Realistic evacuation simulation through micro and macro scale agent-based modelling including demographics, agent patience and evacuation route capacities

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Abstract

Disasters affect millions of people annually, causing large social impacts, and detrimental economic impacts. Emergency professionals recurrently tackle these impacts, therefore they require assessment methods to understand potential consequences and enable the delivery of resilient resolutions. One method of achieving this is through numerical modelling, specifically agent-based modelling. However, current models simulating human behaviours and movement are bespoke in nature and non-transferable. It has also been found that current modelling tools have either focused on the microscale (e.g. individual confined spaces) or macroscale (e.g. city scale), without considering how the two scales may be interlinked. Further to this, the inclusion of human behaviour has been over-simplified and generic, lacking the inclusion of unique populations with varied characteristics.

The aim of this research is to develop a modelling framework, utilising agent-based modelling, to form a more robust representation of human behaviour within an enhanced evacuation model environment. This will allow emergency planners to be better prepared, reduce the interruption after an event (thereby reducing social and economic impacts) and potentially reduce the mitigation required beforehand. The individual agents within the framework capture a range of robust human behaviour indicators (e.g. walking speed, obedience, and patience), allowing the accurate replication of an emergence scenario response. Initially, the research focused on creating a macroscale evacuation model for a test city, to assess whether the inclusion of varied population characteristics and groups of people affected evacuation time. The varied characteristics included a range of ages, gender, and mobility in the form of walking speed. It was then possible to compare this with the parameters of existing evacuation models. This research has found that by enhancing the representation of human behaviour within a model environment more accurate predictions of evacuation time can be produced. To produce more robust human behaviour, models must include a range of population characteristics (such as age, gender and mobility), the grouping of agents and walking speed ratio. When all the variables are included in the model, there is an average increase of 70% in the time to evacuate Newcastle city centre. Even with less variables, i.e. only considering population characteristics, there has been an average increase of 45% in the time to evacuate Newcastle city centre compared with existing models.

To further examine human behaviour and the more intricate and detailed behaviours such as patience, a microscale model was created to consider the capacity of the pathways and to introduce congestion. The two microscale models were created of a pavement and a crossroads,

to replicate people passing and waiting behind slower people, whilst still including the varied population characteristics. When capacity is captured at the microscale, there is an average 61% increase in the time to exit the pavement and when on a crossroads there is an average 87% increase in the time to exit compared to 1.34m/s (3mph) models.

Overall, this research has found that there is a need to provide more robust representation of human behaviour characteristics within evacuation models. This must be carried out not only at the macroscale in terms of enhancing population demographics but also at the microscale by capturing intricate behaviours such as taking over and giving way. Without an ability to exhibit these characteristics evacuation simulations cannot effectively capture human behaviour and therefore produce robust simulation times. The inclusion of more representative human behaviour in simulations and the continual need to improve provides the opportunity to reduce the likelihood of increased fatalities and injuries caused by those unable to evacuate in time due to current underestimations. The improvement of computational simulation of evacuations alongside existing simulation techniques allows emergency professionals to plan and prepare better for a range of events to protect global communities.

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Finally, I want to thank my wonderful family and friends, particularly my husband Chris, son Edward and parents Pam & Andy, who have kept me going through these tough final stages and a global pandemic. All their support and guidance have allowed me to follow my dream of returning to an academic career and achieving a PhD.

List of Publications

As a result of this thesis, two journal papers have been successfully reviewed and published; a further journal is under review. Prior to starting my PhD, I was also involved with a research project at the Institution of Civil Engineers and the report can be found online. Finally, I delivered a public lecture in the final stages of my PhD to explore the importance of including realistic human behaviours in simulations, a link to the YouTube recording is listed below.

Journal Articles

Barnes, B., Dunn, S. and Wilkinson, S., 2019. Natural hazards, disaster management and simulation: a bibliometric analysis of keyword searches. *Natural Hazards*, *97*(2), pp.813-840.

Barnes, B., Dunn, S., Pearson, C. and Wilkinson, S., 2021. Improving human behaviour in macroscale city evacuation agent-based simulation. *International Journal of Disaster Risk Reduction*, *60*, p.102289.

Barnes, B., Dunn, S. & Wilkinson, S., n.d. Replicating Capacity and Congestion in Microscale Agent-Based Simulations. *Travel Behaviour & Society.* (UNDER REVIEW)

Professional Institution Reports

Institution of Civil Engineers (ICE), 2015. Innovation: Stepping up the Industry.

Public Lectures

https://www.youtube.com/watch?v=_ryEbpEu24g&feature=youtu.be

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List of Abbreviations

ABM – Agent-Based Modelling

BBC – British Broadcasting Company

CRED – Centre for Research on the Epidemiology of Disasters

CST – Council for Science and Technology

DDT – Dichlorodiphenyltrichloroethane

EM-DAT – Emergency Events Database, also known as the International Disaster Database produced by the Centre for Research on the Epidemiology of Disasters

FEMA – Federal Emergency Management Agency

GAMMA – Geometric Algorithms for Modelling, Motion and Animation

GDP – Gross Domestic Product

GIS – Geographical Information Systems

IPENZ - Institution of Professional Engineers New Zealand

ITN – Integrated Transport Network

LRF – Local Resilience Forum

LSM – Life Safety Model

NGO – Non-Governmental Organisation

NPCC – National Police Chiefs Council

NRA – National Risk Assessment

NRR – National Risk Assessment

OAPs – Old Age Pensioners

OS – Ordnance Survey

RAC – Royal Automobile Club

RNLI – Royal National Lifeboat Institution

UEFA – Union of European Football Associations

UK – United Kingdom

UN – United Nations

UNDRR – United Nations Office for Disaster Risk Reduction

UNISDR – United Nations International Strategy for Disaster Risk Reduction

USA – United States of America

WHO – World Health Organisation

Chapter 1. Introduction

This chapter will begin to explore the questions posed by this thesis and outline the current research gap that exists. This will introduce the aim of the project as well as the research objectives and questions to be answered throughout the thesis. It is also necessary to detail the scope of the research as this topic area is vast so it would not be possible to cover all potential outcomes. Finally, the structure of the thesis will be set out for the reader, to give a brief overview of the work completed within each chapter.

1.1 Research Gap

Natural disasters affect millions of people annually, causing large numbers of fatalities, detrimental economic impact and the displacement of communities. It has been reported that between 1994 and 2013, 218 million people were affected by natural disasters annually (CRED, 2015). Policymakers and industry professionals are regularly faced with these consequences and therefore require tools to assess the potential impacts and provide sustainable solutions, often with only very limited information. The ability to respond to natural hazard events varies greatly across the globe (Cutter, 2016) (Aka, et al., 2017) (Singh-Peterson, et al., 2015), with those in developed countries able to dedicate time and money towards early warning systems, (Wenzel, et al., 2001) (Durage, et al., 2013) (Glade & Nadim, 2014), creation of risk registers (Glavovic, et al., 2010) (Markovic, et al., 2016) and improved emergency communications (Miao, et al., 2013) (Lu & Xu, 2014). For example, America's Presidential alert was issued to 200 million mobile phone users across the country to test whether crucial information could reach individuals in an emergency scenario, with the hope that the information would reach 75% of all phones in America (BBC, 2018) (Vega, 2018). Whereas communities in the developing world are often ill-prepared and under-resourced to plan mitigation and risk reduction strategies beforehand, resulting in bigger impacts and consequences for those affected (Barnes, et al., 2019) (Monirul Qader Mirza, 2003) (Tingsanchali, 2012) (Ismail-Zadeh & Takeuchi, 2007) (Birkmann, et al., 2010) (Toya & Skidmore, 2007).

This difference can be demonstrated by considering two natural disaster events that occurred 2015. In the UK during the winter of 2015, unprecedented levels of flooding were experienced by communities across Yorkshire, Lancashire and Cumbria. It has been reported that the floods are ranked as the "*most extreme on record in the UK*" (The Guardian, 2016). This resulted in communities being cut off from each other, financial obligations and the destruction of wildlife habitats. A bridge over the River Wharfe in Tadcaster (BBC, 2015 A) and Pooley Bridge in

Cumbria (BBC, 2015 B) both collapsed during the storm events fracturing communities (Figure 1-1). Due to the damage caused, funding needed to be raised to repair these assets and repairs were anticipated to take in the region of 12-18 months before a sense of normality could return. However, twelve months on from the event, over 700 families had still not regained access to their properties and Cumbria County Council approximated the recovery costs to date at £500 million (BBC, 2016).

(a) (b)

Figure 1-1 – (a) Flooding at Pooley Bridge in the Lake District Photo Credit: Owen Humphreys/PA (The Guardian, 2016), (b) Collapse of Tadcaster Bridge over River Wharfe in 2015 Photo Credit: Giles Rocholl (BBC, 2015 A)

In the same year, Nepal was hit by a magnitude 7.8 earthquake on the 25th April 2015 (BBC, 2015 C), followed by severe aftershocks, the consequences were devastating with over 9,000 fatalities (Rafferty, 2016). Over 2.8 million people were displaced by the earthquake and a separate UN report estimated that more than 8 million people (approximately 25% of Nepal's population) were affected by the event and its aftermath (Rafferty, 2016). Initial estimates for the damage cost ranged between $5 billion and $10 billion (Rafferty, 2016). In the aftermath of the event, aid was pledged from across the globe, totalling $4.1 billion towards rebuilding efforts (Rowlatt, 2016). However, one year on from the earthquake "*virtually none of the 800,000 buildings*" destroyed had been rebuilt (Figure 1-2), with political turmoil over the introduction of a new constitution cited as the reason for slow progress (Rowlatt, 2016). In 2018, three years after the earthquake, it was reported that "*only 16% of the $4.2 billion pledged*" had been utilised in reconstruction and recovery efforts (Thapa, 2018) (The Kathmandu Post, 2018).

(a) (b)

Figure 1-2 – (a) Earthquake Damage in Nepal Photo Credit: Niranjan Shrestha/AP Images (Rafferty, 2016), (b) Damage Caused by Nepal Earthquake Photo Credit: Rex Shutterstock (McKie, 2015)

Whilst direct comparisons cannot be drawn between the two events due to the differing event types, it is possible to consider them separately. It is clear to see that there were disproportionate impacts for communities in Nepal from the 2015 earthquake event, this was two-fold. Firstly, unlike the flood event in the UK, the earthquake occurred with no warning preventing the communities from preparing and secondly the event occurred in a country struggling with chronic disorganisation and under-funding at a government level. Whereas, in the UK, when largescale flooding occurred, there was not only pre-warning in the form of flood and storm warnings but a swift and prompt response to the event aftermath. Therefore, it is imperative that policy makers, researchers and industry professionals can make "good" decisions to provide sustainable and resilient risk reduction and mitigation strategies and to lessen the consequences for communities across the globe. Key to this is the development of appropriate tools for emergency professionals to help assess impacts and provide solutions.

The impacts and consequences of natural disasters can be both large and wide reaching in terms of financial damages, people affected and fatalities (Table 1-1). Between 2000 and 2011, a total of 2.7 billion people were affected by a natural disaster, resulting in 1.1 million fatalities and $1.3 trillion in terms of financial damage (Figure 1-3) (International Civil Defence Organisation, 2016). Natural disasters severely hinder the ability of communities to develop and in particular to do this sustainably. When communities are impacted by disasters the immediate need is restoration for present needs whether this be, for example, clean water, shelter or access to healthcare. However, this may not be the most sustainable measures for future generations or in fact even long-term solutions, with structures replaced like for like or worst rather than built back better, this only further adds to the long-term suffering of communities. Hence, government and international NGOs, who have the resources and power to provide post-disaster solutions must balance the immediate needs (e.g. temporary shelters in the response and recovery disaster management phases) with the long-term sustainable and permanent solutions during the learn and prepare phases of the disaster management cycle.

Table 1-1 – Table of Possible Impacts of Disasters (Lindell & Prater, 2003) (CRED, 2015) (see Chapter 2 for further information)

Impacts of Disasters		
Social	**Environmental**	**Financial**
Loss of Housing Loss of Access to facilities Displacement of communities	Pollution of water systems Devastation of habitats Change of predator/prey relationships	Cost to repair, replace and to mitigate or prepare for the next event
Impacts can also be combined e.g. if a water system becomes polluted, communities need to move to find a suitable clean water source or finance the cost of installing a new or repairing an existing water system		

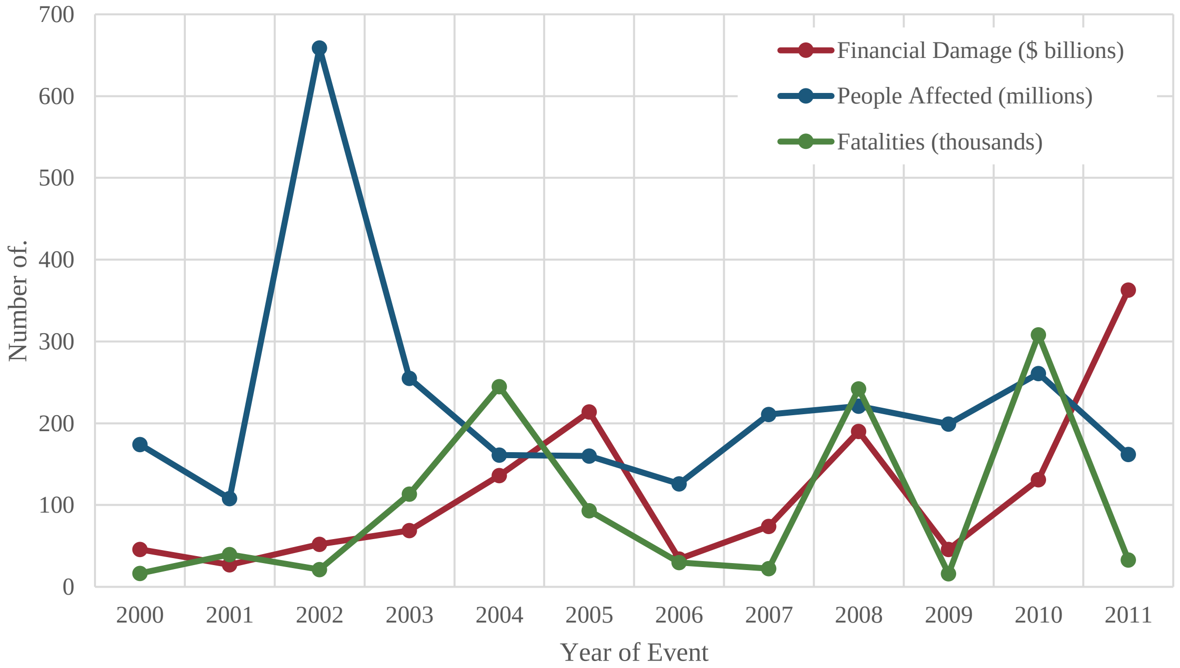


Figure 1-3 – Diagram of the Economic and Human Impact of Disasters (2000 – 2011) Financial Cost of Disasters (Total Damage = $1.3 trillion), People Affected by Disasters (Total Number = 2.7 billion people affected), Fatalities Caused by Disasters (Total Number = 1.1 million people killed), definition of a disaster categorised as a Natural Disaster by EM-DAT (International Civil Defence Organisation, 2016)

During 2016, the UN convened for the first time in its 70-year history a world summit on humanitarian assistance, stating that "*today, the scale of human suffering is greater than at any time since the Second World War*" (United Nations, 2016). It is estimated that up to 130 million people across the globe, currently rely on humanitarian assistance to survive (United Nations, 2016). This has resulted in a renewed focus on disaster management policy (Ismail-Zadeh &

Takeuchi, 2007) (Birkmann, et al., 2010), which has the potential to greatly reduce the suffering of communities across the globe (Cutter, 2016) (Aka, et al., 2017) (Singh-Peterson, et al., 2015). Consequently, there have been many international improvements and a recognition of the rewards of better planning for natural disasters; including improved early warning systems (Wenzel, et al., 2001) (Durage, et al., 2013) (Glade & Nadim, 2014), improved application of risk registers on a range of scales (Glavovic, et al., 2010) (Markovic, et al., 2016) and improved emergency communications (Miao, et al., 2013) (Lu & Xu, 2014). There has also been a recognition that mitigation strategies come hand in hand with impact reduction interventions and emergency responses to produce a full complement of measures and to support communities effectively.

However, in the aftermath of a large-scale natural disaster it has been found that failure of infrastructure systems can have disproportionate impacts on society (Gardoni & Murphy, 2020). Another example were the communities affected by Hurricane Katrina, who should have been able to cope with the impacts of the natural hazard as there was good infrastructure in place, but there was still a large amount of suffering afterwards as their infrastructure failed (Kates, et al., 2006) (U.S. Homeland Security and Counterterrorism, 2006) (Olshansky, 2006). The reason for this is that these systems provide us with access to clean water supplies, transportation and medical supplies, all of which are vital in the aftermath of a disaster and help to minimise short and long term social, economic and environmental impacts. The main event may also not be the main cause of the issues, with secondary events, e.g. aftershocks or tsunami, causing further and in some instances more disastrous consequences (Lubkowski, et al., 2009). It is likely that these effects will be further exacerbated by climate change, either through larger impacts or more frequent event occurrence, as well as through differences in the development of countries and global instability (Riebeek, 2005).

As stated above, in the developed world, natural hazards still affect society; however, in general, developed economies have the resources to be able to consider effective mitigations strategies pre-event, rather than firefighting the consequences post event (Cutter, 2016). This is a far more effective strategy for dealing with natural hazards and is achieved through the development of regulatory frameworks that develop mitigation strategies and plans to minimize the impacts of potential disasters. For example, in the UK the Civil Contingences Act 2004 was brought in to provide a single framework for civil protection in the UK (Cabinet Office, 2013). Whilst, in the USA a national preparedness goal has been set out, which encourages the shared responsibility from the entire nation (FEMA, 2016) (Sadiq, et al., 2016). This demonstrates that informed governmental policy on disaster management can be seen as a driver for change.

The regulatory frameworks encourage government agencies and local offices to create contingency plans for dealing with the aftermath of hazard events. In the UK, these take the form of Local Resilience Forums who create community risk registers (Northumbria Local Resilience Forum, 2014) (London Resilience Partnership, 2017), which sit alongside the National Risk Register (Cabinet Office, 2008) (Cabinet Office, 2015). The aim of the plans and risk registers is to formally categorise the local risks and to put forward a possible plan for emergency professionals to respond to a series of events. However, there is a regulatory demand to thoroughly test these plans, to ensure that the response is appropriate.

Currently, there is a reliance on testing contingency plans, developed through regulatory frameworks, either through real-world simulation, which is costly in both monetary and resource terms (Cabinet Office & National Security and Intelligence, 2013) or through scenario based methodology in table-top exercises, which can be unrealistic. Within the UK, regular real-life simulations are conducted, for example in March 2017, a mock terrorist exercise was conducted on the River Thames in London, including more than 200 Met Police officers (Beake, 2017). Another example occurred in June 2015, when a week long terrorist attack was simulated in central London, this involved over 1,000 police officers, 2,000 causalities made up of actors and dummies and the event took over 6 months to plan and execute (BBC, 2015) (Paton & Warrell, 2015). However, there is an alternative and more robust method to test; using computational approaches, which would allow for multiple runs and adjustments without the large financial or resource costs. However, at present, policies and regulatory frameworks do not explicitly outline the use of computational systems and modelling to help their progress.

To tackle this problem, researchers have been developing modelling techniques and approaches, such as Cellular Automata, System Dynamics and Fault Tree Analysis, to try and simulate hazard types under particular scenario conditions (e.g. fire on a metro network, (Zhong, et al., 2008) (Lo, et al., 2014). However, these models are often non-transferable, meaning it is not possible to keep software "current" or future proofed as the modelled problems are bespoke in nature. An alternative modelling approach is agent-based modelling, which has been described as "*one of the most important generic modelling frameworks to have been developed to date*" (Batty, et al., 2012). It has the capability to allow "*one to simulate the individual diverse agents, measuring the resulting system behaviour and outcomes over time*" (Crooks, et al., 2008).

Despite the benefits of current agent-based modelling, as with any modelling technique, there are some problems with the approach and applicability. For example, existing evacuation and disaster relief models predominantly rely on evacuees following the routes determined by emergency planners based on available data and the expected route of the natural disaster, e.g. hurricane. Also, agents are often determined to all act in the same way during the evacuation, e.g. moving at the same walking speed. However, this has been found to not be the case and more evacuees follow routes decided from their own experience (Dow & Cutter, 2000), (Wu, et al., 2012) and due to age differences, illness and other factors walking speeds are not the same (Wu, et al., 2012). There are also a number of other variables, which have been found to affect the likelihood of an evacuee leaving their home and performing an evacuation (Whitehead, et al., 2000) (Ng, et al., 2016). These include but are not limited to their age, gender, income, home or pet ownership.

Current models do not consider such variables, do not include route preference based on experience and do not realistically simulate human behaviour. Instead current models are generic and lump together agents with the same constraints e.g. all agents are required to move at the same speed (Wood, et al., 2016). Therefore, it can be argued that current models are limited and not well verified, validated and calibrated compared to known conditions.

1.2 Research Aim

The aim of this project will be to create a modelling tool, which includes a set of robust human behaviour rulesets, to enhance the simulation of evacuations. This will be beneficial for a range of management professionals in the NGO sector as well as government**.** This will allow emergency planners to be better prepared, reduce the interruption after an event and potentially reduce the mitigation required beforehand. For communities, robust evacuation models will allow better preparation for hazards, including through evacuation, which may ultimately result in saved lives and a reduction in the levels of human suffering encountered.

This project will use an agent-based modelling framework, to better determine human behaviour and people movement during an emergency scenario for the benefit of emergency planners and managers. This will require individual agents to have unique characteristics and to act independently of each other. It is important to capture robust human behaviour indicators in the model such as walking speed, obedience and crowd dynamics, to be able to accurately replicate a response to an emergency scenario. It will be imperative that the model can consider a range of natural disasters and other emergencies such as terror attacks, to allow planners to be able to implement the model for a range of scenarios.

1.3 Objectives and Research Questions

The primary aim of this project can be separated into several broad areas of research, which in turn can be broken down further into smaller streams. The associated research questions to be answered have been set out alongside the objectives.

The main objectives of the project are:

1. **Identify, review and understand the disaster management methodologies, modelling techniques and anticipated human behaviour traits, including the formulation of a series of case studies based on recent real-life natural hazard events and the definition of a series of probabilistic agent "rulesets".**

   Method: The broad topics to be identified, reviewed and understood are existing disaster relief management methodologies predominantly for evacuation procedures, the challenges, differences and limitations on current modelling practice particularly for agent-based models, the differing city types seen across the globe and their anticipated growth. Exploration of past natural disaster events will be considered, which required some form of evacuation and intervention from emergency managers, including successful and failed events. An analysis will be carried out for each failure occurrence, to identify common themes, mechanisms of failure and barriers to implementation of disaster management plans. Literature will be explored for available human behaviour traits both in normal "everyday" scenarios and under hazard conditions, to identify behaviour types. Where possible quantitative evidence of behaviours will be sought for inclusion within modelling rulesets. Comparisons will also be drawn between the behaviour types and current models, to understand the limitations and successes of software and models to date.

   Research Questions:

   a. What are the current models available for assessing evacuations in natural disasters?
   b. What different types of cities exist and how are they expected to grow and be affected by factors such as climate change?
   c. What are the obstacles and common issues to completing evacuations successfully and reproducing this accurately in simulations?
   d. What are main behaviour types found in literature and can these behaviours be quantified?

Output: A critical literature review covering the broad topics of disaster relief management and human behaviour traits, a series of case studies exploring past natural disaster event evacuations and their successes and failures, as well as the determination of a set of probabilistic agent "rulesets".

2. **Identification of a suitable agent-based model or modelling software, which can be used or adapted for this research.**

   A suitable agent-based model will be identified during the literature review or case study compilation. This model will either be adopted or adapted based on previous studies to enable the simulation and analysis of an evacuation procedure in a city environment. As part of this, a critical review will be required of several models and software packages to ensure appropriate selection. This review will involve initially compiling and running a simple model e.g. a prey-predator model, which are commonly available as a standard. For those that successfully run the model, a simple evacuation model will be formulated to test capabilities further e.g. inclusion of spatial data.

   Research Questions:

   a. What are the successes/limitations of each model or software package?
   b. Can the agents be manipulated as unique agents? E.g. determined by age, gender or family group.

   Output: A critical evaluation of modelling software and available agent-based models, identifying the potential for including more realistic human behaviour traits.

3. **Implementation and testing of the macro agent-based model, to ensure it can reproduce a range of individual behaviours for the analysis of largescale evacuation procedures (e.g. city scale).**

   An initial evacuation model will be constructed on a city scale to explore individual agent behaviour in a largescale environment. The city will be based on Newcastle upon Tyne. This model will aim to reproduce a range of behaviour types identified from literature and critically assess the initial success and limitations.

