by the number of total signs in each building, and the position of the signs. In the Applied Sciences building, agents pass multiple signs on route to the known exits, while in the Civil Engineering and Geosciences building, this number is often closer to zero.

The observation that the influence of signage changed when other factors, predominantly familiarity, were changed, shows the presence of emergence in the evacuation systems. Ultimately, evacuation systems are complex systems, which means that not all outcomes can be explained. A part of researching complex systems is the awareness that there are complexities present.

The fact that the observed effect of social influence was relatively low is likely due to the design of the model. In this model, social influence is formalised as a set of conditions that have to be met in order for an agent to follow another agent. These conditions are universal in the simulation model. In reality, an underlying layer of social factors could impact the social influence decision-making process. These factors could include agent height (Lovreglio et al., 2016; Shen et al., 2014) or the density of the route ahead (Lovreglio et al., 2016).

6.3. Strengths and Weaknesses

A key strength of this study is the use of multiple performance metrics. Traditional approaches would focus only on evacuation time. Here, the incorporation of evacuation time, density, and exit choice provides a more comprehensive evaluation of evacuation performance. The multidimensionality ensures the most optimal scenarios are not focused on evacuation speed, as this could lead to congestion, bottlenecks, and suboptimal exit selection. By using multiple performance metrics, the study presents a more holistic perspective on evacuation performance.

Another strength of this study lies in the systematic approach to scenario testing. By employing a full factorial design with 54 scenarios per building, we can include all possible interactions, even up to four-way interactions. This allows for a more complete understanding of the influence of the socio-technical factors on evacuation performance. The selected analyses, the ranking and the GLM, both provide insight in interactions between factors, which would be less visible if opting for a fractional factorial design.

The inclusion of two distinct buildings further strengthens the narrative of the study by presenting how structural differences impact evacuation performance. This comparative approach again allows for a multidimensional perspective on evacuation performance, as the most influencing factor in the one building might be different in the other building. Analysing two buildings in this study resulted in a deeper layer of structural differences to be presented: incorporating flow rates as an important influencing aspect of evacuation systems.

In addition, the design of the simulation model is another strength of this study. The simulation model is coded in a way that allows for easy adaptation to other buildings. The behaviour of agents is standardised to be identical for both buildings, so that by changing the building layout, the model would work with little changes.

Despite these strengths, the study is subject to certain limitations. One notable limitations is the difficulty in balancing model performance and model correctness. For instance, the agent attribute familiarity determines exit selection, but also makes the agent insusceptible to social influence behaviour and signage, and allows them to act as leaders in groups. However, in reality, people familiar with the building layout and exit locations, might not react rationally in one hundred percent of the situations. Also, a familiar agent might still be persuaded by peer pressure, and follow a group towards an exit which might not be the nearest exit. Furthermore, in the simulation model, familiar agents might walk against in opposite direction of the stream, if this would lead to their closest exit. This would be especially difficult in scenarios where the agent has to pass through doors or stairs.

Another limitation of the study is its difficulty to detect different behavioural patterns beyond structural differences between buildings. Although interpretations can be made on the effect structural difference, such as number of exits, have on the influence of the individual factors, it is difficult to capture behavioural differences of agents. For instance, the functioning of social influence behaviour might be different in the two buildings. In addition, the actual detection rate of signage might differ in real life. In the Applied Sciences building, ceilings are mostly lower than 2.5 metres, resulting in signage placed not higher than that. In the Civil Engineering and Geosciences building, ceilings could reach up to 5 metres, and signage is also placed relatively higher.

Moreover, the use of NetLogo as the modelling platform introduces certain technical constraints. The 1x1 patch structure of NetLogo imposes limitations on the spatial representation of the real-life buildings, especially when modelling irregular shapes. This resulted for instance in the egress width only being adjustable in 1 metre increments. Additionally, the grid-like structure caused difficulties in realistically modelling density-based walking speed, as radius-based density checks would result in the inclusion of non-reachable agents (for instance on opposite ends of a wall) or a large increase in execution times. Although these constraints are inherent to the software, they introduce a degree of abstraction that should be considered when interpreting the results.