   Research Questions:

   a. Are the agents demonstrating unique characteristics and behaving independently of each other?
   b. How realistic is the simulation of the unique agents?
   c. Is the model well calibrated, verified and validated?

Output: A city scale agent-based model of Newcastle upon Tyne featuring a range of behaviour traits to simulate a unique population.

4. **Refinement and testing of the agent-based models to incorporate interactions between agents and hence simulate the intricacies of crowd behaviour on a micro scale (e.g. pavement, crossroads).**

   Two secondary agent-based models will be created to focus on the smaller scale interactions of human behaviour within a crowd. This will take the form of a pavement or single road and a crossroads junction. This model will aim to again reproduce a range of behaviour types as identified in literature and an assessment will be made of the attainment and confines of this.

   Research Questions:

   a. Are the agents demonstrating unique characteristics and behaving independently of each other?
   b. How realistic is the simulation of the unique agents?
   c. Is the model well calibrated, verified and validated?

   Output: Two microscale agent-based models of a pavement and crossroad junction featuring an increased range of behaviour traits to simulate overtaking and giving way.

5. **Recommendations to evacuation simulation users e.g. modellers and emergency management professionals (including: NGOs, charities and governments), plus reflection on the success of the project and recommendations for further research work.**

   Based on the outcomes of the research work, recommendations will be made to the main involved parties in order to improve disaster management procedures. It is important to provide a generalised modelling framework/tool but also to allow a degree of flexibility and adaptation. An assessment of the success of the project will provide useful information on further areas of research, ways to improve the modelling technique as well as the general successes and failures.

   Output: An assessment of the thesis including a recommendation for further work.

1.4 Scope of Research

The potential of this thesis topic is vast and as such it has been necessary to carefully consider the extents to which this PhD can cover. It is important that the PhD is kept to a manageable size and as such there has been a skew towards natural hazards within the thesis. However, there are many similarities between natural and manmade hazards, which means many of the recommendations and findings are also relevant to those threats.

The range of human behaviours are also enormous and initially many behaviour types were identified for inclusion within the modelling environment. This study focuses on key behaviours (such as flee behaviour, routes and crowd behaviour), however other behaviours have not been discounted. For example, cognitive mechanisms are considered but then not included within the model; however, their inclusion within models could still offer further benefits. The intent from the offset was to focus solely on pedestrian behaviours without vehicles impeding on available space. This is an idealised scenario but was based on the increasing amount of pedestrian or shared space which has been constructed in UK cities. This allowed the focus to be tailored towards pedestrians and the intricate movements that they may make. The decision was also made to limit the scope of the pedestrian speeds used, in this case the focus was on walking only and did not include running. Running does form an integral part of an evacuation simulation, however the city simulations covered a 2km x 3km area of Newcastle, with some routes equating to over 4km in distance. A worst-case scenario was therefore assumed that no pedestrians had the ability to run such large distances and walking speeds were instead maintained. Discussion around walking speeds and the potential need to consider running are covered in the conclusions. A high level of compliance is also maintained within this thesis, research within this area was not extensive enough to categorise an appropriate ruleset although it has been suggested that the level of compliance may influence the success of evacuations. Therefore, this was not explored further within the modelling simulations. Finally, thought was given to the inclusion of a hazard model within the simulation, as it is plausible that different hazards will produce different behaviours and potential issues for emergency responses. However, the aim of this thesis was to establish a working evacuation simulation with a robust inclusion of human behaviour that was not specific to a single scenario but had the potential to be transferable to many different scenarios. In the future, it is possible that there will be additional scope to further the modelling techniques identified in this thesis with the addition of other behaviour types and rulesets.

This thesis also needed to set out initial criteria for the choice of modelling platform, as there is a large and ever-increasing number of options available. To limit the scope the criteria for modelling software were limited to options that were free to access, open source, provided comprehensive user guides and model libraries to explore. Hence, a first filtration process occurred which has not been documented in this thesis but did consider a much wider range of platforms. For example, at the time it was not possible to access a free version of Oasys Mass

Motion, consideration was given to purchasing a licence, but this was prohibitively expensive for the scope of this project. A selection of available models was also analysed, similar criteria (e.g. free to access, comprehensive literature available) were again established to manage the scope of the research.

1.5 Structure of Thesis

Chapter 2 – Background: This chapter will set out the background to natural disasters, defining a disaster and the different types of events that are experienced across the world. It will also examine the impacts and consequences of disasters for global communities. It is these impacts and consequences, which make it necessary to consider how improvements can be made and the importance of doing so. Governmental policy can be a key driver in improving responses to disasters and this will be explored for examples of good practice, whilst identifying if further improvements may be beneficial. Finally, modelling options will be examined to consider how models currently deal with disaster scenarios and where developments may be sought.

Chapter 3 – Human Behaviour: This chapter will explore the potential behaviours during a hazard event, then use these behaviours to formulate a series of desired model rulesets. From the rulesets, a literature review will be carried out to capture realistic values to reflect the behaviour traits, which can be verified and validated. This will help to ensure that the agent-based model is robust.

Chapter 4 – Macroscale Model Setup: This chapter will set out the human behaviour that is deemed most important when considering emergency scenarios and based on those behaviours identify a series of rulesets for inclusion within an agent-based model. With the aim that this can improve the representation of human traits in the model environment. To understand the potential impacts of improving human behaviour, a macroscale model (city scale) has been developed to showcase this range of potential behaviours. A detailed description of the model environment and key user variables will be set out. The proposed testing regime has been set out alongside the anticipated outcomes of each test. Validation, calibration and verification of the models has also been considered to ensure the validity of the models proposed.

Chapter 5 – Macroscale Modelling Testing: This chapter will assess the outcomes of the macroscale city evacuation model, which has been tested to ensure that the rulesets have reproduced appropriate behaviours. A series of tests have been carried out to assess the effects of population characteristics, walking speeds and the grouping of agents. The limitations of the model environment will be examined to understand how well human behaviour is represented.

Chapter 6 – Microscale Model Setup: This chapter will address the limitations of the macroscale model by replicating intricate human behaviours in a microscale model environment (a pavement and at a crossroads). With the hope of further improving the representation of behaviour traits in a computational model. A detailed description of the model environment and key user variables will be set out. The proposed testing regime has been set out alongside the anticipated outcomes of each test. Validation, calibration and verification of the models has also been considered to ensure the validity of the models proposed.

Chapter 7 – Microscale Modelling Testing: This chapter will assess the outcomes of the microscale models, which have been tested to ensure that the rulesets have reproduced appropriate behaviours. A series of tests have been carried out to assess the effects of population density, patience levels and population distribution. The limitations of the model environment will be examined to assess the human behaviour represented.

Chapter 8 – Conclusions & Future Work: This chapter draws conclusions from the main findings of the research presented in this thesis and provides recommendations for future research.

Chapter 2. Background

This chapter will set out the background to natural disasters, defining a disaster and the different types of events that are experienced across the world. It will also examine the impacts and consequences of disasters for global communities. It is these impacts and consequences, which make it necessary to consider how improvements can be made and the importance of doing so. Governmental policy can be a key driver in improving responses to disasters and this will be explored for examples of good practice, whilst identifying if further improvements may be beneficial. Finally, modelling options will be examined to consider how models currently deal with disaster scenarios and where developments may be sought.

2.1 What is a disaster event?

Natural disasters are major events that cause adverse effects, through natural earth processes. These may be hydrological (e.g. flooding, tsunamis), geological (e.g. earthquakes, volcanoes) or, meteorological / climatological (e.g. cyclones, tornadoes). There are also manmade events, such as pandemics (e.g. Coronavirus or Ebola) or terrorist attacks which can have similar effects to that of natural disasters.

2.1.1 Types of Events

A disaster can be defined as "*a sudden, calamitous event that seriously disrupts the functioning of a community or society and causes human, material and economic or environmental losses that exceed the community's or society's ability to cope using its own resources*" (International Federation of Red Cross and Red Crescent Societies, 2016). Alternatively, the UN Office for Disaster Risk Reduction (UNDDR) considers disasters as: "a *serious disruption of the functioning of a community or a society involving widespread human, material, economic or environmental losses and impacts, which exceeds the ability of the affected community or society to cope using its own resources*" (UNISDR, 2009).These events are primarily caused by nature but some have human causation. A disaster can be summarised by the following equation, Equation 2-1. This shows that communities are impacted by a hazard of a given severity and it is their ability to withstand the event (i.e. capacity) and initial vulnerability to the event that dictates whether the event results in a disaster.

Equation 2-1

$$\frac{(Vunlerability + Hazard)}{Capacity} = Disaster$$

Hazard events or disasters can be categorised into natural events; hydrological, geophysical, meteorological and climatological or human events; war and terrorism (Table 2-1). Biological events are normally a result of nature but can also be caused by humans.

Table 2-1 – Table of Disaster Definitions and Examples

Event Type	Definition	Example
Hydrological	"*Events caused by deviations in the normal water cycle and/or overflow of bodies of water caused by wind set-up*" (United Nations, 2010).	Floods – river, flash, storm surge, coastal Wet Mass Movement (rock fall) Avalanche
Geophysical	"*A hazard originating from solid earth*" (desinventar - Disaster Information Management System, 2016). Interchangeable with geological.	Earthquakes Landslides Tsunamis Volcanic Activity
Meteorological	"*A hazard caused by short-lived, micro- to meso-scale extreme weather and atmospheric conditions that last from minutes to days*" (desinventar - Disaster Information Management System, 2016).	Tropical Cyclones Fog Convective Storm Extratropical Storm Storm/Wave Surges Extreme Temperature
Climatological	"*A hazard caused by long-lived, meso- to macro-scale atmospheric processes ranging from intra-seasonal to multi-decadal climate variability*" (desinventar - Disaster Information Management System, 2016).	Drought Wildfire
Biological	"*A hazard caused by the exposure to living organisms and their toxic substances (e.g. venom, mould) or vector-borne diseases that they may carry*" (desinventar - Disaster Information Management System, 2016).	Epidemics Pandemics Disease Insect/Animal Plagues
War	"*A state of armed conflict between different countries or different groups*	Fighting Bombing

	within a country" (Oxford Dictionary, 2016 A).	
Terrorist Attack	A surprise incident which "*unlawfully uses violence and intimidation, especially against civilians, in pursuit of political or religious aims*" (Oxford Dictionary, 2016 B).	Bomb Mass shooting Chemical attack Biological attack

It is important to understand whether different types of natural and manmade disasters can have varied impacts and consequences for the communities they affect. It is likely that certain event types cause greater fatalities, whilst others affect greater numbers, and some cause the greatest financial damages.

2.1.2 Evolving Events

Consideration also needs to be given to how hazards evolve, i.e. hurricanes, floods and terrorist attacks can often have cascading failures. There is an initial hazard event i.e. the storm event, this causes an initial impact for a community, which requires a response. However, there then may be further impacts caused by infrastructure failures e.g. if the road network is damaged, it is then difficult to transport supplies into a disaster zone. This was well documented during Hurricane Katrina when cascading failures compounded the impacts of the disaster further, for example, during Hurricane Katrina two dozen hospitals were left without electricity, meaning the duty of care could not be completed, resulting in many potentially preventable deaths (Gray & Herbert, 2007) (Table 2-2).

Table 2-2 – Hurricane Katrina Case Study

Case Study
Hurricane Katrina, USA 2005
Hurricane Katrina hit the Gulf Coast of the United States of America at the end of August 2005. It has been cited as "*one of the most costly and deadly natural disasters ever experienced by the United States*" (Baker, 2014). The hurricane caused over 1,800 fatalities and displaced more than 250,000 people (Baker, 2014). Financially, the hurricane caused devastation with the damage cost estimated to be as high as $150 billion for the federal government, with insurance claims anticipated between $20 - $45 billion (Milken Institute, 2005). On top of this, it was estimated that there was an initial loss of 400,000 jobs in September 2005 (Milken Institute, 2005).

This natural event caused a huge financial and social toll on the public, it also caused complete destruction to the environment and community, due to the breach of the levees and exceptional levels of flooding caused (Figure 2-1 & Figure 2-2). This was a large scale event in a developed country, but due to the unpredictable nature of hurricanes, the late issue of a mandatory evacuation and the lack of available transportation (Reynolds, 2005) (Oslen, 2005), the consequences were overwhelming and severely impacted the sustainable growth of the area until reconstruction was well under way. It is estimated that the full reconstruction of New Orleans may take as long as 11 years (Figure 2-3).

Figure 2-1 – Damage caused by Hurricane Katrina (CNN, 2016)

Figure 2-2 – Flooding caused by Hurricane Katrina (Live Science, 2013)

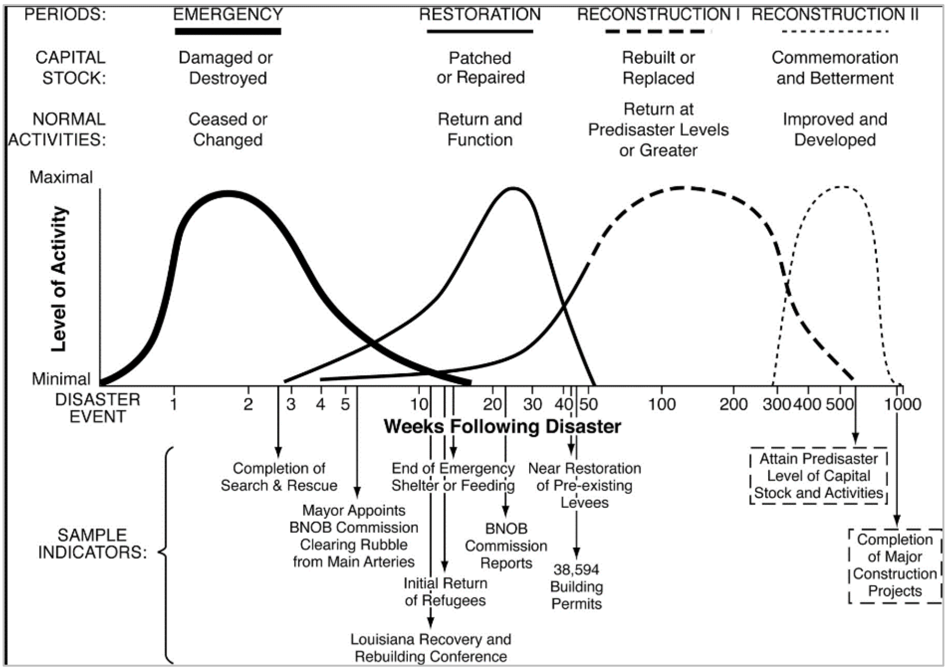


Figure 2-3 – The sequence and timing of reconstruction after Katrina in New Orleans with actual experience (solid lines) and sample indicators for the first year along a logarithmic time line of weeks after the disaster. The long-term projections (dashed lines) are based on an emergency period of 6 weeks, a restoration period of 45 weeks, and a 10-fold historical experience for reconstruction. (Kates, et al., 2006)

2.2 Impacts of Disasters

The data in this section has been collated to demonstrate the frequency of natural disasters and how communities have been affected (including fatalities and economic impacts), to enable an exploration of the current disaster trends across the globe, with emphasis given to the past 20 years. The data has been obtained from the EM-DAT, the International Disaster Database produced by the Centre for Research on the Epidemiology of Disasters (CRED) (Guha-Sapir, et al., 2016) and from the "*The Human Cost of Disasters: A Global Perspective*" report (CRED, 2015). For a disaster to be included within the EM-DAT database, it must meet one of the following criteria: (1) 10 or more people died, (2) 100 or more people were affected, (3) there was a declaration of a state of emergency or (4) there was a call for international emergency assistance (EM-DAT, 2016).

2.2.1 Who is affected by disasters?

The prevalence of natural disasters has remained relatively static over the past 20 years, however the number of people affected, fatalities and economic costs continue to grow (CRED, 2015). It has been reported that between 1994 and 2013, 218 million people were affected by natural disasters annually (CRED, 2015). It has also been estimated that between 2000 and 2011, a total of $1.3 trillion worth of damage, 2.7 billion people have been affected and 1.1 million fatalities were caused as a result of natural disasters (International Civil Defence Organisation, 2016) (Figure 2-4). Figure 2-4 shows several years where there are evident peaks regarding financial damage, number of fatalities and number of people affected. Regarding the economic costs, there are peaks in 2005 (Hurricane Katrina & Hurricane Rita), 2008 (Cyclone Nargis & Sichuan Earthquake) and 2011 (Tohoku Earthquake & Tsunami). In respect of the fatalities, these were highest in 2004 (Boxing Day Tsunami), 2008 (Cyclone Nargis & Sichuan Earthquake) and 2010 (Haiti Earthquake). Concerning the number of people affected, the largest peak was in 2002 (Asia/European Flooding & China Drought).

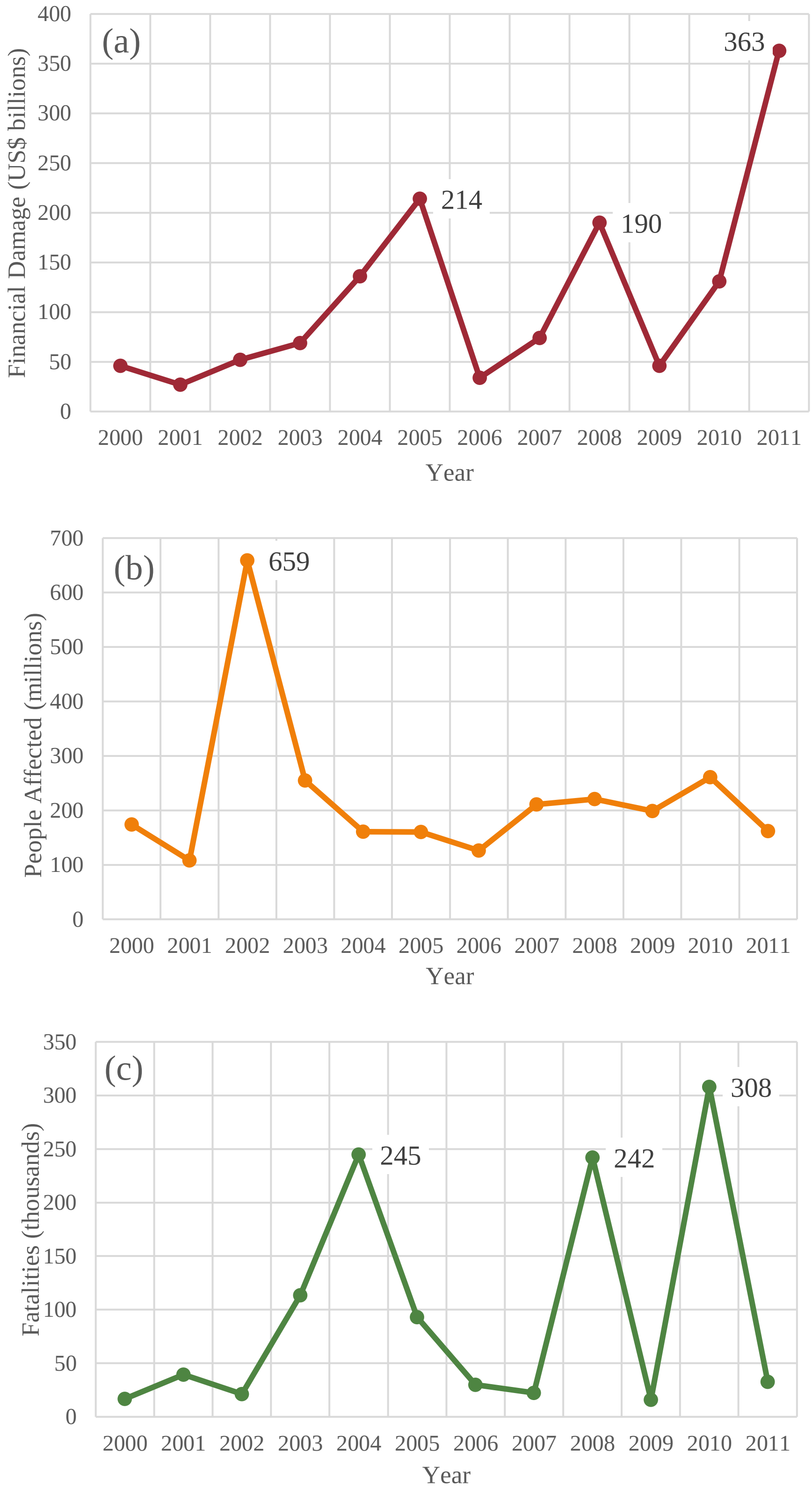
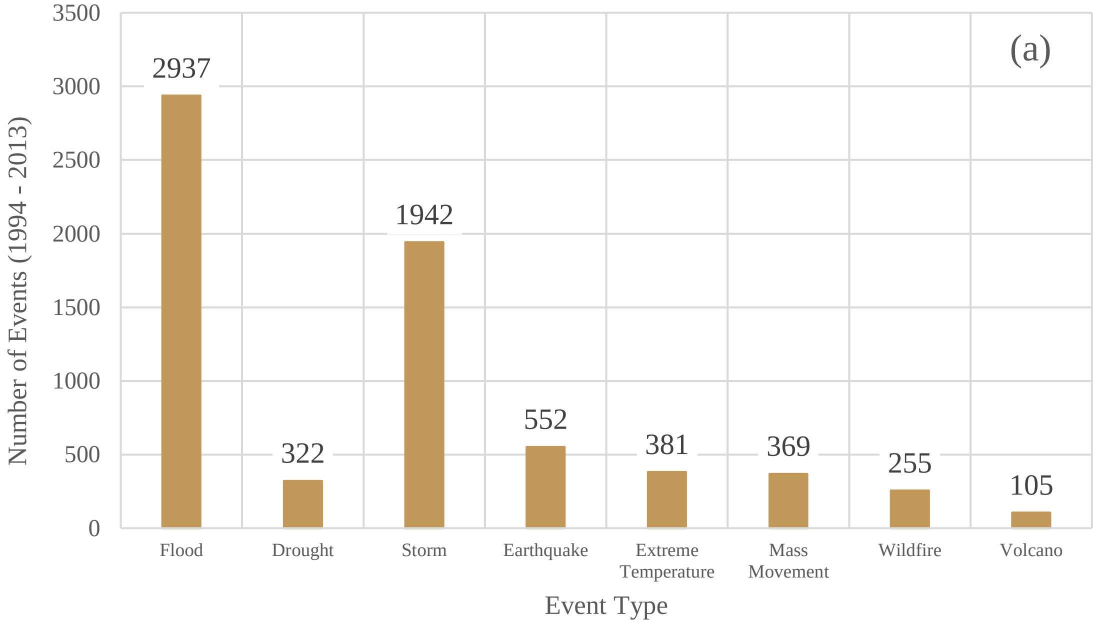
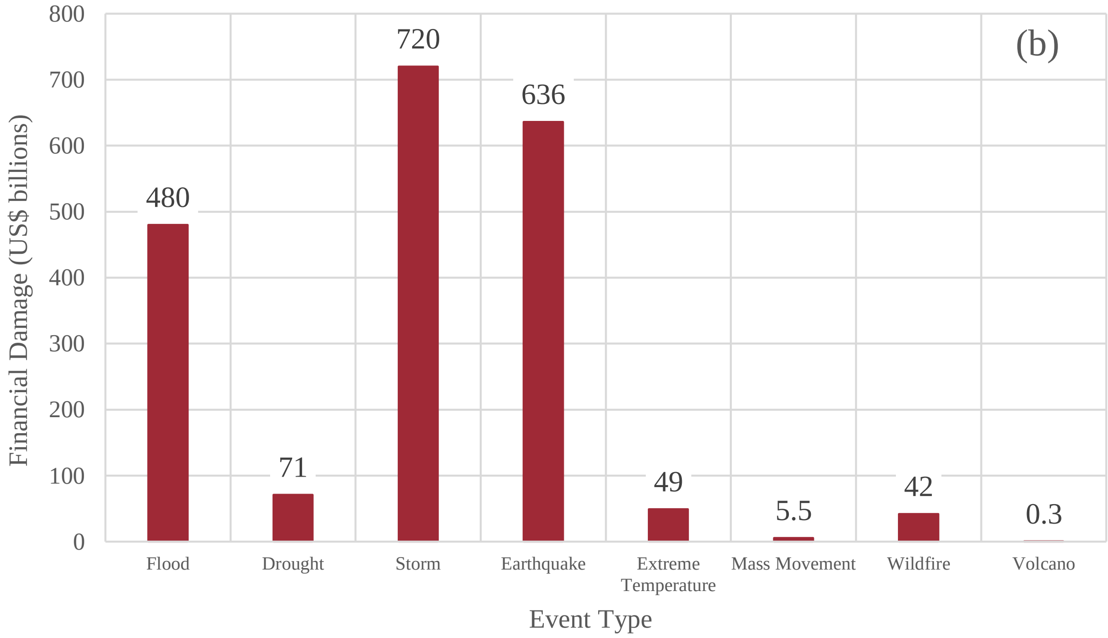


Figure 2-4 – Diagram of the Economic and Human Impact of Disasters (2000 – 2011) – (a) Financial Cost of Disasters (Total Damage = $1.3 trillion), (b) People Affected by Disasters (Total Number = 2.7 billion people affected), (c) Fatalities Caused by Disasters (Total Number = 1.1 million people killed), definition of a disaster categorised as a Natural Disaster by EM-DAT (International Civil Defence Organisation, 2016)

This demonstrates that in terms of natural disasters, the disaster types occur in different proportions, affect different numbers of people, cause differing amounts of fatalities and incur different financial costs, as shown in Figure 2-5 and Figure 2-6(a). The disaster types also affect infrastructure including housing, health facilities and schools differently (Figure 2-6(b)). From these figures it is possible to draw several conclusions; hydrological events are the most frequent, geophysical hazards are the deadliest, hydrological events affect the greatest number of people and meteorological hazards are the costliest. In terms of damaged houses and health/school facilities hydrological events are the worst, but for destroyed health and school facilities the worst is from meteorological events.





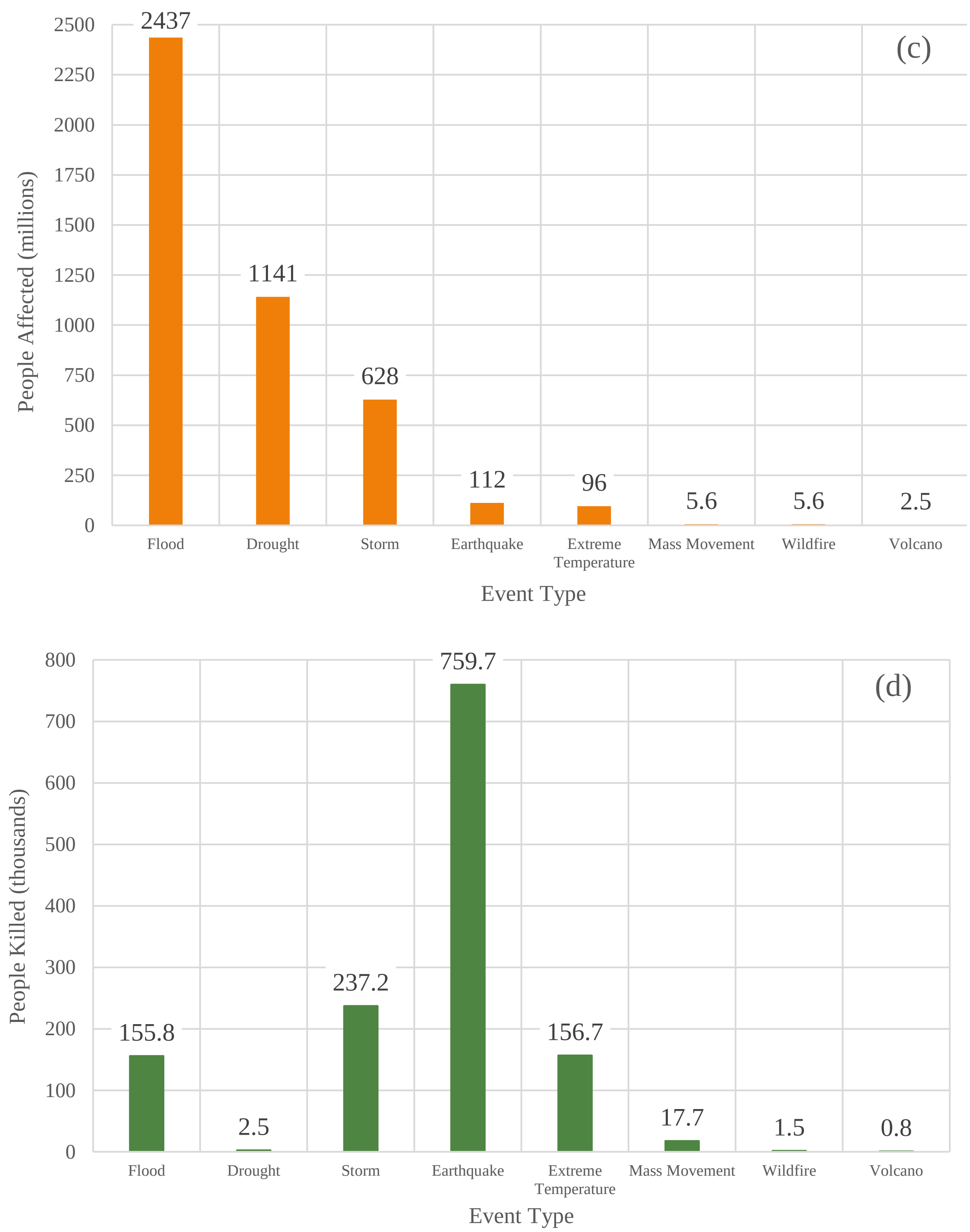


Figure 2-5 – Diagram of the Impact of Disasters by Event Type – (a) Occurrence of Natural Disaster Events 1994 – 2013 (CRED, 2015) (b) Financial Cost of Disaster, (c) People Affected by Disasters, (d) Number of Fatalities by Disasters definition of a disaster categorised as a Natural Disaster by EM-DAT (International Civil Defence Organisation, 2016)

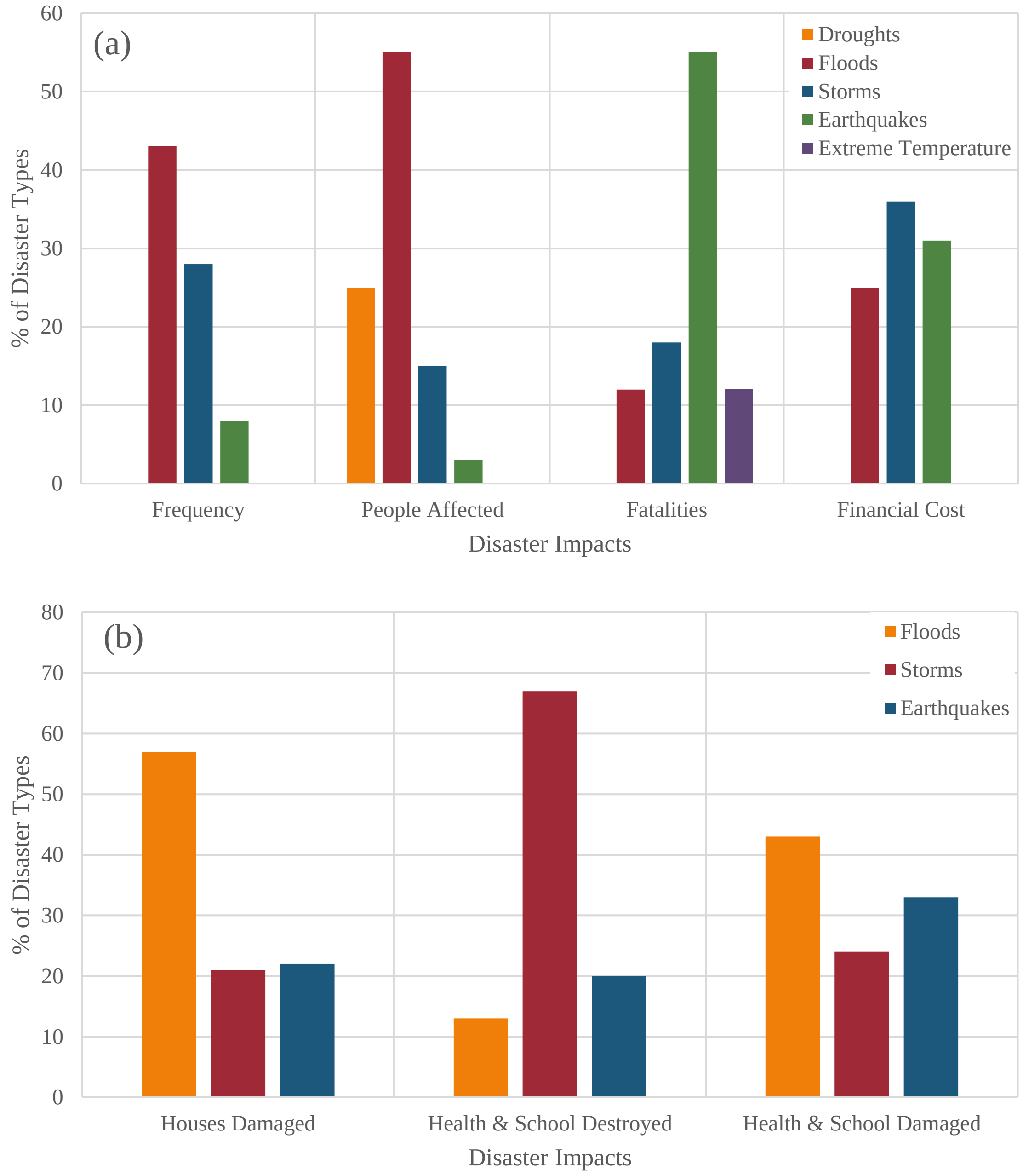


Figure 2-6 – a) Natural Disaster Types: Global frequency of events, people affected by hazards and fatalities caused by different types – information taken from (CRED, 2015), (b) Natural Disaster Types: Global effects on infrastructure in terms of houses damaged and health & school facilities destroyed or damaged– information taken from (CRED, 2015)

2.2.2 Locations affected by disasters

Natural disasters are experienced across the globe, with Asia experiencing the largest number of disasters followed by the Americas, and then Africa and Europe, and Oceania experiencing the smallest numbers (CRED, 2015). In terms of specific countries, India, China, the USA and Philippines have each experienced the largest number of natural disasters, at 243 – 509 disasters across a 20-year period (CRED, 2015). In 2016 this resulted in "*over 65 million refugees and displaced people in the world*" (Cosgrave, et al., 2016) (Figure 2-7), causing increasing numbers of people across the globe who have been displaced to seek refuge and safety elsewhere. The level of protracted displacement, a period of at least three years, has now reached 14 million (Cosgrave, et al., 2016).

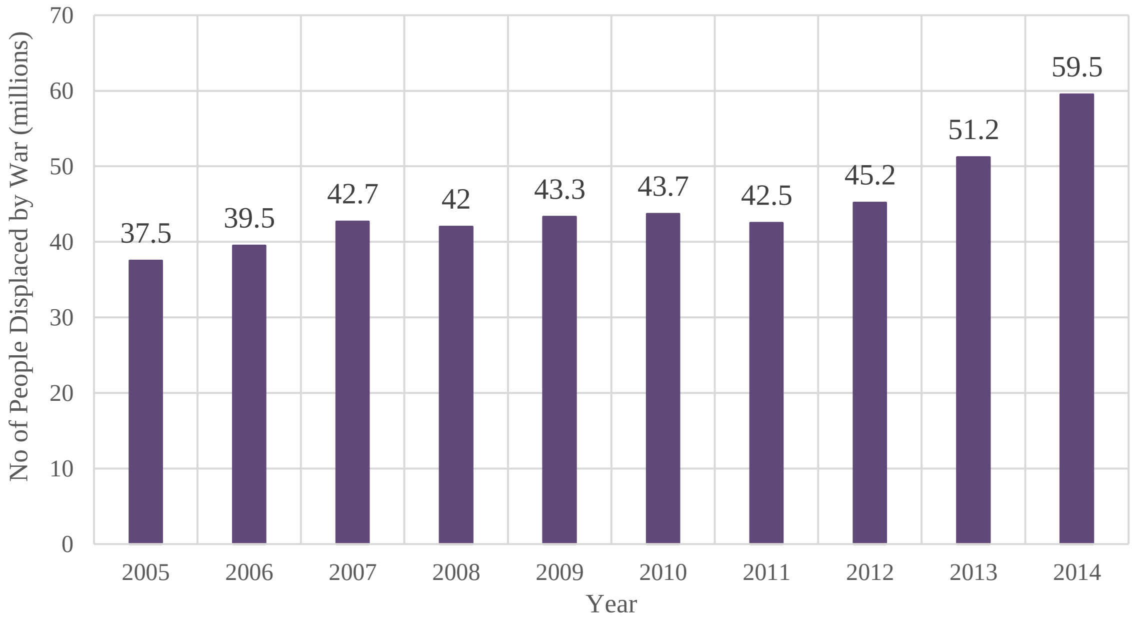


Figure 2-7 – Graph of Number of Displaced People across the Globe (UNHCR - The UN Refugee Agency, 2015)

Prevalence of natural disasters does not necessarily link to the financial impact of disasters. The lowest frequency of natural disasters occur in low-income countries (17%), whilst the other income groups have more of an even split, high income (26%), upper-middle income (30%), lower-middle income (27%) (CRED, 2015). However, the lowest number of fatalities from natural hazards occurs in high-income group (13%), followed by upper-middle (19%), conversely the highest fatalities are in the lower-middle group (35%) and low-income (33%) (CRED, 2015). Therefore, it could be argued that low-income countries are disproportionately impacted by natural disasters, as with each disaster that occurs the community is severely impacted, causing the development of these countries to be broken by the cycle of recovery.

However, in absolute values the USA has experienced the largest financial impact due to natural disasters, followed by Japan then China (CRED, 2015) (Table 2-3). This shows that in some cases, the frequency of disasters impacts the level of financial toil. However, the disaster type (e.g. hydrological, meteorological, or geophysical) has a greater impact on the likely financial cost. The disaster type also significantly contributes to the other impacts such as number of people affected and fatalities.

Table 2-3 – Top Ten Countries reporting Economic Losses from Natural Disasters in terms of Absolute Values adapted from (CRED, 2015)

Country	Largest Disaster Type	Economic Losses (US$ billion)
USA	Storms	739
Japan	Floods	482
China	Floods	453
Italy	Floods / Earthquakes	66
Germany	Floods	56
Thailand	Floods	46
India	Floods	46
Mexico	Storms	39
France	Storms	39
Turkey	Earthquake	35

In terms of economic damage by country's income group, the economic damage in absolute terms shows that high-income countries experience the largest losses (64%) and upper-middle (26%), whereas low-income is much smaller (3%) or lower-middle (7%) (CRED, 2015). Alternatively, if the economic damage is expressed as a percentage of GDP, then for the low-income countries the losses are greatest (5.1%) compared to the lower-middle (0.2%), high-income (0.3%) and upper-middle country groups (0.6%) (CRED, 2015). Financial damage as a percentage of a country's GDP, vastly changes the countries affected by financial hardship (Table 2-4). Korea Democratic People's Republic has the largest proportion of economic losses in terms of GDP (38.9%), followed by Mongolia (33.9%) and Haiti (14.9%) (CRED, 2015). Therefore, it could be argued that again low-income countries are disproportionately impacted, as the disasters that occur result in funds being diverted to recovery efforts rather than allowing communities to continue developing, this can also compound debt problems for low-income countries.

Table 2-4 – Top Five Countries reporting Economic Losses in terms of % of GDP (CRED, 2015)

Country	Largest Disaster Type	Economic Losses (% of GDP)
Korea Democratic People's Republic	Floods	38.9
Mongolia	Wildfires	33.9
Haiti	Earthquakes	14.9
Yemen	Floods	11.1
Honduras	Storms	6

For the period 2000 – 2016, there were many high impact individual natural disasters, the costliest of these was the Tohoku earthquake in Japan (March 2011), with estimated damage of $210 billion, followed by Hurricane Katrina in the USA (August 2005) at $125 billion and then the Sichuan earthquake in China (May 2008) with costs of $85 billion (EM-DAT, 2016). This ties in with the top ten countries reporting economic losses from natural disasters by absolute values, which were USA, Japan, and China. However, as a product of GDP the financial losses would not be as significant, which is partly why these countries have been able to recover from these events alongside the fact that these developed countries have appropriate plans and recovery in place to lessen the impacts of disasters in the first instance.

2.3 Consequences of Disasters

After the initial impact of disasters (i.e. number of people affected, financial losses and fatalities), there can be several short and long-term consequences of a hazard event. This can severely impact community's ability to develop and grow resiliently as each event requires a significant period of recovery and restoration. These recovery and restoration events also divert limited resources (both physical and monetary) from other development opportunities. This has the potential to significantly impede communities.

2.3.1 Infrastructure in Disasters

Infrastructure in disasters will often be severely and significantly impacted by the hazard events that occur. As demonstrated, natural hazard events are not limited to one area of the world and can be experienced across the globe. However, the event type and consequences can be varied depending on the location due to factors such as the type of infrastructure, government policies and GDP of the country etc.

Society relies heavily on infrastructure, including power generation, water supply and transportation, but the reliance is often not seen until a failure occurs. Due to the size of infrastructure networks, the affected community need not even be near the disaster location as networks cover large areas. It can be stated that "*the societal disruption caused by infrastructure failures is therefore disproportionately high in relation to actual physical damage*" (Chang, 2014). Recent disasters, such as Hurricane Katrina, have shown that infrastructure systems are vulnerable and result in both large financial and societal losses. Hence, there is a need to understand and provide more resilient infrastructure. It has been suggested that this should be tackled with three inter-related strands; "*lower probabilities of failure, less-severe negative consequences when failures do occur and faster recovery from failures*" (Chang, 2014) (Bruneau, et al., 2003). Better understanding of the infrastructure, human behaviour, and role of disaster management through computational modelling could aid this by providing a tool to test multiple scenarios (failures). Hence, potentially reducing the consequences of disasters and allowing for faster recoveries to occur.

2.3.1.1 Categorisation of Cities

Despite events affecting different locations, research has shown that cities can be categorised into different types, either through similarities in geometric shapes (Bethelemy & Louf, 2014) or the economic growth of a city (Macomber, 2016). Hence, when developing plans and policies, it may be beneficial to utilise this principle and to work collaboratively towards creating suitable methodology and models in similar city types rather than creating numerous bespoke models.

Bethelemy & Louf (2014) propose a quantitative method for categorising cities according to street pattern. This was applied to 131 cities across the world, resulting in four large city types based on blocks of a certain area and shape (Table 2-5) (Figure 2-8). This categorisation cannot fully capture the intricacies of every city, especially as different neighbourhoods can sometimes exhibit alternative street patterns depending on the historical growth of a city. However, it is possible to use this simplification as an indicator to similar city layouts and street patterns, which could be beneficial for emergency planning professionals.

Table 2-5 – Categorisation of Cities based on Street Pattern adapted from (Bethelemy & Louf, 2014)

Group No.	Representative City	Description
1	Buenos Aires, Argentina (only)	Blocks of medium size, with shapes that are square or regular rectangles. Small areas are almost exclusively square.

2	Athens, Greece	Dominant fraction of small blocks with shapes broadly distributed.
3	New Orleans, USA	Similar to group two for diversity of shapes but is more balanced in terms of areas, with a slight predominance of medium size blocks.
4	Mogadishu, Somalia	Small, square-shaped blocks, together with a small fraction of small rectangles.

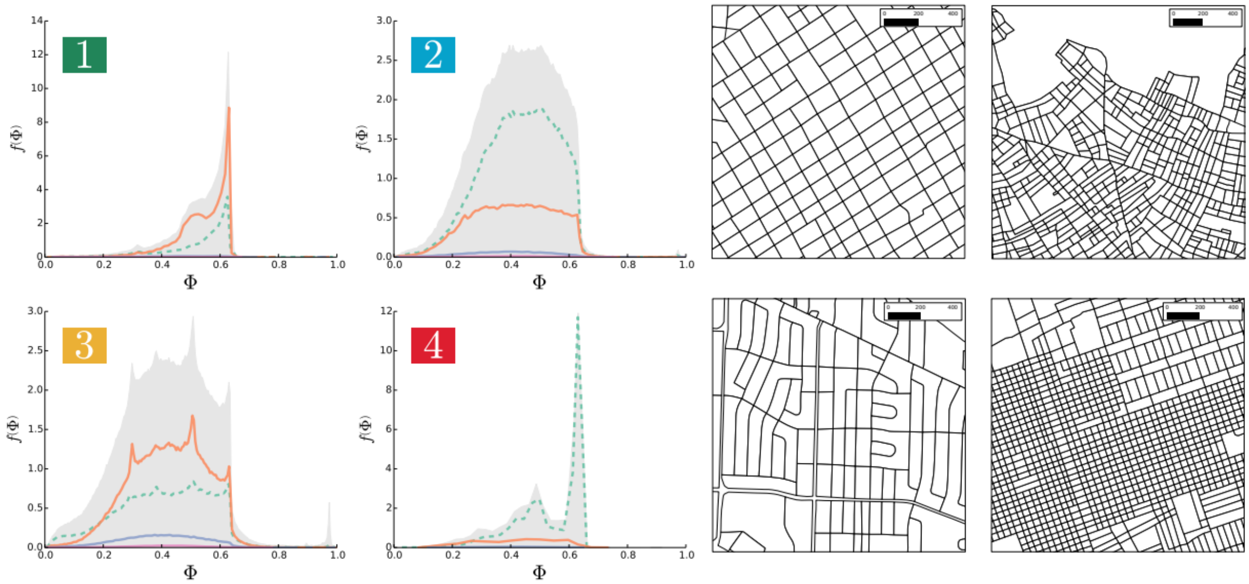


Figure 2-8 – Four City Types (Graphs (LEFT) depict the Average Distribution of the Shape Factor for each group found by the clustering algorithm (the curve corresponds to the area bin from small to large: dashed green, orange, and blue). (City Layouts (RIGHT) typical street patterns for each group (plotted at the same scale in order to observe differences in both shape and areas) Group 1 – Buenos Aires, Group 2 – Athens, Group 3 – New Orleans, and Group 4 – Mogadishu). (Bethelemy & Louf, 2014)

However, the idea of city categorisation is not a new concept and the notion of categorising based on the support of cities and internal structure was proposed in 1945 by Harris & Ullman. A city's support was split into three possibilities; (1) central places performing comprehensive services for a surrounding area, (2) transport cities performing break-of-bulk and allied services along transport routes, and (3) specialised function cities performing one service (Harris & Ullman, 1945). Although the relevance of this has decreased over time, it does highlight that cities can have primary functions but generally for many cities, there will now be a combination of all support mechanisms as cities have grown and amalgamated over time. The other idea explored was that cities have an internal structure made up of business, industrial and residential areas. This was captured within three theories: concentric zones, sectors, and multiple nuclei (Figure 2-9). While the categorisation of cities has moved on since this research was first published, it does illustrate that simple categorisation can be a useful tool, even if just to create generalised city zones, which in turn allows likely infrastructure assets to be identified e.g. homes, offices or factories.

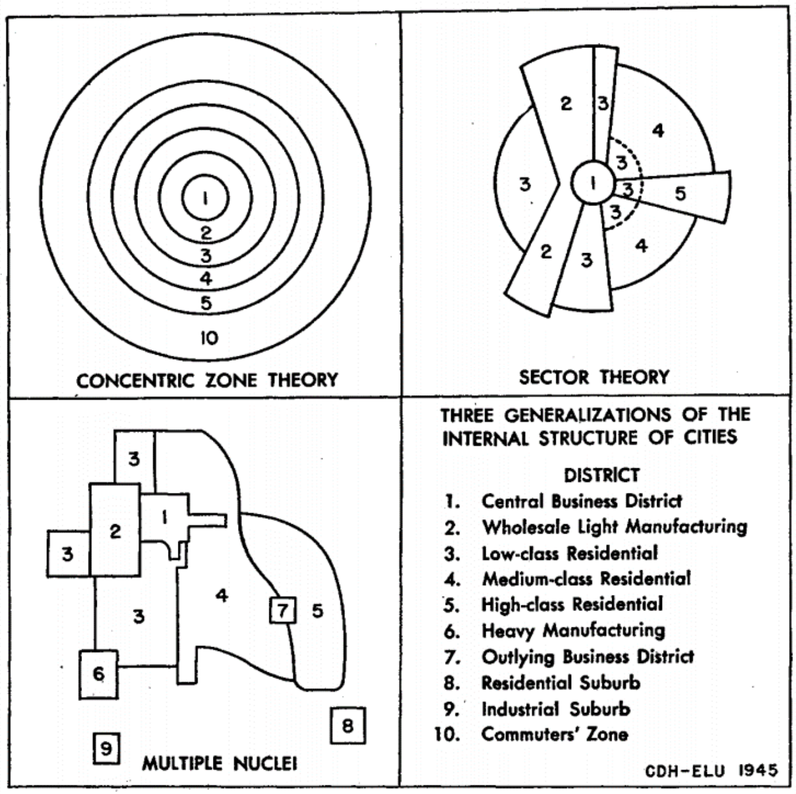


Figure 2-9 – Generalisation of Internal Structure of Cities (The concentric-zone theory is a generalisation for all cities. The arrangement of the sectors in the sector theory varies, from city to city. The diagram for multiple nuclei represents one possible pattern among innumerable variations) (Harris & Ullman, 1945)

An alternative method for categorising cities has been carried out based on the economic growth. The study aimed to identify cities into four areas based on two concepts: legacy vs. new cities and developed vs. emerging economies (Macomber, 2016) (Table 2-6). The study also considered the role of "smart cities" and what a city of the future might look like and by categorising in terms of economic growth, it is possible to highlight investment opportunities. Whilst this may be a welcome opportunity for investors, however it is a less beneficial way of categorising cities for emergency planning professionals as disasters can affect any city regardless of economic growth. Although this may be a base indicator of available funds for recovery and restoration projects, it would not be useful in terms of assessing similar city layouts for computational modelling.