6.4. Practical and Theoretical Implications

The results of this study have direct implications for building design, emergency response planning, and safety policy. In this study, familiarity with the building layout was the largest factor influencing evacuation performance, followed by egress width, signage, and signage. This finding, that familiarity has the strongest impact on evacuation performance, suggests that building management should focus on increasing spatial awareness to their occupants and visitors. For building management, this could include regular orientation tours for employees, and regular evacuation drills. Building designers should prioritise spatial awareness of occupants and visitors in their designs. For instance, if building wings or levels have a near exact layout and design, this could confuse people.

Since egress width also seemed to be a major influencing factor, there are a couple of implications to be made. Building management, while likely unable to alter egress width in their existing building, should keep in mind the influence of egress width on evacuation performance. They should use means to redirect crowd formed near known exits, which are at capacity, to lesser known exits with available capacity. Building designers should ensure egress width, and therefore exit flow rates, correspond with projected occupancy numbers, but also consider upgrading older structures if flow rates are no longer sufficient.

Signage, although less influential than familiarity and egress width, still plays a significant role in guiding occupants toward safe exits. Since this study focused on overall evacuation performance, and did not consider specific points of interests, there is no knowledge on the performance of specific signs. However, building management and building designers should examine signage placement. In scenarios where familiarity is low, signage becomes more important. For these buildings, evacuation performance can probably be improved by implementing advanced signage, like the signs with flashing lights, to improve detection rates.

This study contributes to academic knowledge in two key ways, by employing a standardised ranking analysis, and by including multiple building types. First, it employs a standardised ranking analysis, a method that has not yet been widely adopted in evacuation research. The standardised ranking analysis provided a visual overview of the performance of many scenarios, 108 to be exact, which allows researchers to discover patterns to ultimately describe the order of influence of the socio-technical factors.

Second, by including multiple building types, the study enables the attribution of observed effects to specific building characteristics, thereby enhancing the generalisability of the findings. The buildings investigated in this study have similar population distributions, but different structures. This demonstrates the influences of familiarity, social influence, egress width, and signage, is not confined to a single type of structure, but can be observed for buildings with different configurations. The inclusion of multiple buildings strengthens the validity of the results.

6.5. Future Research

One of the most interesting areas for further investigation is exploring ways to increase occupants' familiarity with the building layout and exits. From the findings of this study, we can see that familiarity is a powerful factor in providing better evacuation results, by resulting in lower evacuation times and more effective exit choices. However, the current research only represents familiarity as a constant input variable, ignoring the potential changes possible in a real-life situation. In reality, university campus buildings are composed of (groups of) occupants with different familiarity levels. For instance, groups of employees might be more familiar than students or visitors. This distinction might cause different partial evacuation results in university buildings, where sections with a higher number of employees exhibit different behaviour than sections with a higher number of students. In the future, researchers might explore the impact of a number of interventions on familiarity levels in occupants, such as, for instance, regular evacuation drills, digital way-finding tools, informational signage, or virtual reality simulations. Finding out what methods are most adaptable for different building types and user groups would be of great value for improving evacuation preparedness and safety planning.

An interesting interpretation of the results is the presence of exit flow rates as a factor influencing the effect of the social, structural, and technical factors investigated in this study. As familiarity became less influential in environments with few exits and larger numbers of occupants, exit flow rates became more important. Future research could investigate the effect of different exit flow rates, as well as hallway flow rates, on evacuation performance.

In this study, four different influencing factors were further investigated, while more were discussed in the literature review. Because of the classification presented in this research, one could argue that social and structural factors are the most influencing. Future research could include a different combination of factors, where e.g. cultural factors, exit positions, or alarm systems, are included.

Since this study did not investigate performance of individual signs, future research could investigate the influence of locations and visibility on evacuation performance. This research could lead to higher signage detection rates, which could lead to a smaller influence of pure building familiarity.

6.6. Conclusion

This thesis investigates the influence of building familiarity, social influence behaviour, egress width, and signage on evacuation time, density, and exit choice of two TU Delft campus buildings. Evacuations are complex socio-technical systems, in which emergence, path dependency, and context dependency are present. Factors influencing evacuation performance can be categorised into social, structural, and technical factors. Evacuation performance was defined as 75% evacuation time, mean density, and exit choice. An agent-based model was built using Netlogo, featuring two TU Delft buildings which differ in structural aspects, but had a similar population distribution. A full factorial experiment was performed, which was analysed through a standardised ranking and a general linear model. The results showed familiarity and wider egress as important influencing factors in both buildings. In buildings with relatively fewer exits, egress width became more important than building familiarity. This difference in strongest influence is likely dependent on exit flow rates, hallway width, and overall building layout. The influence of signage was relatively lower but increased when familiarity was lowered, and the influence of social influence on the evacuation performance was often non-significant. The influence of social influence is highly dependent on its formalisation. Future research should investigate means to improve building familiarity among occupants.