Table 2-6 – Categorisation of Cities based on Economic Development adapted from (Macomber, 2016)

Type	Representative City	Description
Developed Economy, Legacy City	London, Detroit, Tokyo, Singapore	In a city such as this, to build anything new, something that previously existed must be dismantled. There is often slow economic growth in developed economies which results in zero-sum situations. Elites live in these cities so solutions that arise usually function to help people spend their excess cash.
Emerging Economy, Legacy City	Mumbai, Sao Paolo, Jakarta	Many physical and institutional structures already exist within these megacities. But there are fast growing populations and severe congestion, so opportunities can be realised to improve efficiency and liveability, particularly for those with cash to pay for the benefits available.
Emerging Economy, New City	Phu My Hung – Vietnam, Suzhou – China, Astana – Kazakhstan	Cities with high population growth and high GDP/capita growth. There are few obstacles to growth as few physical or social structures exist. Opportunity to build it right first time, but if missed informal sprawl will occur and new settlements will be hard to reach afterwards in terms of vital services.
Developed Economy, New City	N/A	Cities like this are rare, most new cities in the developed world are in fact linked to large existing municipalities e.g. New Songdo City, South Korea or Masdar City, Abu Dhabi.

Categorisation of cities is a beneficial tool as it allows comparisons to be made between similar cities and for mitigation methods to be tried and tested then recommended, whilst ensuring that the recommendations are appropriate due to the similarities. It also allows a model to be created with a series of 'test' cities replicating the most common city types. Hence, permitting more users to benefit from a model environment when creating and developing contingency plans for natural disaster scenarios, rather than relying on entirely bespoke solutions each time.

2.3.2 Communities in Disasters

When disasters do strike, it is not only infrastructure that will be affected by the event but also the people and communities that live and utilise the infrastructure in question. Although it is important to understand how infrastructure fails during these disaster scenarios, it is also imperative that understanding develops regarding how communities respond.

The response of a community can have a large impact on that of the infrastructure, for example if a mandatory evacuation order is put in place to protect lives, then the transport network needs to be able to respond by allowing residents to leave the area in a safe manner. However, human behaviour is not always predictable, and communities do not necessarily respond in the perceived "safest" manner. For example, in the USA, where there are many hurricane warnings and evacuation orders, it is not always guaranteed that the community will choose to leave their homes. This has been attributed to a number of factors such as; homeownership, presence of pets, past damage experiences, access to a vehicle and presence of a disability (Whitehead, et al., 2000) (Ng, et al., 2016). This is not particularly helpful for those tasked with planning for emergency scenarios, but by better understanding the human response to situations, it is possible to create more robust emergency plans.

The impact of human behaviour expected behaviour types and the link with computational modelling will be explored further in Chapter 3.

2.4 Disaster Management

Due to the prevalence of natural hazards, plus the threats of terrorism and epidemics, the need for adequate procedures and policies to deal with these eventualities has come to the forefront. This has led to a recognised disaster management cycle as displayed in Figure 2-10, which has been adapted from (Rosenberg, 2015), (Haigh, 2011) & (Warfield, 2002). Despite the unpredictability of natural hazards, it is possible to carry out Disaster Management or Emergency Management. These management techniques are concerned with the creation of plans and systems, which aim to reduce community vulnerability to hazards and enable them to cope with the impacts of disasters. The cycle contains four main stages: Preparation, Response, Recovery and Mitigation. The cycle is continuous and can begin at any stage, using lessons learned previously.

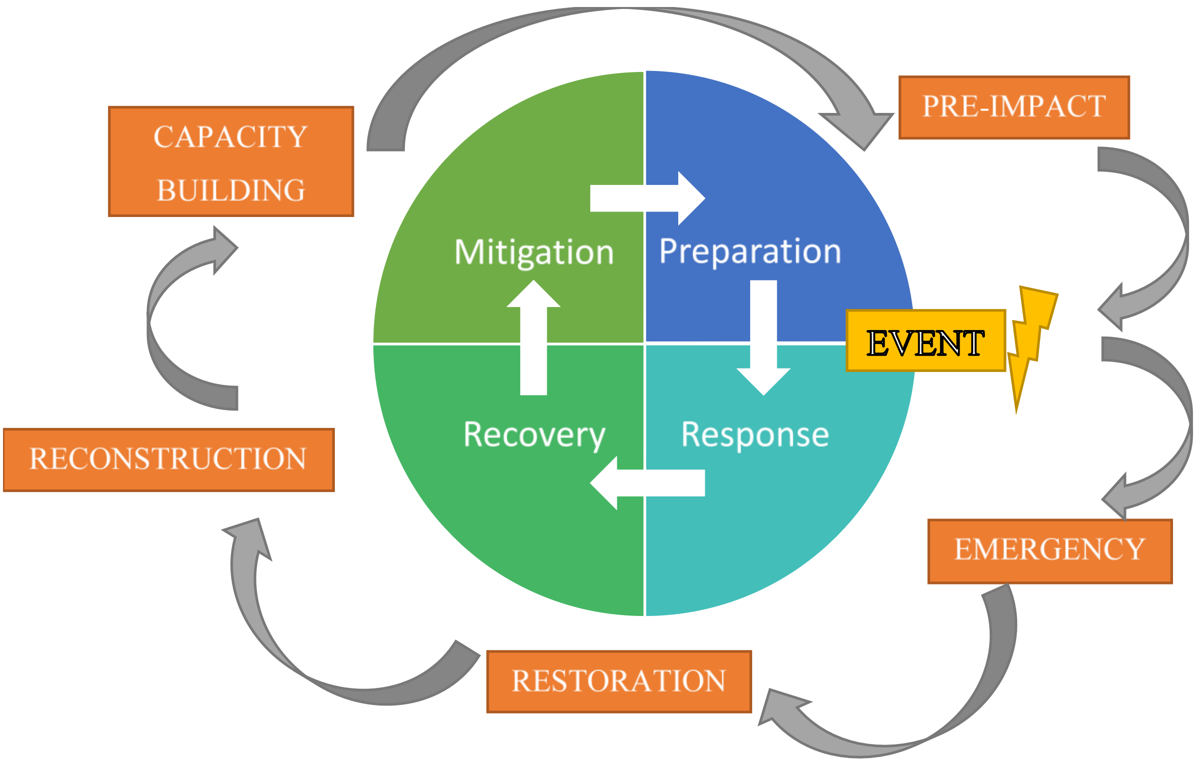


Figure 2-10 – Disaster Risk and Management Cycle

The Preparation, or more commonly known as Preparedness stage, is concerned with planning on how to respond to an event before any event has occurred. Emergency Management Professionals will use this time to prepare plans, exercises, training and/or warning systems to a provide resilience within communities.

The Response stage is associated with the immediate aftermath of an event when efforts will be made to minimise the impacts and hazards caused by the disaster in the short term. This may include initially emergency aid relief or search & rescue teams. The aim is to sustain life by providing but not limited to temporary shelter, clean water, transportation, and food. This stage is an emergency so focuses on the basic needs of a community. In some instances, this may include simple repairs to damaged infrastructure, if this will support the community best.

The Recovery stage encapsulates the restoration and reconstruction of communities to a "normal" state in the longer term. This may include further temporary housing or repairs to houses, grants to allow restoration, and access to medical care. It is hard to determine when the recovery stage begins, and the response stage ends. There is potential within this stage to increase preparedness, which in turn reduces future vulnerability.

Finally, the Mitigation stage, which is almost simultaneous to the recovery stage. The aim of this stage is to minimise the effects of a future disaster and where possible to prevent the same damage occurring again from a similar disaster. Minimisation can occur through changes to building codes and standards, vulnerability assessments, reconstruction of flood protection or landslide protection. This stage may also include community education on disasters to offer communities the opportunity to better prepare for the next instance.

It is vital that lessons are learnt throughout the cycle to ensure communities become more resilient and less vulnerable when events do occur. Therefore, to develop effective plans, there is a requirement to model how these systems behave in these events. This can be particularly challenging as the systems are not only complex, the events that need to be considered are rare and there is often a lack of knowledge surrounding the existing infrastructure before an event occurs, particularly in developing countries.

The modelling tool proposed in this thesis has been developed for use by emergency planners using the disaster management cycle for the mitigation and preparation phases. The aim is to allow planners to test their emergency plans and procedures using computational simulation and other techniques to provide appropriate mitigation strategies and to prepare communities effectively for the potential consequences of hazard events. It is anticipated that the real-world and table-top simulations that are currently used by emergency professionals will be used in collaboration with this tool to provide planners the opportunity to test numerous scenarios in a less resource and cost-intensive manner.

2.5 Policy

Governmental policy can be a key driver for change across the globe and is often closely linked to the Disaster Management Cycle. Examples of good policy practice can be used to drive forward changes in other nations as they strive to meet the benchmarks set out. Institutions such as the United Nations (UN), with their 196 member nations, can also be integral in achieving international cooperation and collaboration on key policies. The UN also set out their own policies regarding topics such as disaster management, such as the International Strategy for Disaster Reduction (UNISDR), and during the 1990s, the UN committed to a decades programme aimed at disaster reduction (UNISDR, 2016). Their most recent programme is the Sendai Framework for Disaster Risk Reduction 2015 – 2030, which is promoting "*concrete actions to protect development gains from the risk of disaster*" (United Nations, 2020). This programme is in collaboration with other 2030 Agenda agreements such as the Sustainable

Development Goals and promotes "The substantial reduction of disaster risk and losses in lives, livelihoods and health and in the economic, physical, social, cultural and environmental assets of persons, businesses, communities and countrie*s"* (United Nations, 2020). The framework features 7 global targets and 38 global indicators through an online tool which requires self-reporting by member states. Hence, it is difficult to assess the success of UN policies in the majority of instances, as the UN cannot enforce any policies. Hence, there is a reliance on countries to choose to create their own plans and policies, driven by global best practice where possible.

2.5.1 UK Policy

2.5.1.1 Local Policy

In the UK, more effective disaster management has been driven through the Civil Contingences Act (2004) (UK Government, 2004), which provides a single framework for civil protection in the UK and introduces the duty to create Local Resilience Forums (LRFs) (Cabinet Office, 2013). At the local level, there is a clear set of roles and responsibilities for emergency preparation and response with responders split into two categories. Category 1 responders are the organisations at the centre of the response to most emergencies e.g. local authorities and emergency services. Category 2 responders are co-operating bodies e.g. transport companies, who would be heavily involved in their own areas of expertise but not in the heart of the planning work (Cabinet Office, 2013). The LRFs have statutory duties as local authorities to prevent serious damage to their local communities. Each geographical area is based on police force boundaries and is "*required to prepare to deliver an appropriate emergency response and to maintain normal services during a crisis*" (Newcastle City Council, 2014).

To help this, risks need to be identified in each area, so community risk registers and frameworks have been set out (Northumbria Local Resilience Forum, 2014) (London Resilience Partnership, 2017). The Northumbria LRF community risk register identifies in the North East of England, local/urban flooding, local/coastal/tidal flooding, industrial accident, localised large release of toxic substance, pandemic influenza or animal disease as the key risks (Northumbria Local Resilience Forum, 2014). In London, a mass evacuation framework has been created by the London Resilience Partnership "*to provide guidance to responders at all levels on the way in which the evacuation of large numbers of people can be achieved*" (London Resilience Team, 2014).

Once risks have been identified and management plans are in place, the validity of these plans needs to be tested to ensure they are adequate in dealing with the anticipated risks. Therefore, there is a requirement to run emergency planning scenarios. These are included within the Civil Contingencies Act, which states that Category 1 responders must include provision for carrying out exercises and training staff on their emergency plans (Cabinet Office & National Security and Intelligence, 2013). Currently, three types of exercises are proposed, (1) discussion based, (2) table top and (3) live (Cabinet Office & National Security and Intelligence, 2013) (Table 2-7). Discussion based exercises are relatively cheap to run and easy to prepare so are often utilised for training purposes. Table-top drills are based on scenarios, which is useful for validation purposes and exploring weaknesses, with low costs other than staff time, but more planning and preparation is required. Live exercises are a real-life simulation of an event, which is expensive to run, demands very extensive planning and can be disruptive to the general public. Three case studies from the UK demonstrate the planning required to host a live simulation and the costs involved (Table 2-8, Table 2-9, and Table 2-10).

All these testing methods are suitable for preparing emergency services or emergency planners, however there is rarely any interaction with the general public. Live simulation exercises usually rely entirely on dummies or actors to provide the "general public". It is important to effectively prepare emergency service personnel, but without sufficient provision of the reaction from the public, the tested plans may be ineffective anyway, as the anticipated reaction is not in line with expectations.

Table 2-7 – Summary of Exercise Types

Discussion Based	**Table-Top**	**Live**
Cheap to run Easiest to prepare Often used for training purposes	Based on simulation Useful for validation Good at exploring weaknesses Cheap to run apart from staff time Need careful preparation	Live rehearsal e.g. practise drill Expensive to set up Demand extensive preparation Can be very disruptive to public

Table 2-8 – Case Study: London Mock Building Collapse at Tube Station

<table>
<tr><th colspan="2">Case Study</th></tr>
<tr><th colspan="2">London Mock Building Collapse at Tube Station</th></tr>
<tr>
<td>
Figure 2-11 – Underground tube carriages used in the Exercise (London Fire Brigade, 2016)

Figure 2-12 – Disused Power Station utilised as venue for the exercise, showing the derailed tube trains and rubble (BBC - Press Association, 2016)</td>
<td>In February 2016, the London emergency services took part in "*Europe's biggest ever disaster training exercise*" (London Fire Brigade, 2016). This involved coordinating the fire, police, and ambulance services into the four-day scenario, with the opportunity to practice disaster response. The exercise involved "*over 1000 casualties, thousands of tonnes of rubble, seven tube carriages and hundreds of emergency service responders… and has been over a year in planning*" (London Fire Brigade, 2016). The event was also observed by independent evaluators, to allow improvements to be made to the response procedures and lessons learnt. The scenario was funded by the European Commission Exercise Program, on behalf of the London Resilience Partnership, in addition over £1 million was donated in kind by partner organisations (e.g. Transport for London – Tube Carriages, McGee Demolition Group – Rubble & Machinery and RWE npower – Littlebrook venue) (London Fire Brigade, 2016). This provided a good opportunity for many different emergency services and interlinked parties to test procedures as part of a real-life simulation, however this was not without significant financial, time and effort costs.</td>
</tr>
</table>

Table 2-9 – Case Study: London Mock Terrorist Attack on River Thames

Case Study	
London Mock Terrorist Attack on River Thames	
 *Figure 2-13 – Simulated terror attack on the River Thames (BBC, 2017 A)*  *Figure 2-14 – Simulated terror attack on the River Thames (BBC, 2017 A)*	In 2017, over 200 Met Police officers simulated a terrorist attack on a tourist boat on the river Thames (BBC, 2017 A). Around 12 “terrorists” hijacked the boat, which was then intercepted by the police as part of their first large training event on water (The Guardian, 2017). This event was carried out in response to a 2016 report that “*found security measures on the river Thames needed to be strengthened*” (BBC, 2017 A). The aim was to test the effectiveness of emergency response in a real life scenario for a number of partner organisations such as the Port of London Authority, London Coastguard, RNLI as well as emergency service personnel (The Guardian, 2017). Arguably this event was significantly smaller than the real-life simulation scenarios carried out in previous years that trained 1000s of response practitioners through the event. This may be in response to the time, effort and monetary commitment involved in a time when budgets are often being squeezed.

Table 2-10 – Case Study: North East Terror Attack Simulation at Intu Metrocentre

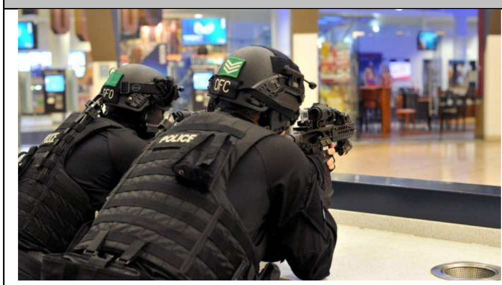
Case Study	
North East Terror Attack Simulation – Metrocentre	
	It is not just London that needs to test emergency response plans, there is a requirement that all Local Resilience Forums plan and test emergency scenarios too. To meet this requirement, in May 2017, Northumbria Police held a mock anti-terror exercise in the Metrocentre in Gateshead, one of

Figure 2-15 – Northumbria Police armed personnel respond to 'terror attack' at Metrocentre (BBC, 2017 B)

Figure 2-16 – Northumbria Police armed personnel respond to 'terror attack' at Metrocentre (BBC, 2017 B)

Europe's largest shopping centres (BBC, 2017 B). The aim of the event was primarily for the police service to test their firearm skills in conjunction with a number of other emergency service personnel (such as the Fire & Rescue Service, Ambulance Service, Local Council, Metrocentre and NHS England) (The Chronicle - Hannah Graham, 2017).

Currently, there is no provision to utilise computational modelling for planning and preparation. However, this could provide a more robust method for testing scenarios, allowing planners to test multiple runs without the resource and cost requirements. It also allows for a robust interpretation of human behaviour modelled on the general public to be included, rather than a reliance on assumptions, dummies or actors as is currently used. This could enhance the understanding of the public's reaction to different events and how this could compromise or enhance scenarios for emergency personnel. Previously, models would not have been capable of this but with the emergence of new techniques and additional computer power, it is now possible to test computationally.

2.5.1.2 National Policy

The UK's National Security Strategy states that "*the security of our nation is the first duty of government"* and that *"it is the foundation of our freedom and our prosperity*" (Cabinet Office & National Security and Intelligence, 2010). Therefore, to supplement the Community Risk Registers produced by LRFs, the UK Government, carries out a National Risk Assessment (NRA) annually. This is a classified document; however, the Government also produces an annual publicly available version of this document, namely the National Risk Register (NRR) (Cabinet Office, 2008). The NRA and NRR were first published in 2008 as a response to the National Security Strategy, (Cabinet Office & National Security and Intelligence, 2010) with the aim of capturing a range of emergencies that might have a substantial impact on all, or a significant part of the UK. These documents outline the larger, national picture of risks compared with the localised risks considered by the LRFs (Cabinet Office, 2008).

The 2008 NRR showed that highest impact event was anticipated to be pandemic influenza, but that the most likely events were attacks on transport or electronic attacks, although the impacts were deemed to be smaller (Cabinet Office, 2008) (Figure 2-17). An updated NRR was produced in 2015, this adapted the previous register and better quantified the likelihoods of risks and impacts, by indicating the relative likelihood of events occurring in the next five years such as "*between 1 in 20 and 1 in 2*". The register was split into two parts: risks of terrorist or malicious attacks and other risks (Cabinet Office, 2015). In terms of terrorist attacks, a catastrophic terrorist attack was seen as medium-low plausibility but the highest impact, but cyber-attacks compromising data confidentiality is highly plausible but low impact (Cabinet Office, 2015) (Figure 2-18(a)). For the other risks, pandemic influenza has the highest impact and its relative likelihood of occurring in the next 5 years is between 1 in 20 and 1 in 2 (Cabinet Office, 2015) (Figure 2-18(b)). In 2017, the NRR was further updated, splitting into two categories malicious attacks and hazards, diseases, accidents, and societal risks. In terms of the malicious attacks, an attack on crowded places or transport was identified as the highest likelihood, whereas a largescale chemical, biological, radiological or nuclear attack was identified as having the highest impact (Figure 2-19). For the hazards, diseases, accidents and societal risks, a larger number of possible events had been identified compared to previous editions, but pandemic influenza was still deemed to be the most likely and highest impact event, followed by cold and snow which was highly likely but marginally lower impact (Figure 2-20).

To supplement this, the UK government have provided several guidance documents on emergency planning and preparation. "*The government aims to ensure all organisations have effective, well-practiced emergency plans in place*" (Cabinet Office, 2013). Hence, emergency planning can be used to reduce, control, and mitigate the effects of emergencies.

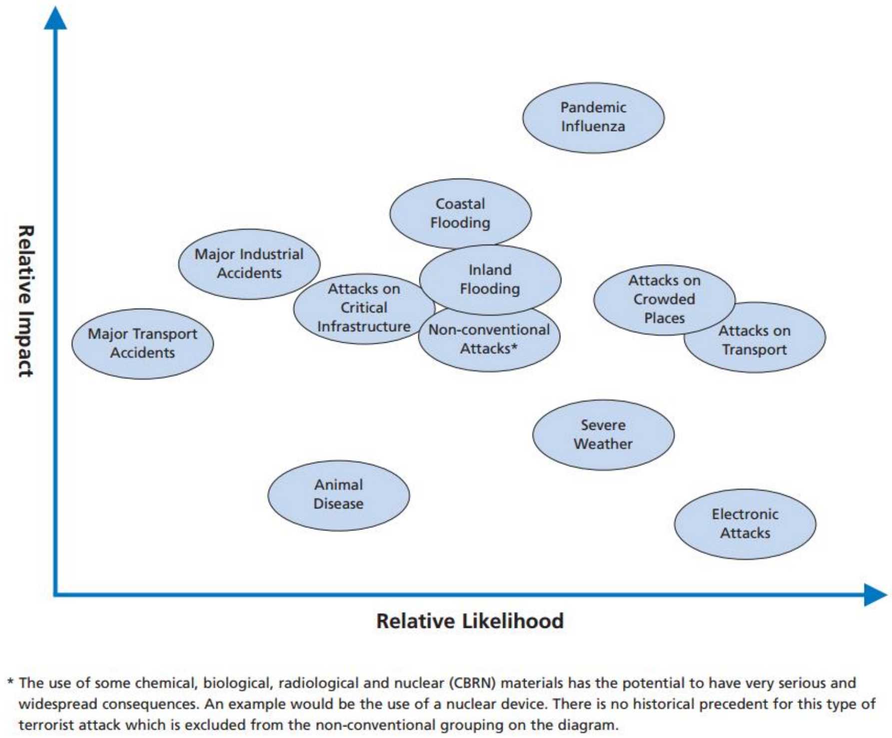
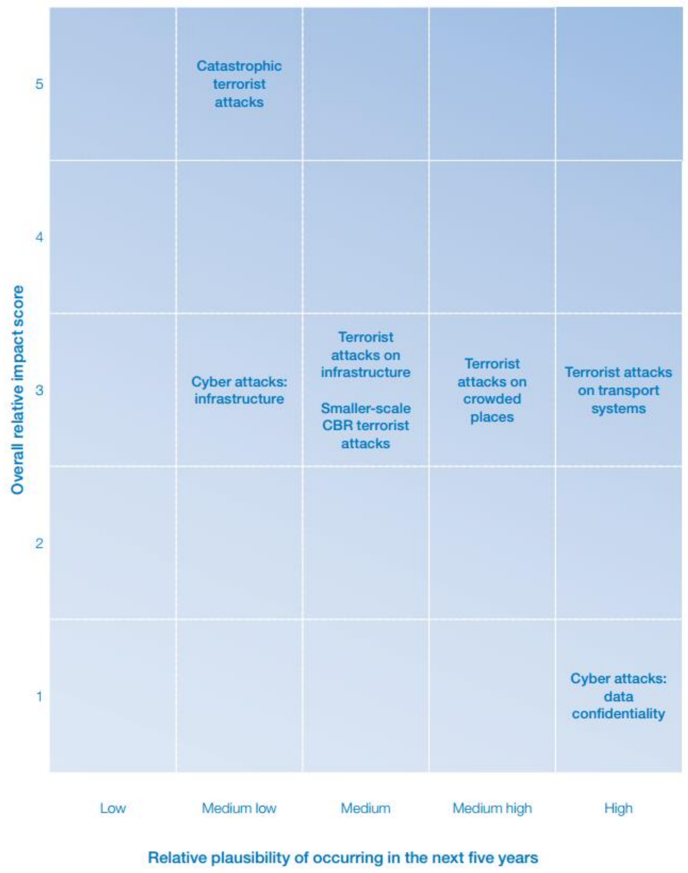


Figure 2-17 – UK National Risk Register 2008 – An Illustration of the High Consequence Risks in the UK (Cabinet Office, 2008)

(a)



(b)

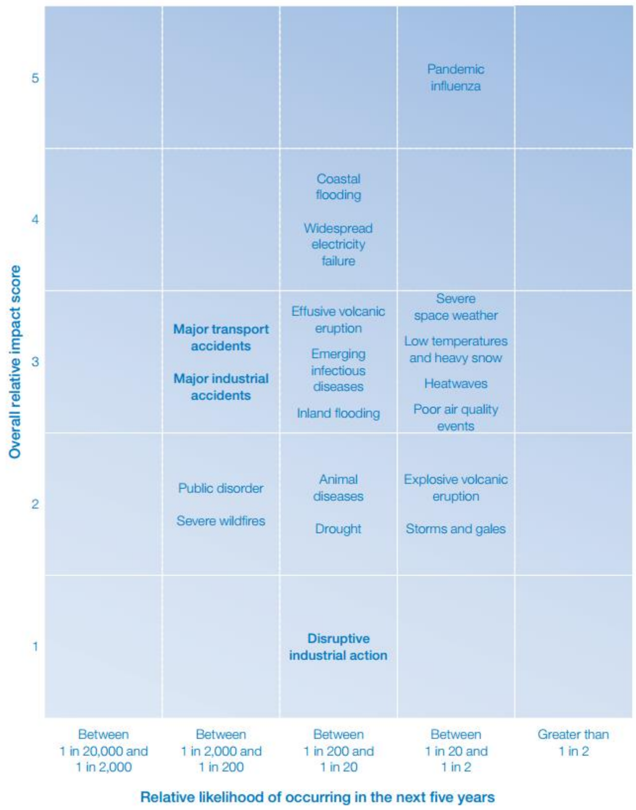


Figure 2-18 - UK National Risk Register 2015 (a) Risks of Terrorist and Malicious Attacks (Cabinet Office, 2015) & (b) Other Risks (Cabinet Office, 2015)

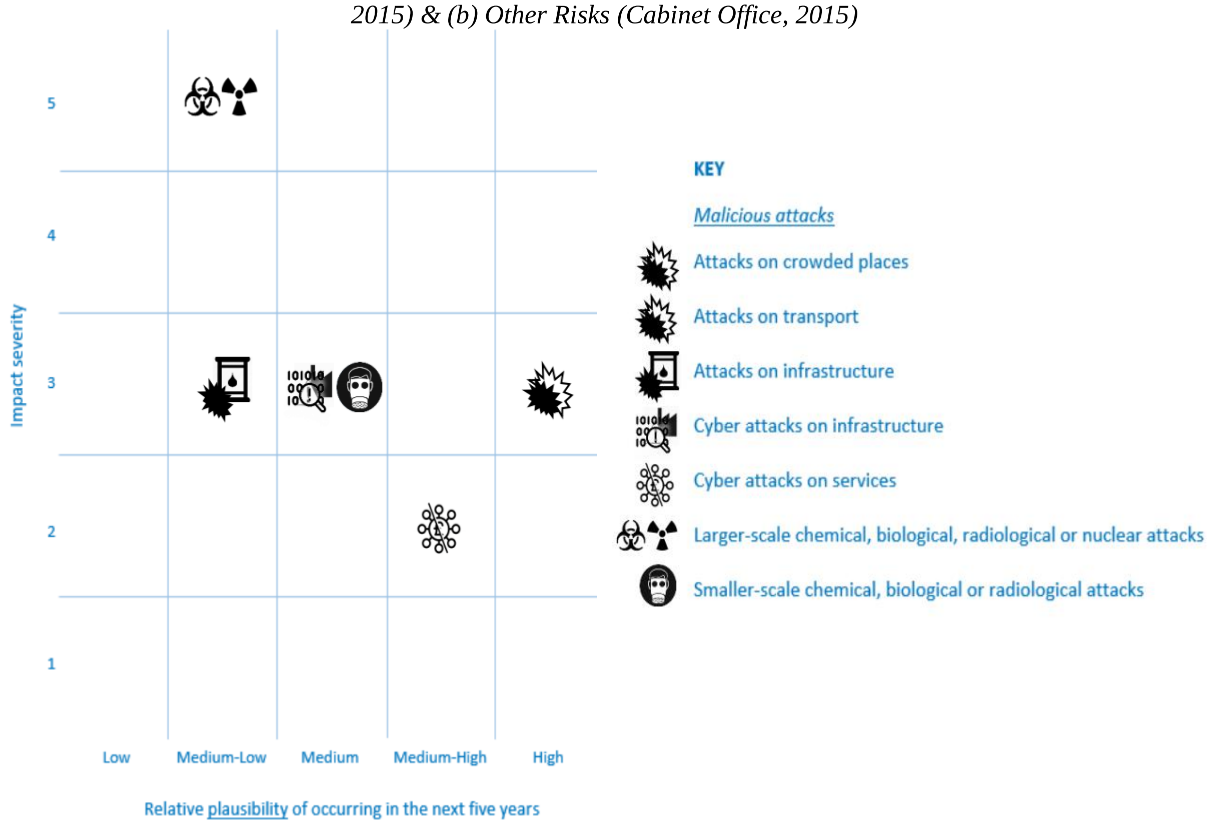


Figure 2-19 – UK Malicious Attack Risk according to National Risk Register 2017 (Cabinet Office, 2017)

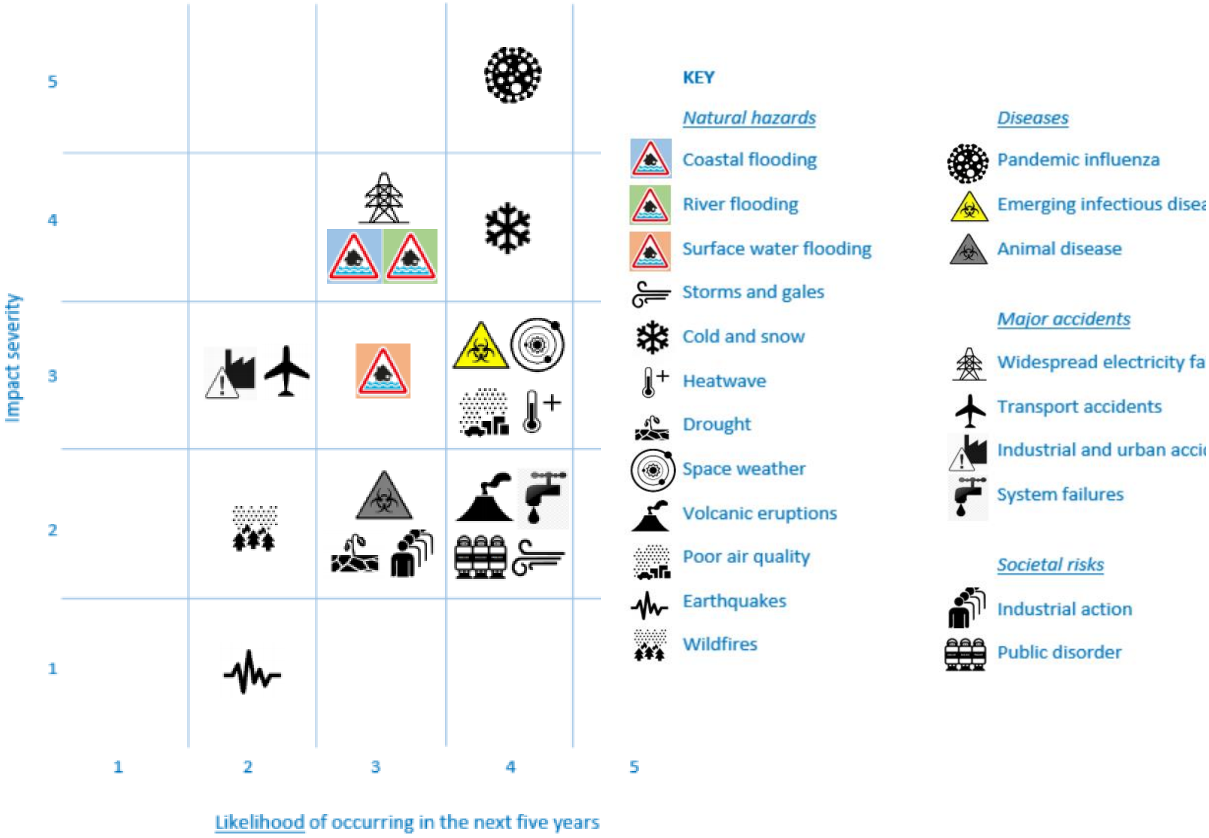


*Figure 2-20 – Hazards, diseases, accidents and societal risks to the UK according to the National Risk Register 2017***Invalid source specified.**

2.5.2 USA Policy

The USA, like the UK, is subjected to a number of natural and man-made hazards every year, for example in 2015 the USA experienced 28 recorded natural disasters with financial costs of approximately $21 billion (Guha-Sapir, et al., 2016), so there is a need to develop and improve disaster management strategies. The USA Department for Homeland Security has approached this by forming a national preparedness goal. This is set out as "a *secure and resilient nation with the capabilities required across the whole community to prevent, protect against, mitigate, respond to, and recover from the threats and hazards that pose the greatest risk*" (US Department of Homeland Security, 2015), deeming a shared responsibility across the entire nation (FEMA, 2015). Overall, FEMA's mission can be described as ensuring; "*that as a nation we work together to build, sustain, and improve our capability to prepare for, protect against, respond to, recover from and mitigate all hazards*" (FEMA, 2017). The National Preparedness Goal is capability based, with 32 core capabilities (identified as part of a strategic national risk assessment), which are organised into five mission areas, namely: prevention, protection, mitigation, response and recovery (US Department of Homeland Security, 2015) (Figure 2-21). This has been used to identify the types of threats that posed the greatest risk to the USA's security, including natural, technological/accidental and adversarial/human-caused hazards. Currently, natural hazards, pandemic influenza, technological hazards, terrorism and cyber-attacks are classified as a significant risk to the USA in their strategic national risk assessment (US Department of Homeland Security, 2015).

<table>
<tr><th>Prevention</th><th>Protection</th><th>Mitigation</th><th>Response</th><th>Recovery</th></tr>
<tr><td colspan="5">Planning</td></tr>
<tr><td colspan="5">Public Information and Warning</td></tr>
<tr><td colspan="5">Operational Coordination</td></tr>
<tr><td colspan="2">Intelligence and Information Sharing</td><td rowspan="4">Community Resilience
Long-term Vulnerability Reduction
Risk and Disaster Resilience Assessment
Threats and Hazards Identification</td><td colspan="2">Infrastructure Systems</td></tr>
<tr><td colspan="2">Interdiction and Disruption</td><td rowspan="3">Critical Transportation
Environmental Response/Health and Safety
Fatality Management Services
Fire Management and Suppression
Logistics and Supply Chain Management
Mass Care Services
Mass Search and Rescue Operations
On-scene Security, Protection, and Law Enforcement
Operational Communications
Public Health, Healthcare, and Emergency Medical Services
Situational Assessment</td><td rowspan="3">Economic Recovery
Health and Social Services
Housing
Natural and Cultural Resources</td></tr>
<tr><td colspan="2">Screening, Search, and Detection</td></tr>
<tr><td>Forensics and Attribution</td><td>Access Control and Identity Verification
Cybersecurity
Physical Protective Measures
Risk Management for Protection Programs and Activities
Supply Chain Integrity and Security</td></tr>
</table>

Figure 2-21 – USA National Preparedness Goal Core Capabilities and Mission Areas (US Department of Homeland Security, 2015, p. 3)

2.5.3 New Zealand Policy

New Zealand is also susceptible to many natural hazards, including the Christchurch earthquake (February 2011), which caused 65 fatalities and $3 billion worth of damage (BBC, 2011). Therefore, to reduce this vulnerability, risks categorised by type (e.g. geophysical, social, and technological) have been identified and analysed by the Institution of Professional Engineers New Zealand (IPENZ), to enable measures to be put in place to either eliminate or reduce their impacts. This analysis covers the characteristics of hazards, in order to understand their relationship with national planning measures, which includes a range of likelihoods and consequences. The indicative risks show that cyber-attacks affecting data confidentiality are likely to occur at least once a year but are likely to have only minor consequences (Institution of Professional Engineers New Zealand (IPENZ), 2012). Whereas, a very large volcanic eruption is only likely to occur once in a millennium, however, the consequences would be considered catastrophic (Institution of Professional Engineers New Zealand (IPENZ), 2012) (Figure 2-22). In particular, the IPENZ highlights that for natural hazards, each threat has a different profile thereby suggesting that it is not appropriate to "lump together" all-natural hazards and it would be more appropriate to target hazard specific reduction measures to each individual hazard type. The national risk framework also incorporates the localised risks, with a risk exposure calculated for major settlements in New Zealand. This shows that any measures to mitigate natural hazards need to recognise the regional differences in terms of risk.

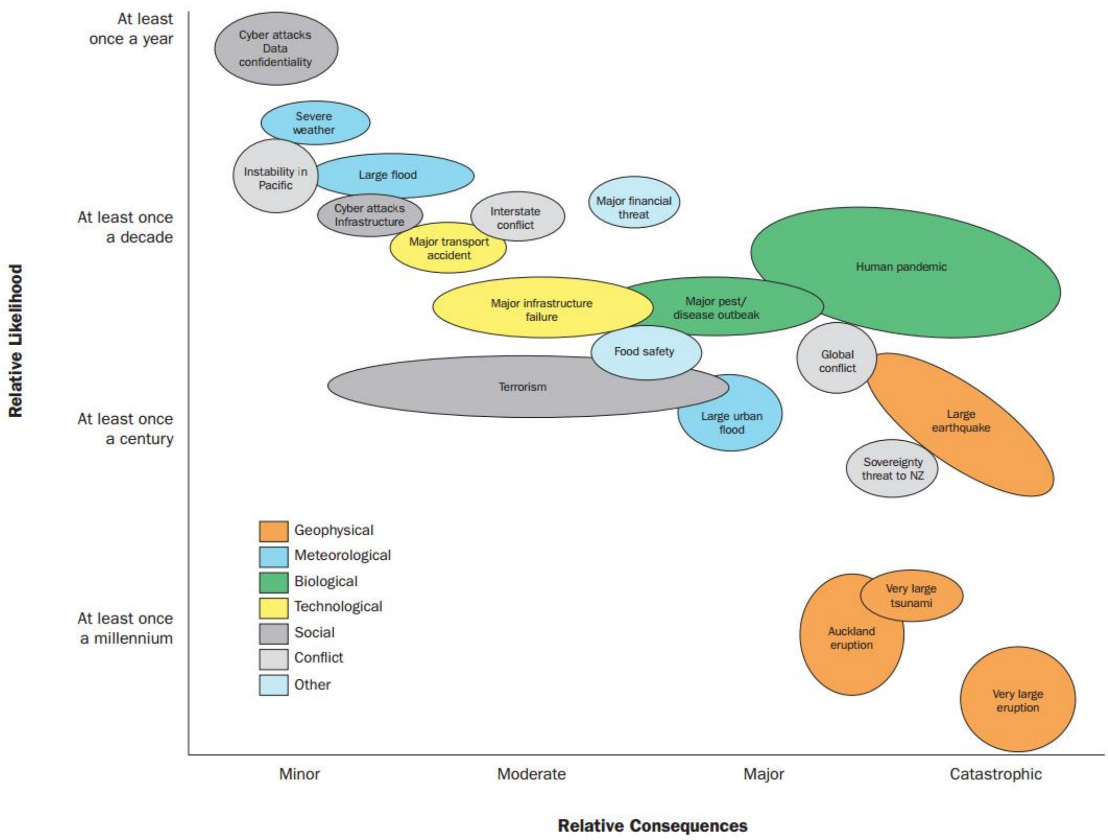


Figure 2-22 – New Zealand Indicative National Risks (Institution of Professional Engineers New Zealand (IPENZ), 2012, p. 7)

New Zealand currently has a number of acts included in a regulatory framework, similar to the UK, including; the Resource Management Act 1991, the Building Act 2004, the Civil Defence Emergency Management Act 2002, the Local Government Act 2002 and the Local Government Official Information and Meetings Act 1987 (Institution of Professional Engineers New Zealand (IPENZ), 2012). However, these acts are inconsistent with their definitions of natural hazards, do not include some important threats and the range of restrictions to be imposed are limited (Institution of Professional Engineers New Zealand (IPENZ), 2012).

2.5.4 Future UK Policy Developments

Despite the lack of recognition across the globe of the merits of computational modelling for disaster scenarios, the UK Government noted that; "*modelling and simulation techniques are important ways of enabling complex systems to be understood and manipulated in a virtual environment*" (Council for Science and Technology (CST), 2009). As such, there is an understanding of the benefits of completing computational modelling from a government perspective. This commitment was shown through the recommendations made in "*A National Infrastructure for the 21st Century*" report (Council for Science and Technology (CST), 2009). Recommendation Three recommended "*stimulating better understanding of the complexity and resilience of the national infrastructure, by commissioning research into scenario planning and modelling national infrastructure systems, from physical, economic and social perspectives*" (Council for Science and Technology (CST), 2009). Underlining the UK government's commitment to facilitating the simulation and modelling of disaster management systems in natural hazard scenarios.

The creation of modelling tool such as the one developed in this thesis should be used in conjunction with the scenario testing (table-top and real world) currently carried out at a local level. In the future, computational evacuation simulation will allow multiple scenarios to be run with smaller financial and resource contributions. This will then be able to feed into real-world simulation of events with emergency service personnel able to focus on worst case scenarios and able to have a stronger understanding of the human behaviour dynamic in play during hazard events. At a national level ABMs simulating hazard events will be able to support policy decisions and planning around the National Risk Registers used in nations such as the UK, USA, and New Zealand. This will allow governments to increase their resilience, robustly protect communities and provide appropriate action plans.

2.6 Modelling of Natural Disasters

Although still in its infancy, developed country's governmental policy is beginning to identify the benefits of being able to model complex situations and scenarios computationally. The only alternative presently is to complete costly and time-consuming real-life simulation or unrealistic table-top exercises, which do not allow emergency planners to be sufficiently prepared for a variety of disaster events.

To model effectively computationally it is important to choose the appropriate technique that can complete the required task to the necessary level of detail. Previously computational power has been a barrier to this type of simulation, but this is no longer anticipated to be an issue. A clear set of criteria for a model, such as inclusion of a dynamic population or agent to agent communication, is vital from the offset as is the need to effectively calibrate, verify and validate any models. There are lots of available techniques for modelling computationally, for example agent-based modelling, system dynamics and cellular automata, and it is imperative to make an appropriate choice.

2.6.1 Available Modelling Techniques and Software for Natural Disasters

Management professionals have developed numerous modelling techniques such as system dynamics, cellular automata, microsimulation, and fault tree analysis to simulate human behaviour during evacuation and hazard scenarios. Several different techniques will be evaluated, to ascertain the most appropriate technique for this project.

2.6.2 Event & Fault Tree Analysis

Event and fault tree analysis is an analytical method that is most commonly used in system reliability, maintainability and safety analysis (Pilot, 2016). It is classified as a "*logical and diagrammatic method to evaluate the probability of an accident resulting from sequences and combinations of faults and failure events*" (Tanaka, et al., 1983). Using this method, it is possible to calculate the probability of the top event, by logically understanding the mode of occurrence for an event. This also helps to identify potential failures of a system before an event occurs. However, a flaw with this analysis is often that exact failure probabilities need to be used but this can be difficult to evaluate from past events as system environments change. It may also be necessary to consider the failure of elements that have never failed before (Tanaka, et al., 1983). This means that for this thesis, this method could only be useful for working through the disaster management cycle with past events e.g. Hurricane Katrina. However, this technique would not allow for the creation of a detailed agent population to be included within a model environment and would only be suitable to use to indicate overall failures rather than the actions of individuals.

2.6.3 Microsimulation

Microsimulation is a form of computational modelling that examines the interactions of self-governing individual units' dependant on randomised parameters, which should represent the preferences of individuals e.g. the possible choices a vehicle could make at a crossroads or for pedestrians crossing a road. Microsimulation is often a tool utilised by social sciences for applications such as tax and benefit reform (Spielauer, 2011) as well as within transport research for pedestrian behaviour (Yang, et al., 2006) or traffic demand (Balmer, et al., 2006). Microsimulation does have a number of benefits over conventional models including, "*computational savings in the calculation and storage of large multidimensional probability arrays, larger range of output options and explicit modelling of the decision-making processes of individuals*" (Balmer, et al., 2006).

However, the challenge remains that microsimulation relies on creating individual demand often out of general input data, which can have a large variability particularly in terms of quality, spatial resolution and intended purpose (Balmer, et al., 2006). On top of this to realistically simulate a society requires; "*detailed data, complicated models, fast computers and extensive testing*" and the more complicated a model gets the more the complexity increases in terms of understanding operations and assessing predictive power (Spielauer, 2011). Computational power has significantly increased over recent years, meaning that microsimulation usage has intensified, and data is routinely collected but it is essential to ensure that this data is "good" i.e. verified, calibrated, and validated. Despite this, microsimulation does not demonstrate any ability to allow agents to communication with each other or provide feedback on their interactions, both of which are required when attempting to robustly simulate human behaviour in a model environment.

2.6.4 Cellular Automata

Cellular automata are *"examples of mathematical systems constructed from many identical components, each simple, but together capable of complex behaviour*" (Wolfram, 1984), which "*can be considered as computational systems*" (Wolfram, 1985, p. 170). The typical use is usually for biological or physical systems. "*Cellular automata are especially suitable for modelling any system that is composed of simple components, where the global behaviour of the system is dependent on the behaviour and local interactions of the individual components*" (Young, 2006). A cellular automata model consists of a grid of cells, where each cell can have a number of finite states, over discrete time steps, the cell's state changes according to a set of rules, which are either dependant on the previous time step or its neighbours state (Malamud & Turcotte, 2002).

Cellular Automata has been used for modelling natural hazards (Cai, et al., 2014) (Ntinas, et al., 2016), as the model is suitable at simulating the spread of hazards e.g. wildfires or flooding.

This is due to there being a finite set of outcomes e.g. fire lit, no fire. However, this is not ideal for simulation of a natural disaster evacuation or response due to the numerous possibilities rather than the population simply being ‘alive’ or ‘dead’.

2.6.5 System Dynamics

System dynamics is “*the mathematical modelling and analysing of devices and processes for the purpose of understanding their time-dependant behaviour*” (Palm III, 2012). A system can be defined as “*a combination of elements intended to act together to accomplish an objective*” (Palm III, 2012). A system can be defined as dynamic “*if an element’s present output depends on past inputs*”, e.g. subject to changes over time (Palm III, 2012). Tied to this is that in system dynamics, an input and output can be defined as a cause and an effect. Hence, system dynamics is suitable for applications where there are multiple types of components and processes involved, which change over time. This means it is possible to use system dynamics for modelling emergency responses. Two of the most popular software packages for modelling system dynamics are MATLAB and Simulink; Simulink is based on MATLAB but features a diagram-based interface (Palm III, 2012).

System dynamics could be utilised for a disaster management application; however, it is not as optimal due to the limitations regarding the inclusion of a unique population. It is also “*relatively widely accepted within the field of system dynamics that models are not designed to and cannot perfectly imitate the real world*” (Featherston & Doolan, 2012) (Sterman, 2000) (Forrester, 2003) (Lane, 2000). It has also been claimed that system dynamics is dehumanising and “*relegates people to ‘cogs in a system’ and disregards free will*” (Featherston & Doolan, 2012) (Jackson, 1991).

2.6.6 Agent Based Modelling

Agent-based modelling allows over time, for a model to simulate a population, with each member of the population as a separate agent. Agent-based modelling “*simulates the operations and interactions of multiple agents with macro-level system behaviour emerging from these individual interactions. Agent behaviour is determined by rules of interactions with each other and the environment*.” (Dawson, et al., 2011). Agents are “*endowed with behaviours that are usually proscribed in a series of rules that are activated under different conditions … in the manner of stimulus and response … and in this sense, agents always engender change*” (Batty, et al., 2012). Hence, agent-based modelling relies on an element of movement or at least a change between agents (Batty, 2012). The model’s ability to simulate movement and interactions from multiple agents at once make it an effective and robust tool to apply to human behaviour, where there may be many individual decisions made and not just a binary choice. However, it is not a flawless modelling technique and there are still issues to overcome, it is accepted that "*a model is only as useful as the purpose for which is it constructed*" (Crooks & Heppenstall, 2012). Common issues include aspects such as: (1) path dependency as models can be very sensitive to their initial conditions, which makes using ABM for predictive purposes difficult, (2) disaggregated systems as models need to be separated into many agent characteristics, behaviours and interactions, this can be aided through multiple runs and varying initial conditions to aid robustness, (3) poor scalability in that models can be created at the micro or macro scale but combining the differing scales is challenging (Crooks & Heppenstall, 2012).

2.6.7 Summary of Available Modelling Techniques

An overview of potential methods for simulation of natural disasters has been set out and has been summarised (Table 2-11). There are several criteria that need to be considered to effectively model human behaviour. The criteria used:

- Agent hierarchy – the ability to arrange/rank as above, below, or on same level as other agents within the model environment based on a series of values, status, or authority.
- Agent-agent communication – the ability to allow agents to be able to exchange, send or receive information within the model.
- Agent heterogeneity – the ability for agents to have diverse characteristics or rules.
- Spatially explicit – the ability to vary location in space.
- Representation of feedback – the ability to provide information on the interactions taking place within the model.

The above criteria are all necessary characteristics for robustly simulating human behaviour, one of the main modelling aims of this thesis. Based on these, it can be demonstrated that agent-based modelling is superior in terms of these criteria.