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A

Experimental Setup

The global input variables, their explanation, and the values of the base case are shown in Table A.1. This chapter also contains the Netlogo syntax to perform the sensitivity analysis, and the full factorial experiment.

Table A.1: Global Input Variables and their base value

Variable	Explanation	Base Value
Building	The building number	22 (AS) or 23 (CEG)
Number of agents	The number of agents in the building	2000
Gender distribution	The ratio of male agents to female agents	65
Main floor percentage	The ratio of agents which spawn on the main floor	50
Unfamiliars entered correctly	The ratio of agents which entered to the entrance closest to them of all entrances	50
Familiar with building	The ratio of agents familiar with the building layout and exits	50
Persuasiveness threshold	The level of persuadability the agent has to have to become persuadable	50
Min group size	The minimum size of a group to be detected be agents	10
Max proximity to group	The maximum distance from an agent to a group that is of the minimum size	10
Wider egress	Boolean determining the width of the exits	false
Signage	The type of signage used (None, Basic, Advanced)	basic
Detection rate basic	The detection rate of basic signage	38%
Detection rate advanced	The detection rate of advanced signage	77%

A.1. Sensitivity Analysis

[["building" 22 23] ["number-of-turtles" 2000] ["gender-distribution" 65] ["main-floor-percentage" 50] ["unfamiliars-entered-correctly" 50] ["familiar-with-building" 60] ["persuasiveness-threshold" 50] ["min-group-size" 10] ["max-proximity-to-group" 10] ["group-gender-distribution" 50] ["wider-egress" false] ["signage" "Basic"] ["detection-rate-basic" 38] ["detection-rate-intermediate" 77] ["detection-rate-advanced" 77]]

[["building" 22 23] ["number-of-turtles" 2000] ["gender-distribution" 65] ["main-floor-percentage" 50] ["unfamiliars-entered-correctly" 45] ["familiar-with-building" 54] ["persuasiveness-threshold" 50] ["min-group-size" 10] ["max-proximity-to-group" 10] ["group-gender-distribution" 50] ["wider-egress" false] ["signage" "Basic"] ["detection-rate-basic" 38] ["detection-rate-intermediate" 77] ["detection-rate-advanced" 77]]

[["building" 22 23] ["number-of-turtles" 2000] ["gender-distribution" 65] ["main-floor-percentage" 50] ["unfamiliars-entered-correctly" 55] ["familiar-with-building" 66] ["persuasiveness-threshold" 50] ["min-group-size" 10] ["max-proximity-to-group" 10] ["group-gender-distribution" 50] ["wider-egress" false] ["signage" "Basic"] ["detection-rate-basic" 38] ["detection-rate-intermediate" 77] ["detection-rate-advanced" 77]]

[["building" 22 23] ["number-of-turtles" 2000] ["gender-distribution" 65] ["main-floor-percentage" 50] ["unfamiliars-entered-correctly" 50] ["familiar-with-building" 60] ["persuasiveness-threshold" 55] ["min-group-size" 11] ["max-proximity-to-group" 9] ["group-gender-distribution" 55] ["wider-egress" false] ["signage" "Basic"] ["detection-rate-basic" 38] ["detection-rate-intermediate" 77] ["detection-rate-advanced" 77]]

[["building" 22 23] ["number-of-turtles" 2000] ["gender-distribution" 65] ["main-floor-percentage" 50] ["unfamiliars-entered-correctly" 50] ["familiar-with-building" 60] ["persuasiveness-threshold" 45] ["min-group-size" 9] ["max-proximity-to-group" 11] ["group-gender-distribution" 45] ["wider-egress" false] ["signage" "Basic"] ["detection-rate-basic" 38] ["detection-rate-intermediate" 77] ["detection-rate-advanced" 77]]