Table 2-11 – Overview of Potential Methods for Simulating Natural Disasters adapted from (Dawson, et al., 2011)

Method	Agent Hierarchy	Agent-agent Communication	Agent Heterogeneity	Spatially Explicit	Feedback Represented
Event and Fault Trees	✗	✗	N/A	✗	✗

Microsimulation	✓	✗	✓	Maybe	✗
Cellular Automata	✓	✓	✗	✓	✓
System Dynamics	✗	✗	✗	✗	✓
Agent-Based Models	✓	✓	✓	✓	✓

2.7 The Potential Role of Computational Modelling

It has been demonstrated that there is a growing demand and capability to begin modelling hazard events using computational modelling and that there is a potential to save money, time and lives if implemented robustly. This would alleviate the need to used current methods which are inefficient and often unable to simulate several different scenarios. Hazard events will continue to occur, resulting in devastating impacts and consequences for communities across the globe. By analysing past events it is possible to examine the potential role computational modelling and more specifically agent-based modelling could have in responding to events.

2.7.1 Disaster Case Studies

Hazard events do not all have the same impacts and consequences, nor do they have the same levels of warning. Three case studies have been chosen; Tohoku earthquake & tsunami, the UK winter flooding, and Fort McMurray wildfire, which demonstrate the different scales, event types and responses possible.

2.7.2 Case Study: Tohoku Earthquake & Tsunami, March 2011

The Tohoku earthquake and tsunami hit the Pacific Coast of Japan on the 11th March 2011. The event "*caused enormous damage… due to seismic motion and the tsunami it triggered*" (Kazama & Noda, 2012) (Figure 2-23). The earthquake was magnitude 9.0 and was "the strongest earthquake experienced by Japan since the country began taking measurements" (Kazama & Noda, 2012). The earthquake and resulting tsunami caused over 15,000 fatalities and a further 2,500 persons remained missing (Osborne, 2016). During the event nearly 48,000 buildings plus 230,000 vehicles were destroyed and the damage was estimated to be approximately $300 billion (Osborne, 2016) (Figure 2-23).

On top of the environment that was destroyed by the earthquake and tsunami, the Fukushima Daiichi power plant was severely impacted, "*causing one of the worst nuclear disasters in history*" (Osborne, 2016). To this day, years after the event, the impacts of this persist as an exclusion zone remains in place around the plant and thousands of communities continue to live in temporary accommodation. This demonstrates that the area has struggled to recover sustainably due to the economic, social, and environmental consequences of the disaster.

(a)

(b)

(c)

Figure 2-23 – (a) Devastation Caused by Tohoku Earthquake & Tsunami Photo Credit: Dylan McCord. U.S. Navy (Oskin, 2017), (b) Damage and Debris Left by Tohoku Earthquake and Tsunami Photo Credit: Reuters (Van, 2019), (c) Wave Caused by Tohoku Tsunami Photo Credit: Reuters (BBC, 2011).

2.7.2.1 Evacuation Plan

Japan is considered a pioneer in disaster management and is well versed in creating plans for preparing and responding to hazard events (Zare & Ghaychi Afrouz, 2012). This includes a far-reaching public engagement programme to help influence evacuation behaviours and promote appropriate evacuee responses, as well as early warning systems. An initial earthquake early warning was issued within 8 seconds of the detection of the earthquake's first P-wave (Imamura & Anawat, 2012). This was followed by a further tsunami warning within 3 minutes of the earthquake and revisions were made to the warning after real-time seismic and tsunami data was received (Imamura & Anawat, 2012). The revisions were made 28 minutes after the earthquake, increasing the tsunami amplitude from 6m in Miyagi and 3m in Iwate and Fukushima to 10m instead (Imamura & Anawat, 2012).

2.7.2.2 Evacuation Successes & Failures

One study of 870 refugees on evacuation behaviours during the 2011 Tohoku earthquake and tsunami estimated that "there were 496 immediate evacuees and 267 delayed evacuees" with 16% evacuating due to the tsunami warning, 31% evacuating after initially hesitating and 11% who could not evacuate immediately (Yun & Hamada, 2012). The study also found that 34% returned to their homes to search for family and 11% did not believe that a wave of such predicted magnitude could strike the area from past experiences (Yun & Hamada, 2012). This shows the influence of early warning systems on behaviours but demonstrates that behaviour can be influenced by previous experiences, which ultimately resulted in greater fatalities.

Although early warning systems issued both earthquake and tsunami warnings, the delay of 28 minutes stating the true anticipated height of the tsunami resulted in those on the coast being unable to receive the correct information as the communication networks had already been damaged (Imamura & Anawat, 2012). The initial estimates also meant the tsunami would likely be contained by the sea wall and break water at Sanriku and other areas (Imamura & Anawat, 2012), which likely affected evacuation behaviours as residents did not believe there was an immediate threat to their lives.

However, there were large numbers of inhabitants that made the decision to evacuate, but their journeys were hinder by large traffic jams (Yun & Hamada, 2012), caused by the earthquake damage. There were also many that travelled to evacuation shelters but those placed on the coast were actually inundated by the tsunami, resulting in additional fatalities when people thought they were in a place of safety (Imamura & Anawat, 2012). It was also reported that the tsunami hit areas, which had not been included in the potential danger zones on maps, suggesting the predictions may have been inadequate (Imamura & Anawat, 2012).

2.7.2.3 Disaster Management Cycle

Phase	Earthquake & Tsunami 2011	Next Event or Year
Mitigation	Japan has an established Central Council for Accident Prevention, chaired by the Prime Minister. This has resulted in a comprehensive ruleset for response to events, a research system and public education programme. Japan has an advanced earthquake and tsunami early warning	Recovery efforts continue with the aim of building back better and reducing the size of the exclusion zone around the nuclear power plant. Earthquakes

	system, set up from 2003 – 2007. Warnings are broadcast using the Japanese media and mobile phone networks. (Zare & Ghaychi Afrouz, 2012)	have hit Japan since the 2011 event but not in the same location or at the same magnitude.
Preparedness	The Japanese Meteorological Agency is responsible for issuing any warnings regarding tsunamis. The warnings were released quickly on the 11th March, the first occurred within three minutes of the earthquake and a second was released after 28 minutes to warn that the expected height of the tsunami was greater than ten metres (Yun & Hamada, 2012). There was also an initial earthquake warning issued within 8 seconds of the earthquake (Imamura & Anawat, 2012).	
Response	The Japanese Government initially held a National Committee for Emergency Management, led by the Prime Minister, declaring an emergency, and deploying their self-defence forces to aid rescues. Ministries and departments were tasked with relief efforts. A state of nuclear emergency was also issued by the government, which allowed 140,000 residents within 20km of the plant to be evacuated. The Japanese Red Crescent Society also had a significant role in the initial response. (Zare & Ghaychi Afrouz, 2012)	
Recovery	Efforts to rebuild and rebuild better were established almost immediately after the event. The first construction of temporary housing began only eight days after the disaster, with construction of the first homes expected to take just a month (Zare & Ghaychi Afrouz, 2012).	

	However, there is still an exclusion zone in place around the Fukushima Daiichi power plant, which is anticipated to remain in place with only small additional areas opened from 2023 (Stewart, 2018).	

2.7.2.4 Potential Role of ABM

The use of an ABM evacuation simulation alongside hazard model could have allowed emergency managers to predict the scale of the disaster and the number of people to be affected. With events such as earthquakes and tsunamis, there is often little warning, but the use of an ABM model may have helped to predict the number of people who would need to leave and the number of possible fatalities dependant on differing evacuation rates. In this case, it may also have served as a warning for the nuclear power plant, which had not been built to withstand such a large-scale tsunami. It would also allow countries to be better prepared to respond to large scale events such as this, through improved logistically planning and suitable placement of emergency services. The model could also have helped more robustly predict appropriate safe zones, which could have been communicated to communities to ensure a route to safety was known through the existing public engagement programmes. By making use of a robust computational model, it may be possible to run multiple simulations of varied earthquake intensities and tsunami inundation, thereby providing information to communities for several scenarios including a worst case to increase evacuation rates rather than relying on past experiences. In 2012, an ABM was created for the Tohoku event focusing on the village of Arahama, which after a 1000 simulations achieved an evacuation rate of approximately 82.1% with 498 agents reaching safety, which correlated with the 90% evacuation rate and 520 evacuees reaching shelter during the actual event (Mas, et al., 2012). This demonstrates the possibility of capturing complex evacuation behaviours during a tsunami in computational simulations, which if successful can aid mitigation and preparation phases for future events.

2.7.3 Case Study: UK Winter Flooding, Winter 2015/16

In the UK during the winter of 2015/16, across Yorkshire, Lancashire and Cumbria unprecedented levels of flooding were experienced by communities. It has been reported that the floods are ranked as the "*most extreme on record in UK*" (The Guardian, 2016). This resulted in communities being cut off from each other, financial obligations, and the destruction of wildlife habitats.

A bridge over the River Wharfe in Tadcaster (BBC, 2015 B) and Pooley Bridge in Cumbria (BBC, 2015 C) both collapsed during the storm events fracturing communities (Figure 2-24). Due to the damage caused, funding needed to be raised to repair these assets and repairs were anticipated to take in the region of 12-18 months before a sense of normality could return. However, twelve months on from the event, over 700 families had still not regained access to their properties and Cumbria County Council approximated the recovery costs to date at £500 million (BBC, 2016 A). A later assessment of the economic damages of the flooding estimated that £1.6 billion of costs had been incurred to restore housing, businesses, transport infrastructure and utilities (Environment Agency, 2018).

On top of this, were the numerous insurance claims for homes and businesses, the estimated insurance bill was more than £1.3 billion (BBC, 2016 B). Plus, the effects on future insurance or more likely the lack of it. In this example, even on a relatively small scale, in a developed country, the consequences can be devastating and can easily affect the sustainable growth of an area.

(a)

(b)

(c)

Figure 2-24 – (a) Flooding at Pooley Bridge in the Lake District Photo Credit: Owen Humphreys/PA (BBC, 2019), (b) Flooding in Lake District Town Centre Photo Credit: Getty Images (BBC - Press Association, 2016), (c) Collapse of Tadcaster Bridge over River Wharfe in 2015 Photo Credit: Giles Rocholl (BBC, 2015 D).

2.7.3.1 Evacuation Plan

Numerous storm warnings were issued during each of the storms, to alert those in storm's path that there was potential for flooding and danger to life. For example, during Storm Eva, "*the Environment Agency issued 149 flood warnings, seven of them severe and 123 alerts*" (BBC, 2015 E). However, due to the previous flood defences that had been built, particularly in Cumbria following flooding in 2005, many people did not evacuate their homes (BBC, 2015 E). The flood defences did not successfully protect all the homes though and many people were left trapped in their homes, this resulted in the need to evacuate after the flood event.

2.7.3.2 Evacuation Successes & Failures

Due to the volume of flooding, inadequacy of the flood defences and the number of people that remained in their homes during the storm events, both the Army and Royal National Lifeboat Institution (RNLI) were drafted in to help facilitate evacuations (BBC, 2015 E). This was also further exacerbated by the prolonged period of poor weather, which resulted in some areas being "*under water for a third time in a month*" (BBC, 2015 E). The UK government did claim though that 20,000 homes had been protected by the flood defences (BBC, 2016 C). Evacuation attempts were also hindered by the devastation caused by the flooding, which saw many homes without power and several bridges such as Tadcaster bridge in North Yorkshire or Pooley Bridge in the Lake District damaged resulting in lengthy detours to reach communities (BBC, 2015 E) (BBC, 2016 B).

2.7.3.3 Disaster Management Cycle

Phase	Flooding 2015	Next Event or Year
Mitigation	Previous flood defences had been constructed, for Cumbria this was in 2005. However, these were not sufficient in protecting all properties from the levels of flooding experienced.	The Cumbria Flood Action Plan was set out to include short term and long-term actions to reduce flooding in response to the flooding in 2015 (Department for Environment & Environment Agency, 2016).
Preparedness	There was plenty of advance warning for the flooding. These were issued as flood warnings or alerts by the Environment Agency.	
Response	Due to the levels of flooding experienced and the numbers of people needing rescuing, both the Army & RNLI responded to evacuate those stuck in homes.	

	An initial clean-up of homes occurred, which was primarily carried out by homeowners.	
Recovery	Further cleaning up and removal of debris was carried to start the recovery process. Access to financial aid was speedier than after other events (BBC, 2016 C). Numerous rebuild projects took place to reconnect communities including bridges, roads and other infrastructure.	

2.7.3.4 Potential Role of ABM

The use of an ABM simulation could have been beneficial for the flooding that occurred during in the UK in 2015/16, particularly for emergency planners. The positive of flooding is that it often comes with plentiful warning, although exact hazard paths and true intensity may be unpredictable, there is a relatively large information known and warnings tend to be accurate. This data can therefore be easily accommodated within an agent-based model to help emergency professionals understand the number of properties potentially affected, the potential levels of evacuation required, possible amounts of shelter required and the safe location of shelters. It would also be possible to vary the storm intensity, to run multiple simulations for different storm events and provide a range of estimates.

Additionally, a model could be used to predict the effects on infrastructure and in turn how this may affect any evacuation or rescue attempts, for example, the effect of losing Pooley or Tadcaster Bridge during a flood event. It could also be used as a tool to assess if additional evacuation routes were provided, whether evacuations could occur quicker. This also works in reverse if aid needs to be coordinated into communities by understanding beforehand the potential effects of infrastructure being disrupted.

2.7.4 Case Study: Fort McMurray Wildfires, May 2016

During May 2016, a wildfire broke out southwest of Fort McMurray, in Alberta, Canada, Alberta's 5th largest city (Markusoff, et al., 2016) (Figure 2-25). In the surrounding area, the

Alberta oil sands rank as one of the world’s largest reserves of oil and the city had already been affected by the slumping oil prices.

More than 80,000 residents had to evacuate the area as the dry, windy weather fuelled the fire further and destroyed 80% of homes in one neighbourhood, Beacon Hill (Kassam, 2016). The evacuation was hastily ordered after a change in conditions meant that the fire, which was under control had become an inferno. Evacuation orders were used in the wildfire but a combination of voluntary and mandatory as well as downgrading then upgrading again occurred. This meant that the evacuation was rushed, and traffic came to a standstill on Highway 63, the only route in and around the city. Evacuated residents had to endure over 3 weeks out of the city, with little time to prepare adequately.

The fire spread from 1200 hectares to 10,000 hectares over the course of two days (Kassam, 2016). “Officials estimated that 1,600 – 2,400 structures had been damaged or destroyed by fire” (Kassam, 2016) (Markusoff, et al., 2016). The economic disruption was also felt in the oil sands, with disruption in production estimated at 40% of the usual output (Markusoff, et al., 2016). Total damages are estimated at between $4 billion and $9 billion, but the rebuild could add $1.3 billion to Alberta’s economy in 2017 (Canadian Business, 2016).

(a)

(b)

(c)

Figure 2-25 – (a) *Wildfire in Fort McMurray Photo Credit: MacLean’s (Markusoff, et al., 2016), (b) Vehicles Fleeing the Wildfire Photo Credit: Jonathan Hayward/Canadian Press (The Canadian Press, 2016), (c) Damage caused by Wildfire in Fort McMurray Photo Credit: Jason Franson (Canadian Business, 2016)*

2.7.4.1 Evacuation Plan

The evacuation plan was to initially target those most in danger starting with the Centennial trailer park, with adjacent neighbourhoods of Beacon Hill and Gregoire on alert. At 10pm, the mayor declared a state of emergency and issued a mandatory evacuation order for at least 500 residents, opening a refuge at leisure centre in the downtown area of the city. By the next morning, firefighters had worked overnight and were doing well so officials decided to downgrade some evacuation notices. This was despite the fact that the fire was only 1km from Highway 63, the only road around and out of the city. In the afternoon, it became clear that the city needed to be evacuated. Initially voluntary evacuation orders were made to some neighbourhoods, within 10 minutes these were upgraded to mandatory. The decision making could be described as haphazard.

2.7.4.2 Evacuation Successes & Failures

The evacuation of the city had both successes and failures during the event. The successes included evacuating 88,000 residents successfully from the city. This equates to 2% of Alberta's population and is the longest prolonged evacuation in Canada's history (Markusoff, et al., 2016). There were no fatalities caused by the wildfire, but two teenagers died when their SUV crashed into a tractor-trailer, this occurred 200km out of the danger zone (Markusoff, et al., 2016). The local radio stations became a key communication tool for evacuation orders, playing out the voluntary then mandatory orders. When the station itself needed to be evacuated an automated evacuation order was left in place.

However, there were aspects of the evacuation that could have been managed more effectively. Confusion was caused by downgrading some of the evacuation notices when the fire was only 1km from Highway 63. This was the city's only escape route too. For some residents the evacuation was rushed with some residents only having 30 minutes to leave their homes (Kassam, 2016). Traffic on Highway 63, the only route out of the city, quickly escalated into bumper to bumper traffic jams due to the panic caused. On top of this, many of those in the traffic ran out of fuel for their vehicles and vehicles that travelled south on Highway 63 had to travel 20 minutes through a wall of fire on two sides (Markusoff, et al., 2016).

2.7.4.3 *Disaster Management Cycle*

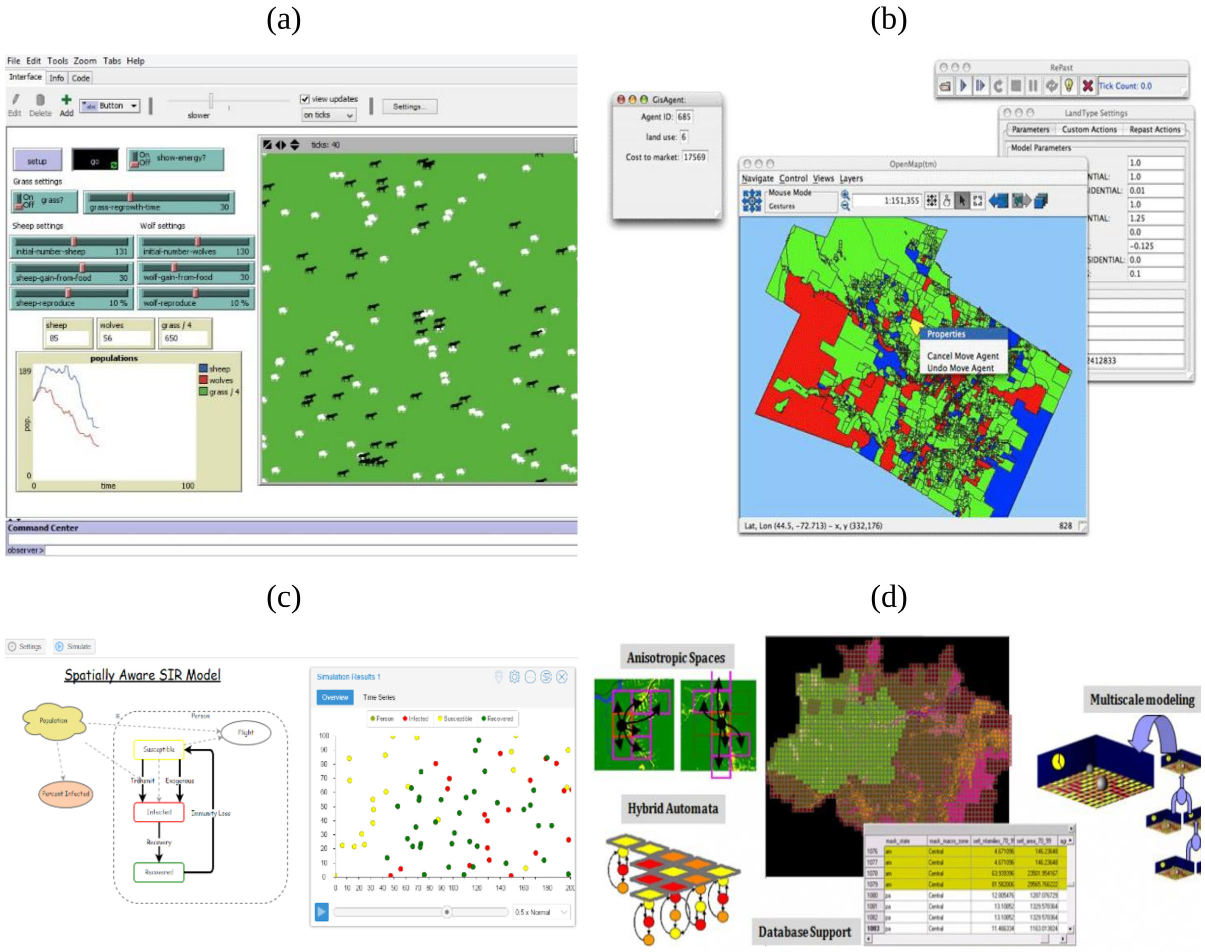
Phase	Wildfire 2015	Next Event or Year
Mitigation	Fire breaks were placed across the area but were not sufficient to stop the fire. Strategic placement was made of city's emergency operations centre which was similar to a bunker in the municipal water treatment plant	The rebuilding process is under way. Safety initiatives to clear away tinder-dry underbrush.
Preparedness	Evacuation orders were made by the mayor, but decision making was not clear, and the mandatory evacuations were rushed causing traffic to back-up.	
Response	Firefighters and other emergency personnel tackled the blaze to try to minimise the damage to the city. 88000 people evacuated from Fort McMurray. Evacuation centres supported by local communities helped evacuees in the immediate aftermath, providing, food, shelter, water, and clothing.	
Recovery	15% of the city needs to be rebuilt.	

2.7.4.4 *Potential Role of ABM*

The use of an ABM evacuation simulation would have allowed emergency managers to understand the congestion issue with evacuating the area with little to no warning. It could also allow exploration of the number of exit routes required for a settlement, as there was only one exit route available for inhabitants. Logistically, a model could have helped better prepare the location of safe zones and the location of emergency resources.

2.7.5 *Available Agent-Based Software*

Over recent years there has been an increase in the abundance and accessibility of agent-based modelling software, meaning there is a vast amount of available options. There are numerous open-source and free to download software packages, such as NetLogo, RePast, Insight Maker and TerraME (Figure 2-26). On top of this, there is commercialised software and models available such as Life Safety Model (LSM), SimWalk and Oasys Mass Motion (Figure 2-26). Hence, to limit the scope of this thesis, an initial set of criteria for the choice of modelling platform were chosen. The criteria were that the platform needed to be free to access, open source, provide comprehensive user guides as well as example model libraries to explore. A first filtration process occurred which has not been documented in this thesis but did consider a much wider range of platforms. A selection of available models was also analysed under similar criteria (e.g. free to access, comprehensive literature available) to manage the scope of the research. Hence the modelling platforms reviewed are: Netlogo, GAMMA, Miarmy, SimWalk, and available models: Life Safety Model and Flood Evacuation Model.



(e) (f)

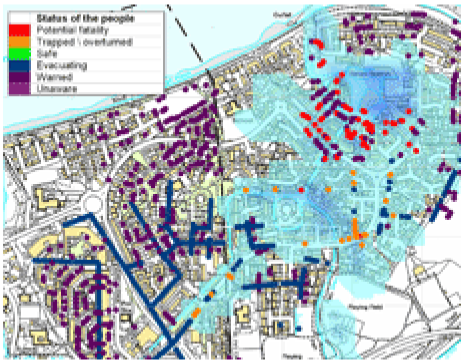
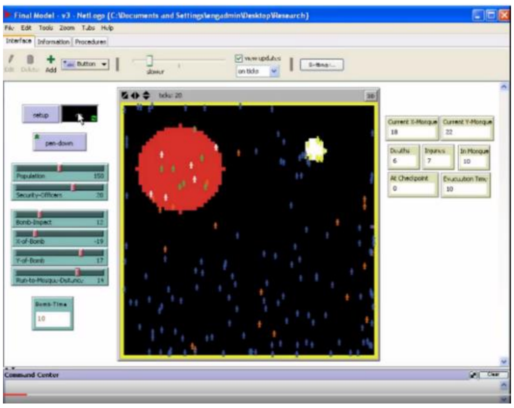


Figure 2-26 – Agent-Based Modelling Software Screenshots, showing (a) Netlogo Predator -Prey Model (Blades, 2013); (b) RePast Model with GIS Data (Altaweel, 2016); (c) Insight Maker Disease Model (Insight Maker, 2016), (d) TerraME Software (TerraME, 2016), (e) Life Safety Model (Life Safety Model, 2002); and (f) Oasys Mass Motion (AEC Magazine, 2011)

2.7.5.1 NetLogo

Netlogo is a "*multi-agent programmable modelling environment*", which is available in a free to download, open source format (NetLogo, 2016) (Wilensky, 1999). It was first created by Uri Wilensky in 1999 at the Centre for Connected Learning and Computer-Based Modelling (NetLogo, 2017). The most recent version of the software is 6.0.4, which was released in June 2018. Previous versions of the software are still available to download from their website, dating back to version 1.3.1. The software is provided with a library of sample models, these are carefully checked and verified as examples of good coding. One of the available and checked library models is the Predator-Prey model, in both a rabbits, grass, weeds and wolf, sheep, grass format (Figure 2-27(b)). The software is readily compatible with other software, such as ArcGIS using a GIS extension. The software has its own language, which is programmable by the user for the intended purpose, this allows a greater degree of flexibility. The graphics are simplistic and rely on a grid system, which can at times make the models appear crude (Figure 2-27(a)).

(a) (b)



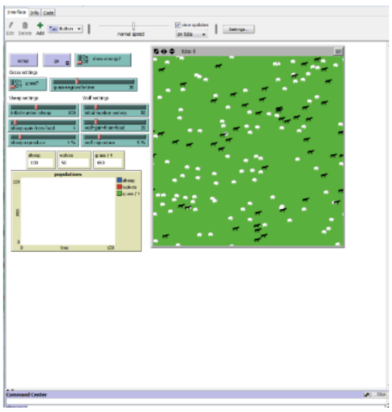


Figure 2-27 – (a) Screenshot of Netlogo Hazard Model from YouTube (Youtube, 2010) , (b) Screenshot of Netlogo Grass, Sheep and Wolf Predator Prey Model from Model Library (Wilensky, 1997).

2.7.5.2 GAMMA

GAMMA is a research group based at the University of North Carolina, researching Geometric Algorithms for Modelling, Motion and Animation (GAMMA) using general-purpose computations using graphics processors (GAMMA UNC, 2015). A key part of their research is crowd and multi-agent simulation, including; collision avoidance, real-time path and motion planning and crowd flows (Figure 2-28) (GAMMA, 2016). However, it is not known to what extent the actions of individuals can be modelled to form part of an emergency response.

(a) (b)

Figure 2-28 – (a) Screenshot of GAMMA research of Crowd and Multi-Agent Simulation (Youtube, 2009), (b) Screenshot of GAMMA research of Crowd and Multi-Agent Simulation (Youtube, 2009).

2.7.5.3 Miarmy

Miarmy is "a *human logic engine-based Maya plugin for crowd simulation, AI & behavioural animation, creature physical simulation and rendering*" (Basefount, 2017 A). Maya is a computer animation software created by Autodesk, which can be used for "*animation, environments, motion graphics, virtual reality and character creation*" (Autodesk, 2017). The Miarmy plugin is a free to download software, which allows a user to; "*build human fuzzy logic network without any programming or node connecting, create stunning crowd VFX and support all renderers*" (Basefount, 2017 A). The software has many applications but is widely used in the video games and film industry, such as in War and Order, Independence Day Resurgence and The Walking Dead (Basefount, 2017 B) (Figure 2-29). Due to the popularity with video games and film industries, the software is most applicable when large "army" or crowd scenes need to be created, this can at times result in a lack of individuality for agents, instead resulting in whole crowd movements and actions.

(a) (b)

Figure 2-29 – Screenshot of Miarmy software (Youtube, 2014), Screenshot of War and Order Mobile Game (Basefount, 2017 C).

2.7.5.4 SimWalk

SimWalk is "*a leading provider of pedestrian simulation products for public transport, aviation, sports venues, architecture, urban planning and evacuation*" (SimWalk, 2017 A). The software has been produced by a consultancy team based in Switzerland, with a vision "*to improve walkability, efficiency and safety of the built environment, in railway stations, airports, stadiums, streets, buildings and landscapes*" (SimWalk, 2017 A) (Figure 2-30(a)). The software is used by clients and research institutes across the globe such as Zurich Airport, SNCF France, Queensland Rail, University of Pennsylvania and the University of British Columbia (SimWalk, 2017 B). The software has many features and applications including; timetable integration, boarding/alighting analysis, rail network analysis, group modelling, rolling stock library and shopping analysis (SimWalk, 2017 C). This allows users the flexibility to incorporate individuality into agents using several pre-defined features such as walking speed, breadth or handicaps of agents (Figure 2-30(b)). This software is not free to use, other than the demo version, although this does not have full functionality, the full Pro version requires a licence fee of $12,500 (SimWalk, 2017 D). It is also not possible to manipulate the rulesets behind the programme, limiting its possible uses for this application.

(a) (b)

Figure 2-30 – (a) Screenshot of SimWalk Fire Hazard Model (Youtube, 2013), (b) – Screenshot of Agent Profiles in SimWalk (Youtube, 2016)

2.7.5.5 Life Safety Model

The Life Safety Model is "*a dynamic model that represents people's interactions with a flood and provides estimates of the number of people that are likely to be injured or killed as a result of a flood event, as well as the time that is required for them to evacuate the area at risk*" (HR Wallingford, et al., 2016). The model has been developed over a period of 15 years, using a number of methods, to allow simulation for a range of events types (e.g. slow rising floods, dam and flood defence failures, tsunamis and flash floods) (HR Wallingford & BC Hydro, 2016). Several case studies have been used to validate the model, including; Humber Estuary UK Sea Surge, Canvey Island UK Sea Surge and Windsor New South Wales Australia River Flooding (HR Wallingford & BC Hydro, 2016). The model captures individual receptors such as people or cars and their interactions with the floodwater, to provide the estimates for fatalities, injuries, time to evacuate and damage. The functions of the model are:

- "*The number of people that are killed or injured by inundation.*
- *The movement of vehicles modelled by a simple traffic model.*
- *The dynamic interaction of the flood wave with vehicles.*
- *The capacity of each building to withstanding the floodwater.*
- *People being modelled as individuals and as groups (e.g. families).*
- *The speed of dissemination of flood warnings.*
- *The evacuation of people along roads or footpaths, toward refuges (predetermined by the user)*" (HR Wallingford & BC Hydro, 2016).

The model is not free to use other than a 30-day trial and a one year licence fee costs £5000 (HR Wallingford & BC Hydro, 2016) (Figure 2-31). It is also not known if it possible to manipulate this existing model for alternative applications.

(a) (b)

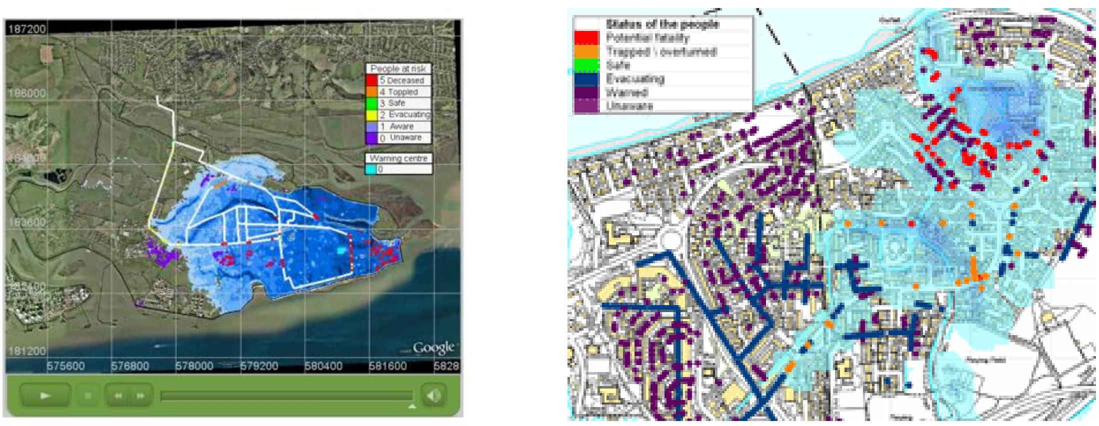


Figure 2-31 – (a) Screenshot of Life Safety Model (HR Wallingford, et al., 2016), (b) Output from Life Safety Model showing the potential fatalities and injuries (HR Wallingford, et al., 2016).

2.7.5.6 Flood Evacuation Model

The Flood Evacuation Model has been developed by a team of researchers at Newcastle University using NetLogo, for a flood event in Towyn, North Wales (Figure 2-32). The model incorporates remotely sensed information (topography, buildings, and road networks), with empirical survey data of communities and a hydrodynamic model. The aim of the model is to "*estimate the vulnerability of individuals to flooding under different storm surge conditions, defence breach scenarios, flood warning times and evacuation strategies*" (Dawson, et al., 2011). The model can be used to "*analyse the risks of flooding to people, support flood emergency planning and appraise the benefits of flood incident management measures*" (Dawson, et al., 2011). This demonstrates well the possible uses of Netlogo and its potential success, although it is not anticipated that this model can be easily adapted to suit different applications.

(a) (b)

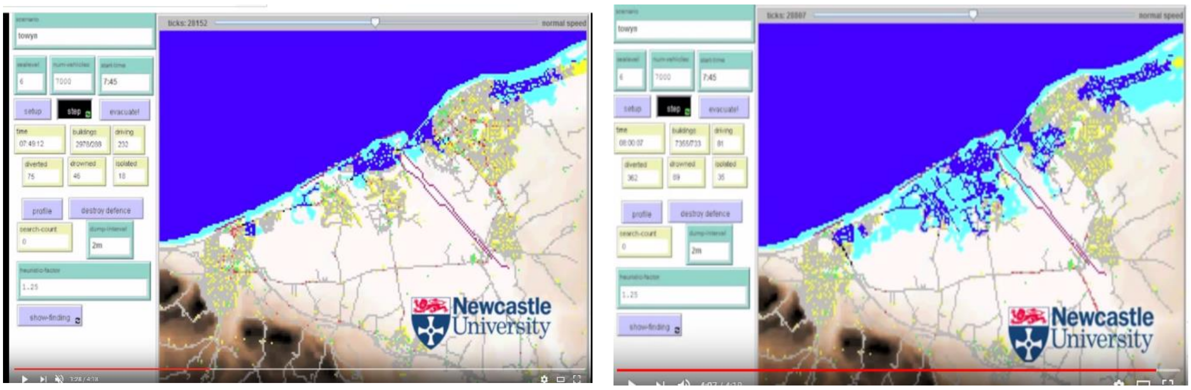


Figure 2-32 – (a) Screenshot of Flood Evacuation Model (Youtube, 2010), (b) Screenshot of Flood Evacuation Model (Youtube, 2010).

2.7.5.7 Summary Available Agent-Based Software

An overview of several available agent-based software and existing models has been outlined (Table 2-12). This has shown that the existing models are unlikely to be suitable for adaptation for this project as their intended purposes are overly specific. There are lots of available software packages that are open source and free to use, which is beneficial for this project. Although, there are software packages that have advanced the graphical output and user interface, it is anticipated that Netlogo will be most suitable for this thesis. Netlogo offers the flexibility to create a model environment, which incorporates several rulesets based on anticipated human behaviour during emergency scenarios, as well as spatial data and a hazard model if required. Netlogo is also written in its own language and allows a user to fully determine the extents for their model, whilst not being constrained by existing rules.

Table 2-12 – Summary of Available Agent-Based Models & Software

Software Name	Pros	Cons
Netlogo	Readily compatible with other software e.g. ArcGIS Own language – flexibility for intended uses Free to download Many applications	Graphical output is not very advanced/simplistic Relies on a gridded system
GAMMA	Crowd and multi-agent simulation/flows Collision avoidance Real-time path and motion planning Free to download Many applications	Lack of individuality of agents No inclusion of spatial data Unsure of possibility to include hazard model
Miarmy	Whole crowd movements and actions Free to download Many applications Good graphical output	Lack of individuality of agents No inclusion of spatial data Unsure of possibility to include hazard model
Model Name	**Pros**	**Cons**
SimWalk	User-friendly interface Number of predefined profiles e.g. walking speeds, transport layouts Multiple applications	Licence cost Designed for specific use – transport Inability to alter the "rules"
Life Safety Model	Includes spatial data Includes a hazard model	Licence cost Designed for a specific use – flooding
Flood Evacuation Model	Includes a large amount of spatial data Includes a hazard model	Designed for a specific use – flooding

2.8 Main Findings

It has been demonstrated that natural disasters and manmade events are happening across the globe, causing large financial, social and environmental impacts, which hinders sustainable development of many communities. The effects of which are disproportionately experienced by the poor and developing world, who are the least equipped to deal with the after-effects and often end up "fire-fighting" hazard event to hazard event. However, regardless of location communities across the globe need to develop appropriate plans and responses to hazard events, to limit where possible the consequences for communities.

The failure of infrastructure has a big impact and it has been shown that it may be beneficial to categorise cities into similar types to allow emergency planners to pool resources and robustly test methodologies. But arguably the "real" losses are for the communities and individuals affected. However, presently there is a lack of understanding regarding their behaviour which is often unpredictable. A more robust understanding of human behaviour responses to natural hazard events would allow us to prepare emergency services better and in turn understand the impacts on infrastructure systems.

This is supported by the disaster management cycle which has been developed to prepare, respond, recover and mitigate against events. A major part of this is the creation of plans by emergency planning professionals but even in the developed world these plans are flawed as it is difficult to robustly test plans, meaning the methods and plans proposed may be ineffective and unsuitable. Policy has been developed at both national and local level in the UK, but the current testing methodology is either through unrealistic table-top, discussion-based exercises or more costly real-life simulation. Despite this ineffectiveness, computational modelling has not been introduced even though the UK government has acknowledged the potential benefits.

Computational testing will only be an effective tool to aid emergency management professionals if appropriate modelling techniques are utilised, which are verified, calibrated and validated. An evaluation of possible modelling techniques has identified that agent-based modelling, where appropriately applied, has the most potential to robustly simulate human behaviour in an emergency scenario. From the software and existing models explored, Netlogo has been identified as the most appropriate software choice, as it allows flexibility and adaptation throughout the project as well as being open source and free to download. Several case studies have also demonstrated the potential benefits of creating agent-based models to aid emergency planners.

Chapter 3. Human Behaviour and How to Create Model "Rulesets"

It has been shown in Chapter 2 that it is vital that during disaster events, emergency planners do not only comprehensively understand how infrastructure may react to events but also how the affected communities may respond. This is closely inter-linked with infrastructure and the behaviour of communities should be considered when formulating robust emergency procedures and plans. Attempts have been made to study human behaviour in varied disaster scenarios and incorporate these traits within computational models, but this is not exhaustive, and improvements can still be made. Hence, it is important to first understand the types of behaviour, which may be present, then to understand how these behaviours could be incorporated into a model environment. To successfully capture realistic human behaviour, it is necessary to ensure that the behaviours can be first quantified but then also validated, verified and calibrated effectively to ensure their robustness. This chapter will explore the potential behaviours during a hazard event, then use these behaviours to formulate a series of desired model rulesets. From the rulesets, a literature review will be carried out to capture realistic quantifiable values to reflect the behaviour traits, which can be verified and validated. This will help to ensure that the agent-based model is robust.

3.1 Current Behavioural Models

During an emergency event, human behaviour can be both predictable, for example human instincts which have developed over centuries and unpredictable due to the stresses and strains of an unknown event with a range of potential outcomes. Data must be sought to find quantifiable datasets that can form the basis of human behaviour "rulesets" to include within computational simulations of hazard events. An element of this will be based on predictable behaviours whilst other "rulesets" will need to accommodate the anticipated unpredictability of events. Current models and plans have focused on making all agents the same e.g. same walking speed (Wood, et al., 2016). However, other studies have identified that not all human behaviours are the same, for example, more evacuees follow routes decided from their own experience than the routes dictated to them in emergency scenarios (Dow & Cutter, 2000), (Wu, et al., 2012) and due to age differences, illness and other factors walking speeds are not the same (Wu, et al., 2012). Another study has found there are a number of variables such as ethnicity, income, home ownership that can affect the likelihood of a household evacuating in the first instance (Whitehead, et al., 2000) (Ng, et al., 2016). Hence, it is hard to anticipate exactly how humans will react to a scenario until it is presented to them. This does not make it impossible to predict some behaviours, but to do this, it is necessary to create a more robust interpretation of human behaviours based on a wider range of factors than is currently undertaken in computational simulations. By improving the representation of human behaviour, emergency professionals will be able to better plan and prepare for hazard events, which in turn will reduce the suffering of communities.

At present, many hazard events are simulated in real-life with the aim of better understanding human behaviours and responses, however these events are costly in monetary terms as well as in resources and time. During June 2015, a week long terrorist attack was simulated in central London, this involved over 1,000 police officers, 2,000 causalities made up of actors and dummies and the event took over 6 months to plan and execute (BBC, 2015) (Paton & Warrell, 2015), demonstrating the time and resources required to simulate hazard events in real life. This also highlights the training received by blue light personnel without capturing the "true" interaction with the general public, who were made up only of dummies and actors. It can therefore be argued that real-life simulation serves the purpose of testing plans and protocols of emergency services but does not grant the opportunity to understand how the public reaction might affect outcomes. Therefore, it is vital that emergency managers can more accurately incorporate human behaviour within their plans, and it is envisaged that this can be done with the appropriate use of robust computational simulation.

It is proposed that human behaviours can take the form of "rulesets" backed with quantifiable data from studies from across several sectors, within computational simulation. This will allow emergency planners the opportunity to run numerous scenarios, interlinking this with existing real-life simulations to test worst-case scenarios and prepare blue light personnel appropriately. However, it will be necessary to ensure the model is appropriately verified, validated and calibrated to ensure it is a robust representation of human behaviour.

3.2 Behaviour Types

During hazard events, a range of behaviours are anticipated. This is dependent on several factors, for example; the type of event (e.g. whether there is clear and present danger, unseen danger or forecast danger), the population involved, the age of the population, location of the event and level of warning, which is potentially dominated by the event type. Hence, it is important that robust models capture a range of human behaviours and within this thesis, the following 11 behaviours are prioritised as the most important traits to be quantified in rulesets:

1. Flee behaviour – run from the hazard, different walking speeds;
2. Interpersonal distance – proximity of humans and interactions;
3. Crowd behaviour – crowd flows, following like sheep behaviour, herding;

4. Leader behaviour – influence of leaders on crowds;
5. Aggressive behaviour – aggression within a crowd;
6. Panic behaviour – levels of panic, distress;
7. Stop and drop behaviour – fear of the event, inability to move;
8. Capacity – of streets, roads, safe zones or shelters;
9. Routes – shortest path, known routes, following the leader;
10. Use of social media and communication – ability to influence routes or to cause panic;
11. Cognitive Mechanisms – the time taken for humans to make decisions.

It is argued that the inclusion of these traits will provide a more realistic and robust representation of human behaviour as it is seen today, whilst focusing on behaviour types expected during times of stress e.g. panic and fleeing as well as those that affect our everyday decisions e.g. route planning and use of social media.

3.2.1 Flee Behaviour

Flee behaviour can be categorised as the desire to move away from the hazard, this is applicable to clear and present danger, unseen danger and forecast danger. The behaviour requires a human to evacuate to escape the hazard path (Figure 3-1). This will result in a range of walking or running speeds and will also be influenced by the distances different age or fitness groups can travel. The movement may also change depending on the units present i.e. single people, couples or families. The overall average age of the group will also influence flee behaviour, as there is an anticipated link between walking speed and age. There also needs to be thought given to the ability to move using alternative methods of travel e.g. own vehicles or public transport. Physical or mental impairments may also result in a reduced level of mobility and therefore an ability to exhibit flee behaviour during a hazard event.

(a) (b)

Figure 3-1 – (a) Inhabitants fleeing Hurricane Rita, USA (Getty Images, 2015) , (b) Evacuating Residents after Storm Desmond, UK (PA, 2015)

3.2.2 *Interpersonal Distance*

Interpersonal distance can be described as the distance between each human within a crowd. The distance is changeable and depends on the size of the crowd and the space in which the crowd exists. It is anticipated that the tolerated distance between humans decreases during hazard events when compared to "normal" behaviour (Figure 3-2). This has impacts on both capacity and safety measures during a hazard event and can change the dynamic of the crowd.

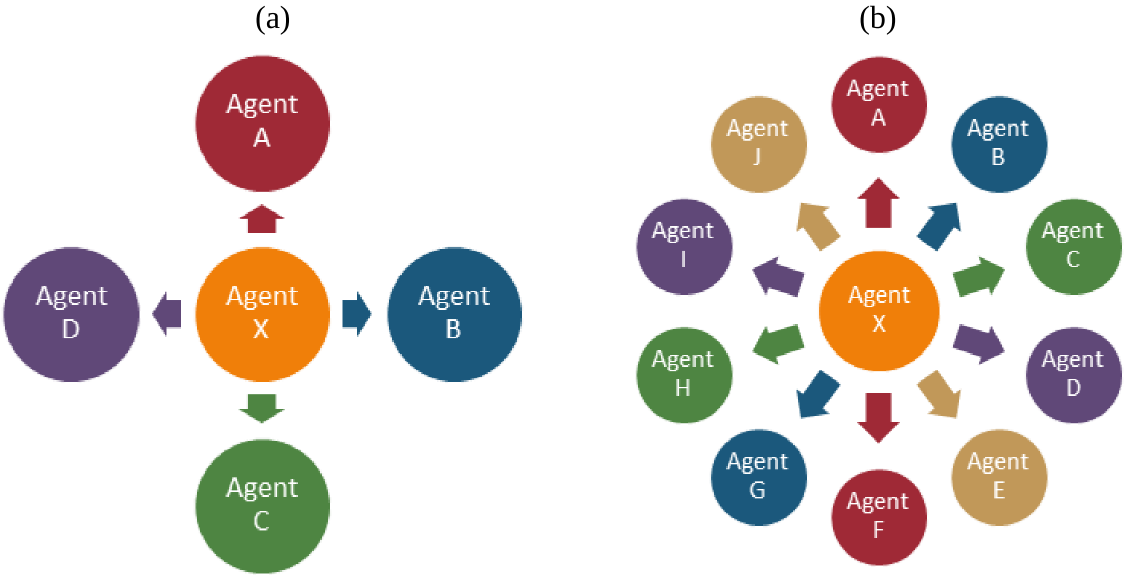


Figure 3-2 – (a) Five Agents in Crowd Scenario idealised "normal" behaviour, (b) Eleven Agents in Crowd Scenario idealised "hazard" behaviour

3.2.3 *Crowd Behaviour*

Crowd behaviour is related to the crowd as a whole and how they behave as a collective (Figure 3-3). This will influence the flow of the crowd and how easily it moves through an area. This human behaviour is very similar to that of sheep who move in flocks. The term "the crowd followed like sheep" is linked to the idea that those in the crowd will not act independently and instead follow blindly in an identical manner. In real life, crowd behaviour will be directly influenced by other human behaviours such as the number of leaders present, panic and aggression.

Figure 3-3 – Image of a Crowd exiting a music concert in Paris (Cridland, 2007)

3.2.4 *Leader Behaviour*

The number of a leaders in a crowd can have a positive effect on a crowd in terms of influencing direction as shown by the studies at Leeds University (Univeristy of Leeds, 2008). This type of behaviour is again associated with animals, particularly sheep and cattle (Figure 3-4). In hazard events, there should be a number of "informed" individuals within a crowd such as Police or security personnel, their influence on the crowd is anticipated to be significant and could be captured through leader behaviour (Figure 3-4).

(a) (b)

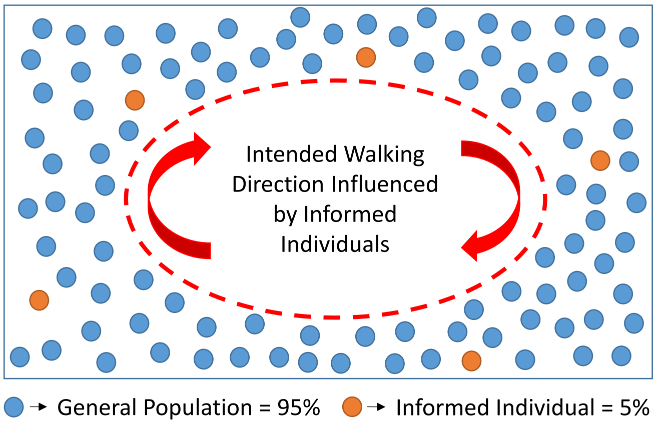


Figure 3-4 – (a) Flock of Sheep (Jenkins, 2008) (Jenkins, 2008), (b) Diagram based on Studies carried out at Leeds University (Univeristy of Leeds, 2008) (Science Daily, 2008)

3.2.5 *Aggressive Behaviour*

Aggression in a crowd is not always present within a hazard event, but frustrations about lack of communication and despair at the event, can at times manifest as aggression. The presence of a crowd can have a neutralising effect to reduce the aggression in some cases. However, the idea of crowd mentality can influence others to become aggressive or carry out illicit activities as others are carrying out the same actions, for example the looting seen during the riots in London in 2011 (Figure 3-5) , arguably this crowd began as an aggressive crowd intent on rioting. On the other hand, the presence of a large crowd allowed for the illegal activities such as looting to be carried out by the masses as it appeared appropriate if everyone else was doing it. Another example of aggressive behaviour in crowds is demonstrated by football fans. Despite, most fans being in attendance to enjoy the football, a small minority may be there with the purpose of carrying out aggressive behaviour and inciting the rest of the crowd to join them. This is often present at large local football matches or international tournaments. For example, during the 2016 UEFA European Football Championship large groups of Russian and English fans clashed in episodes of football hooliganism, which resulted in innocent fans being injured by the violence (Figure 3-5) (BBC, 2016) (Boffey, 2016).