[["building" 22 23] ["number-of-turtles" 2000] ["gender-distribution" 65] ["main-floor-percentage" 50] ["unfamiliars-entered-correctly" 50] ["familiar-with-building" 60] ["persuasiveness-threshold" 50] ["min-group-size" 10] ["max-proximity-to-group" 10] ["group-gender-distribution" 50] ["wider-egress" true] ["signage" "Basic"] ["detection-rate-basic" 38] ["detection-rate-intermediate" 77] ["detection-rate-advanced" 77]]

[["building" 22 23] ["number-of-turtles" 2000] ["gender-distribution" 65] ["main-floor-percentage" 50] ["unfamiliars-entered-correctly" 50] ["familiar-with-building" 60] ["persuasiveness-threshold" 50] ["min-group-size" 10] ["max-proximity-to-group" 10] ["group-gender-distribution" 50] ["wider-egress" false] ["signage" "Intermediate"] ["detection-rate-basic" 38] ["detection-rate-intermediate" 77] ["detection-rate-advanced" 77]]

[["building" 22 23] ["number-of-turtles" 2000] ["gender-distribution" 65] ["main-floor-percentage" 50] ["unfamiliars-entered-correctly" 50] ["familiar-with-building" 60] ["persuasiveness-threshold" 50] ["min-group-size" 10] ["max-proximity-to-group" 10] ["group-gender-distribution" 50] ["wider-egress" false] ["signage" "Advanced"] ["detection-rate-basic" 38] ["detection-rate-intermediate" 77] ["detection-rate-advanced" 77]]

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[["building" 22 23] ["number-of-turtles" 2200] ["gender-distribution" 65] ["main-floor-percentage" 50] ["unfamiliars-entered-correctly" 50] ["familiar-with-building" 60] ["persuasiveness-threshold" 50] ["min-group-size" 10] ["max-proximity-to-group" 10] ["group-gender-distribution" 50] ["wider-egress" false] ["signage" "Basic"] ["detection-rate-basic" 38] ["detection-rate-intermediate" 77] ["detection-rate-advanced" 77]]

[["building" 22 23] ["number-of-turtles" 2000] ["gender-distribution" 72] ["main-floor-percentage" 50] ["unfamiliars-entered-correctly" 50] ["familiar-with-building" 60] ["persuasiveness-threshold" 50] ["min-group-size" 10] ["max-proximity-to-group" 10] ["group-gender-distribution" 50] ["wider-egress" false] ["signage" "Basic"] ["detection-rate-basic" 38] ["detection-rate-intermediate" 77] ["detection-rate-advanced" 77]]

[["building" 22 23] ["number-of-turtles" 2000] ["gender-distribution" 58] ["main-floor-percentage" 50] ["unfamiliars-entered-correctly" 50] ["familiar-with-building" 60] ["persuasiveness-threshold" 50] ["min-group-size" 10] ["max-proximity-to-group" 10] ["group-gender-distribution" 50] ["wider-egress" false] ["signage" "Basic"] ["detection-rate-basic" 38] ["detection-rate-intermediate" 77] ["detection-rate-advanced" 77]]

A.2. Full Factorial Experiment

[[”building” 22 23] [”number-of-turtles” 2000] [”gender-distribution” 65] [”main-floor-percentage” 50] [”unfamiliars-entered-correctly” 50] [”familiar-with-building” 0] [”persuasiveness-threshold” 62.5] [”min-group-size” 12.5] [”max-proximity-to-group” 7.5] [”group-gender-distribution” 50] [”wider-egress” false] [”signage” ”None”] [”detection-rate-basic” 38] [”detection-rate-intermediate” 77] [”detection-rate-advanced” 77] [”sight” 6] [”play-sound-effects” false]]

[[”building” 22 23] [”number-of-turtles” 2000] [”gender-distribution” 65] [”main-floor-percentage” 50] [”unfamiliars-entered-correctly” 50] [”familiar-with-building” 0] [”persuasiveness-threshold” 62.5] [”min-group-size” 12.5] [”max-proximity-to-group” 7.5] [”group-gender-distribution” 50] [”wider-egress” false] [”signage” ”Basic”] [”detection-rate-basic” 38] [”detection-rate-intermediate” 77] [”detection-rate-advanced” 77] [”sight” 6] [”play-sound-effects” false]]

[[”building” 22 23] [”number-of-turtles” 2000] [”gender-distribution” 65] [”main-floor-percentage” 50] [”unfamiliars-entered-correctly” 50] [”familiar-with-building” 0] [”persuasiveness-threshold” 62.5] [”min-group-size” 12.5] [”max-proximity-to-group” 7.5] [”group-gender-distribution” 50] [”wider-egress” false] [”signage” ”Intermediate”] [”detection-rate-basic” 38] [”detection-rate-intermediate” 77] [”detection-rate-advanced” 77] [”sight” 6] [”play-sound-effects” false]]

[[”building” 22 23] [”number-of-turtles” 2000] [”gender-distribution” 65] [”main-floor-percentage” 50] [”unfamiliars-entered-correctly” 50] [”familiar-with-building” 0] [”persuasiveness-threshold” 62.5] [”min-group-size” 12.5] [”max-proximity-to-group” 7.5] [”group-gender-distribution” 50] [”wider-egress” true] [”signage” ”None”] [”detection-rate-basic” 38] [”detection-rate-intermediate” 77] [”detection-rate-advanced” 77] [”sight” 6] [”play-sound-effects” false]]

[[”building” 22 23] [”number-of-turtles” 2000] [”gender-distribution” 65] [”main-floor-percentage” 50] [”unfamiliars-entered-correctly” 50] [”familiar-with-building” 0] [”persuasiveness-threshold” 62.5] [”min-group-size” 12.5] [”max-proximity-to-group” 7.5] [”group-gender-distribution” 50] [”wider-egress” true] [”signage” ”Basic”] [”detection-rate-basic” 38] [”detection-rate-intermediate” 77] [”detection-rate-advanced” 77] [”sight” 6] [”play-sound-effects” false]]

[[”building” 22 23] [”number-of-turtles” 2000] [”gender-distribution” 65] [”main-floor-percentage” 50] [”unfamiliars-entered-correctly” 50] [”familiar-with-building” 0] [”persuasiveness-threshold” 62.5] [”min-group-size” 12.5] [”max-proximity-to-group” 7.5] [”group-gender-distribution” 50] [”wider-egress” true] [”signage” ”Intermediate”] [”detection-rate-basic” 38] [”detection-rate-intermediate” 77] [”detection-rate-advanced” 77] [”sight” 6] [”play-sound-effects” false]]

[[”building” 22 23] [”number-of-turtles” 2000] [”gender-distribution” 65] [”main-floor-percentage” 50] [”unfamiliars-entered-correctly” 50] [”familiar-with-building” 0] [”persuasiveness-threshold” 50] [”min-group-size” 10] [”max-proximity-to-group” 10] [”group-gender-distribution” 50] [”wider-egress” false] [”signage” ”None”] [”detection-rate-basic” 38] [”detection-rate-intermediate” 77] [”detection-rate-advanced” 77] [”sight” 6] [”play-sound-effects” false]]

[[”building” 22 23] [”number-of-turtles” 2000] [”gender-distribution” 65] [”main-floor-percentage” 50] [”unfamiliars-entered-correctly” 50] [”familiar-with-building” 0] [”persuasiveness-threshold” 50] [”min-group-size” 10] [”max-proximity-to-group” 10] [”group-gender-distribution” 50] [”wider-egress” false] [”signage” ”Basic”] [”detection-rate-basic” 38] [”detection-rate-intermediate” 77] [”detection-rate-advanced” 77] [”sight” 6] [”play-sound-effects” false]]

[[”building” 22 23] [”number-of-turtles” 2000] [”gender-distribution” 65] [”main-floor-percentage” 50] [”unfamiliars-entered-correctly” 50] [”familiar-with-building” 0] [”persuasiveness-threshold” 50] [”min-group-size” 10] [”max-proximity-to-group” 10] [”group-gender-distribution” 50] [”wider-egress” false] [”signage” ”Intermediate”] [”detection-rate-basic” 38] [”detection-rate-intermediate” 77] [”detection-rate-advanced” 77] [”sight” 6] [”play-sound-effects” false]]

[[”building” 22 23] [”number-of-turtles” 2000] [”gender-distribution” 65] [”main-floor-percentage” 50] [”unfamiliars-entered-correctly” 50] [”familiar-with-building” 0] [”persuasiveness-threshold” 50] [”min-group-size” 10] [”max-proximity-to-group” 10] [”group-gender-distribution” 50] [”wider-egress” true] [”signage” ”None”] [”detection-rate-basic” 38] [”detection-rate-intermediate” 77] [”detection-rate-advanced” 77] [”sight” 6] [”play-sound-effects” false]]

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