(a) (b)

Figure 3-5 – (a) Looting during London Riots 2011 (Reuters, 2011), (b) England fans facing Russian fans during Euro 2016 (Horocajuelo & EPA, 2016)

3.2.6 Panic Behaviour

Panic behaviour does not always present during a hazard event and is often related to the type of hazard event (e.g. clear and present danger, unseen danger or forecast danger), which can trigger the levels of alarm for an individual. Communication can also play a part in panic, but it can be difficult to strike the right balance between ill informed, well informed and over informed. Panic can have different effects on individuals, within simulations irrational behaviours that were out of character such as a stampede may be the most important to characterise.

3.2.7 Stop and Drop Behaviour

Stop and drop behaviour is linked to panic and for some individuals the hazard event will cause them to "freeze". In some cases, it may also be the appropriate safety advice to stop and drop rather than fleeing the hazard. For example, this behaviour may be appropriate when the hazard has an unknown hazard path or there can be a high level of uncertainty should humans continue moving. This may be appropriate for terrorist attacks that involve firearms or weapons, the current advice in the UK is to run to a place of safety rather than surrendering, if not then to hide away from danger and then only when safe to do so tell the emergency services (Figure 3-6) (NPCC, 2017).

Figure 3-6 – UK Advice for Firearms and Weapons Attack (NPCC, 2017)

3.2.8 Capacity

Capacity is not necessarily a human behaviour but often dictates the human behaviour displayed. The capacity is related to the number of people a venue, street or safe zone can accommodate. Where there is insufficient capacity, there are more likely to be outbreaks of panic and aggression as people fight for the available space. Capacity needs to be determined on a case by case basis based on up to date spatial data. The Hillsborough Disaster on the 15th April 1989 is an example of how a lack of understanding about capacity can result in fatal consequences, with the deaths of 96 people (Conn, 2017). The crowd at Hillsborough were not only hindered by capacity but experienced multiple other behaviours such as crowd behaviour and reduced and non-existent interpersonal distance. Several errors compounded the number of deaths and injuries caused, and a better understanding of the capacity of the venue would have helped alleviate some of the issues.

(a) (b)

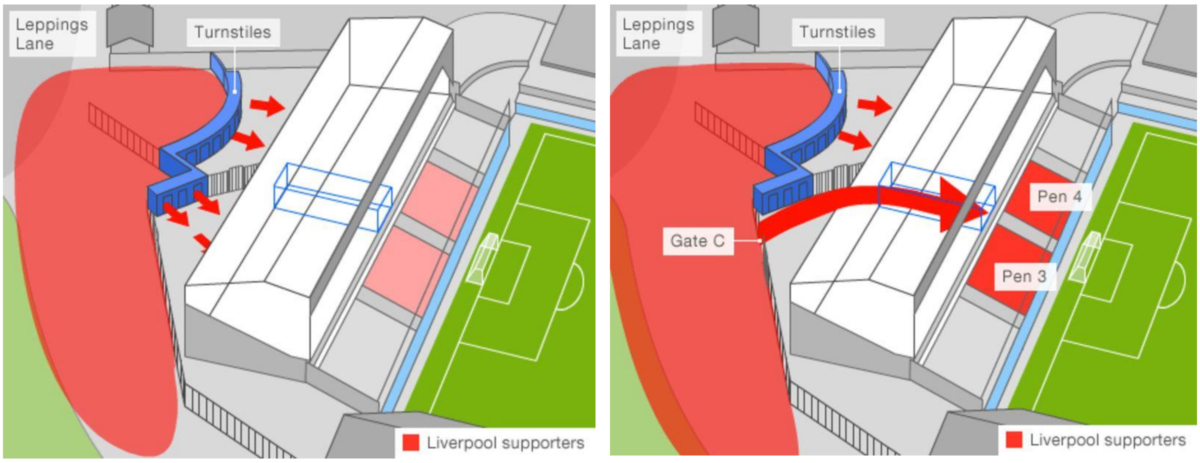


Figure 3-7 – (a) Figure showing Hillsborough football ground at 14:15 – 14:40 (several thousand Liverpool supporters are gathered outside the ground at the Leppings Lane end, as there are only seven turnstiles, admission to the ground is slow, (b) Figure showing Hillsborough football ground at 14:52 (Police order Gate C (a large exit gate) to be opened to alleviate the crush outside the ground, approximately 2000 supporters enter the ground and head for the tunnel leading directly to pens 3 and 4) (BBC, 2016 B).

3.2.9 Routes

The routes individuals take during a hazard event may be different from their “normal” route. However, it is also plausible that prescribed routes will be overridden by those with local knowledge. For the most part shortest path algorithms will be sufficient to ensure that individuals reach their destination in a timely manner, but this needs to be verified and validated to ensure it is realistic, as well as capturing the alternative possibilities (Figure 3-8).

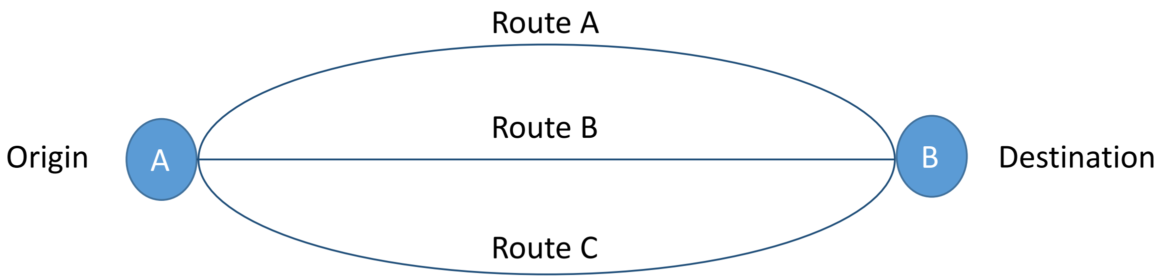


Figure 3-8 – Possible Route Selection from Origin to Destination

3.2.10 Social Media Presence and Communication

Social media usage has greatly increased in recent years and can have a big influence on a range of events. This includes hazard events, where places of refuge, safe routes and resources can be offered up easily in the immediate aftermath of events, as seen after the recent Westminster, Manchester, London Bridge and Finsbury Park terrorist attacks in the UK (Figure 3-9). It is also possible that social media can offer up to date information on places of safety and routes from emergency personnel, which can in turn directly influence human behaviour during a hazard event. As previously stated there needs to be a balance struck with communication to make sure individuals are well informed.

Figure 3-9 – (a) Twitter Screenshot of offer of help after Manchester Arena attack (Twitter (JesyRae), 2017), (b) Twitter Screenshot of offer of help after Manchester Arena attack (Twitter (Alix Long), 2017), (c) Police statement issued on social media after Manchester Arena attack (Twitter (Alix Long), 2017) (Twitter (GM Police), 2017), (d) Further Police update from the Manchester Arena attack (Twitter (GM Police), 2017)

3.2.11 Cognitive Mechanisms

It is important that any model of human behaviour realistically simulates anticipated behaviours. A significant aspect of this is to replicate a human's ability to think before acting. Humans follow an input – decision – action –cycle and it is vital that any model captures this effectively. Whereby a human receives a piece of information, processes it to choose an appropriate action then performs the chosen decision. For example, a fire alarm goes off in a building, the individual then processes this information and could choose to stay or flee, the action is chosen then performed. The length of the cognitive mechanism may vary depending on the hazard present e.g. clear and present, unseen or forecast.

3.3 Desired Rulesets

From the behaviours described, it is important to capture the main behaviours that are seen in a hazard event and that also have the potential to be quantified into a "ruleset" as well as being verified, validated and calibrated within a model. It should also be noted that modelling human behaviour in agent-based models can be a complex process and it should be considered that a hierarchy of behaviours may need to exist to achieve an overall "ruleset". The hierarchy may range from initial simple movements i.e. running or walking, to direction or following and finally to more complex social behaviours such as queuing or herding (Figure 3-10). It is important that models can capture this range of behaviours and any hierarchy that is present to create a more robust interpretation.

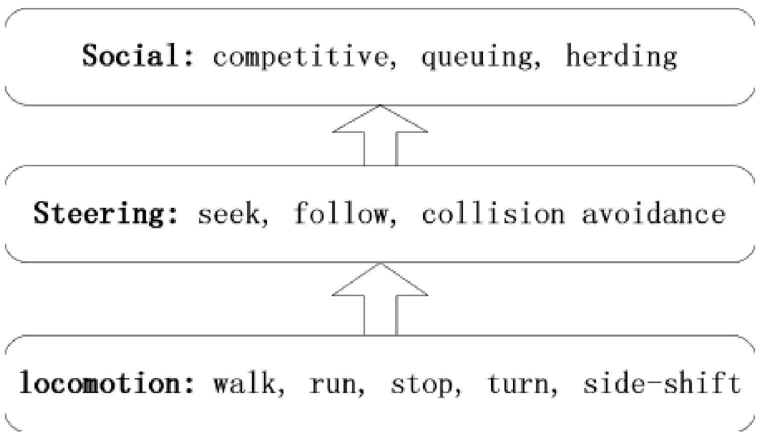


Figure 3-10 – Hierarchy of Agent Behaviour (Pan, et al., 2007)

It is not possible to consider all the behaviours described within an agent-based simulation therefore the behaviours have been evaluated to explore which behaviours will be most appropriate for inclusion (Table 3-1). Based on this evaluation, the main desired behaviours to simulate are flee behaviour particularly the walking speed distribution in a population, interpersonal distance, crowd behaviour, capacity and routes.

Table 3-1 – Potential Behaviours to Incorporate into Modelling Tool

Behaviour	Description	Exists in Current Software/Model	Input Parameters	Qualitative / Quantitative?
Priority Behaviours to Model				
Flee behaviour	Run from the hazard, varied walking speeds.	Yes	Can input set walking speeds for different populations but needs external validation e.g. from medical journal.	Quantitative
Interpersonal Distance	Proximity of humans	Possibly e.g. NetLogo Party	Attempts have been made to create buffers around agents, but this has not been accurately verified.	Quantitative
Crowd behaviour	Crowd flows, following like sheep behaviour	Yes e.g. NetLogo Shepherds	Lots of models are available in libraries showing general crowd behaviour and movement. There are many studies on animal behaviour, but it is assumed that the model has not been validated.	Quantitative / Qualitative
Capacity	Of streets, roads, safe zones/shelters	Yes	Capacity has been captured in some models and it would be possible to modify this, but it would need to be verified on a city by city basis.	Quantitative

Routes	Shortest path, known routes, follow the leader	Yes	Shortest path algorithms available, need to be verified on a city by city basis to ensure correct.	Quantitative
Additional Behaviours to Consider Modelling				
Leader behaviour	Influence of a leader on a crowd	Yes e.g. NetLogo Follower	This is often based on insects such as ants. Although this may be verified there would need to be changes made to accommodate human behaviour.	Quantitative
Aggressive behaviour	Aggression within a crowd	No	This behaviour is not currently captured but could be interpreted from psychological studies.	Quantitative / Qualitative
Panic behaviour	Levels of panic, distress	No	This behaviour is not currently captured but could be interpreted from psychological studies.	Qualitative
Stop and drop behaviour	Due to panic/fear	No	This behaviour is not currently captured but could be interpreted from psychological studies.	Qualitative
Use of Social Media	Influence of route, causing panic	No	Lots of data available on social media usage and patterns but not currently combined with a model and verified.	Quantitative / Qualitative

Cognitive Mechanism	The ability for agents to receive information, compute it then chose an action.	Yes e.g. THERP (Technique for Human Error-Rate Prediction) and Cream (Cognitive Reliability and Error Analysis Method)	There are existing cognitive mechanisms within models, which use the input – action – decision cycle. However, it needs to be determined how realistic these mechanisms are and therefore what level of verification has been carried out to date.	Qualitative

3.4 Available Studies on Desired Behaviours – Flee Behaviour

It has been demonstrated that to improve existing models, a more complex and robust model of human behaviour needs to be included, this has been split down into several priority behaviour traits. To back-up these rulesets, the rules need to reflect real world data and behaviours wherever possible. Therefore, a review of existing datasets has been carried out to form the initial parameters of the desired behaviour types; flee behaviour, interpersonal distance and crowd behaviour. It is anticipated that the routes and capacity will be captured within these three main behaviour categories. When considering flee behaviour, the elements that are of greatest importance are; the walking speed distribution, the distance and speed of running and the unit movement that occurs e.g. families. A literature review has been carried out to identify suitable sources of datasets that can be used to aid the understanding of flee behaviour, to enable appropriate and realistic rulesets to be created.

3.4.1 Flee Behaviour Literature Review

The first study considered is the one-mile walking test. This test is a way of measuring aerobic fitness, based on the concept of how quickly a participant can complete one mile at moderate exercise intensity (Anderson & Nichols, 2010) (American Council on Exercise, 2003). The tests are not completed on treadmills as this would alter the results. The results of the test (Table 3-2) are split into male and female plus several fitness levels. The general results show that walking speed declines with age (approx. 20-30%) and is highest in the youngest participants regardless of sex (Figure 3-11). The male partaker's record higher walking speeds than the female regardless of age or fitness levels (approx. 9 -20% difference) (Figure 3-11). There are a range of fitness levels for each age group, the difference in fitness results in an approximate change of 17-26% within each age group. The results also show that when fitness is lower from the offset the walking speed decreases more than those that are fitter, this is seen more obviously with the male participants (approx. 20-30%). Finally, walking speed decreases more with age in females than males (male decrease 19-29% and female decline 28-32%).

One downside of this study is that there are no results for participants under 20 or over 70 i.e. children and the elderly. Another negative of this study is that participants were aware that they were completing a test. Therefore, it could be argued that these walking speeds are unrealistic as they were not observed whilst carrying out everyday activities and instead “pushing” to complete the test in the best possible time. However, it could be argued that in stressful situations there may be elements of “pushing” the human body to extremes and in doing so higher walking speeds are reached. This would need to be validated against real world observations. Hence, it will be necessary to compare the results of this study to other walking speeds, to assess the appropriateness of the values.

Table 3-2 – Average Walking Speeds from 1 Mile Walking Test (Anderson & Nichols, 2010) (Anderson & Nichols, 2010) (American Council on Exercise, 2003)

Age		**20-29**		**30-39**		**40-49**		**50-59**		**60-69**		**70+**	
Gender		**M**	**F**	**M**	**F**	**M**	**F**	**M**	**F**	**M**	**F**	**M**	**F**
Fitness	**Excellent**	2.25	2.03	2.16	1.96	2.08	1.89	2.00	1.82	1.90	1.77	1.77	1.47
	Good	2.15	1.97	2.07	1.90	1.99	1.83	1.93	1.77	1.83	1.71	1.73	1.40
	Average	2.01	1.84	1.94	1.77	1.87	1.72	1.81	1.65	1.70	1.59	1.55	1.28
	Fair	1.90	1.70	1.84	1.65	1.77	1.60	1.69	1.53	1.60	1.46	1.37	1.17
	Poor	1.85	1.63	1.79	1.58	1.73	1.53	1.63	1.48	1.55	1.40	1.32	1.11

Speed measurements for each gender are given in metres per second (m/s), calculated from the minutes taken to complete the 1-mile walking test at each fitness level

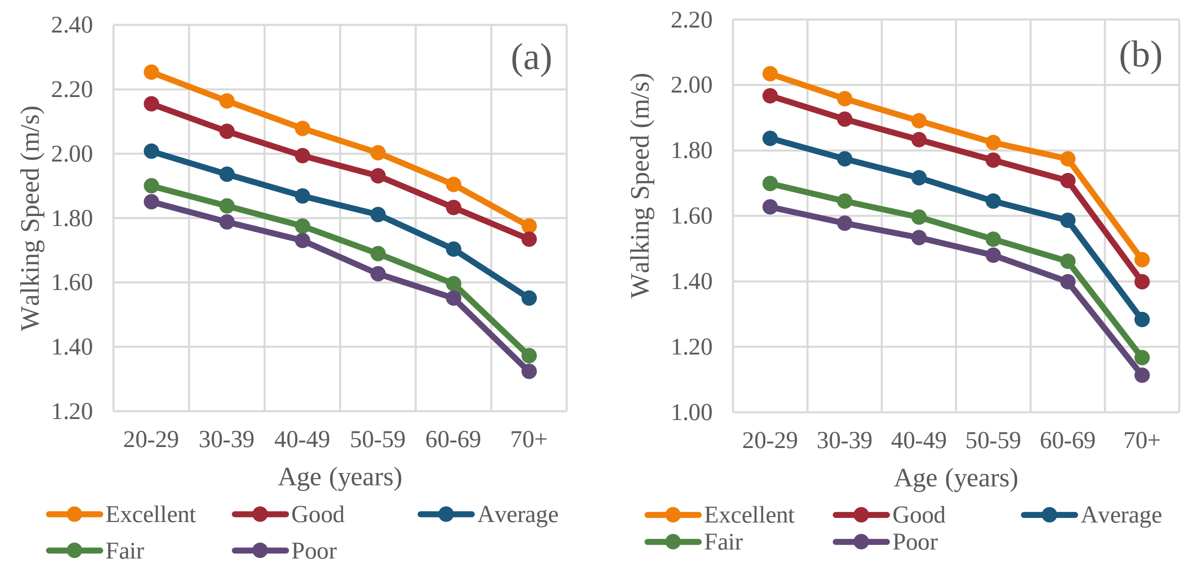


Figure 3-11 – (a) Graph of Average Walking Speeds for 1 mile Walking Test (Males Only) (Anderson & Nichols, 2010) (American Council on Exercise, 2003) (Anderson & Nichols, 2010) (American Council on

Exercise, 2003), (b) Graph of Average Walking Speeds for 1 Mile Walking Test (Females Only) (Anderson & Nichols, 2010) (American Council on Exercise, 2003) (Anderson & Nichols, 2010) (American Council on Exercise, 2003)

The study by Schimpl et al (2011) was "*to evaluate the relationship of gait parameters, and demographic and physical characteristics in healthy men and women*". This was based on the idea that human motion is considered as an important indicator of health in individuals. The study included 358 male and female participants from the Cambridge CardioResource study; demographic data, physical characteristics (e.g. height, weight) and assessment of activity parameters were collected, to analyse walking speed and health.

The results of this study have shown that walking speed decreases with age, as does the range of walking speeds (Figure 3-12). The walking speed decreases by 0.0037m/s per year, this is equivalent to a difference of 1.2 minutes if walking 1km at the age of 20 and then again at the age of 60 years (Schimpl, et al., 2011). There are several outliers in the 40-59 age bracket, which may be a result of those with extreme fitness levels who continue to maintain these with age. The median walking speed is similar from the age of 30 to over 60 in this study, this suggests that the greatest difference in speed would be seen between those under and over 30 years of age.

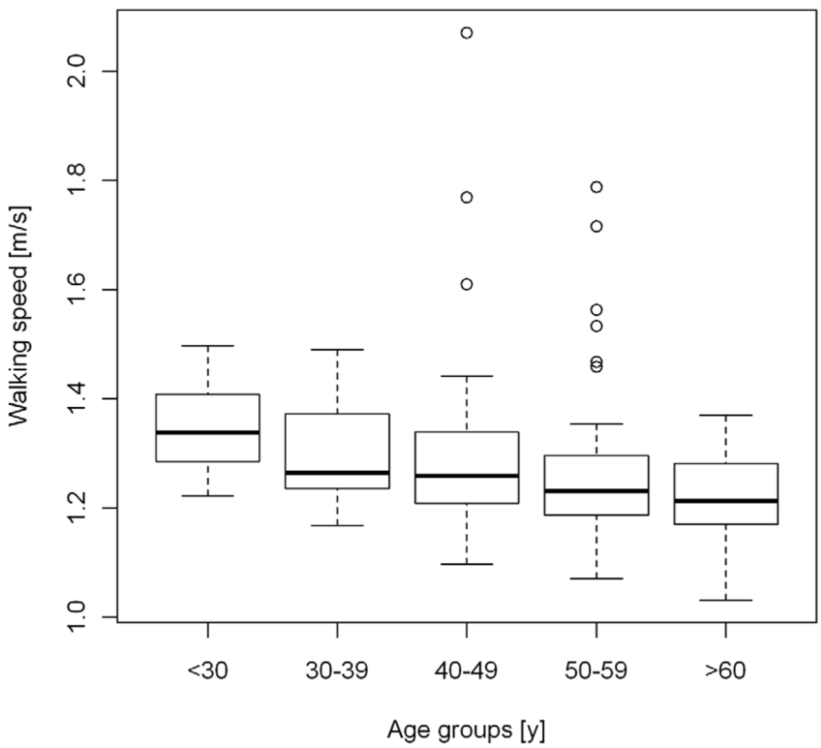
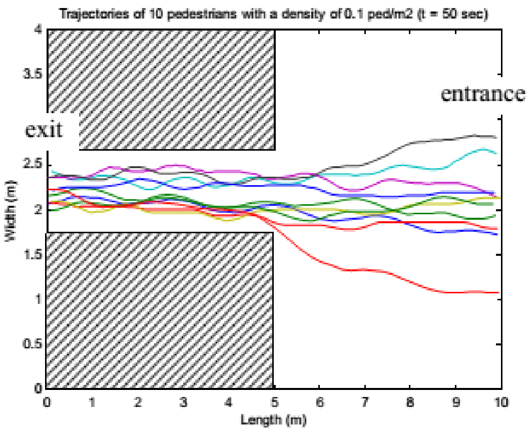
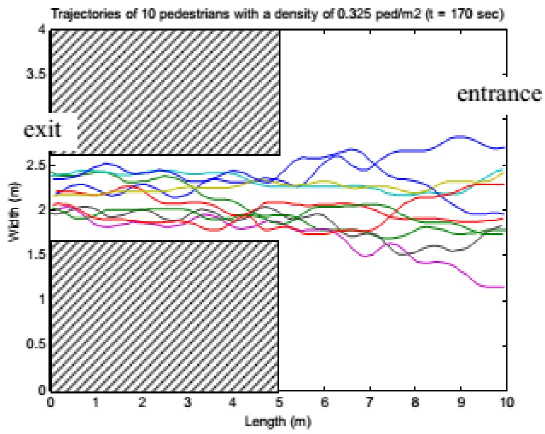


Figure 3-12 – Boxplot showing relationship between walking speed and age (Schimpl, et al., 2011)

The research by Daamen & Hoogendoorm (2003) focused on pedestrian free speed distribution and the assessment of walking infrastructure and timetables for public transport. This was carried out using microscopic and macroscopic pedestrian flow models, which could be validated with detailed pedestrian flow data. The pedestrian flow data was collected as part of this study in several experiments. Four variables were considered; free-speed, walking direction, density and the effect of bottlenecks. The results of the experiments have shown that when there are no flow constraints on pedestrians, pedestrians walk through the centre of the bottleneck, which maximises the distance between themselves and the walls (Figure 3-13) (Daamen & Hoogendoorm, 2003) (Daamen & Hoogendoorm, 2003). However, when at capacity two lanes are formed, with pedestrians walking diagonally behind each other, therefore minimising the headway (Figure 3-13) (Daamen & Hoogendoorm, 2003) (Daamen & Hoogendoorm, 2003). In addition, when congestion does occur, only the width of the bottleneck is used, whereas upstream the pedestrians "spread out" to use the entire width (Figure 3-13). The results of the free-speed distribution show that when pedestrians are not constrained by other pedestrians, that there are a range of speeds to be expected, including a number of individuals who will walk either very fast or very slow (Figure 3-13). The lowest speed is measured at 0.86m/s, the highest at 2.18m/s and the mean is 1.58m/s (Daamen & Hoogendoorm, 2003) (Daamen & Hoogendoorm, 2003).





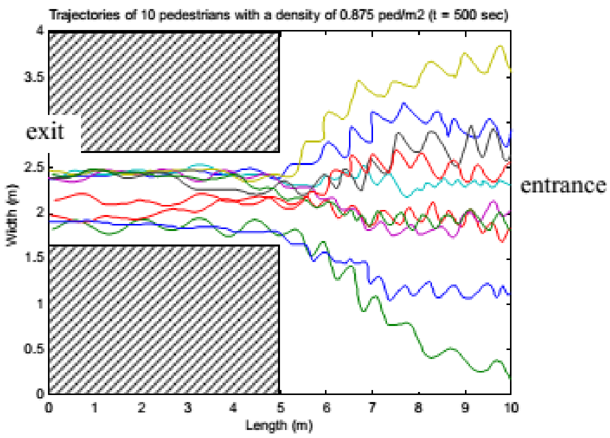


Figure 3-13 – Example trajectories of pedestrians for three different situations (a) density = 0.1P/m², (b) density = 0.325P/m2, (c) density = 0.875P/m2. Note: Pedestrians walk from right (x = 10m) to left (x = 0m) (Daamen & Hoogendoorm, 2003) (Daamen & Hoogendoorm, 2003)

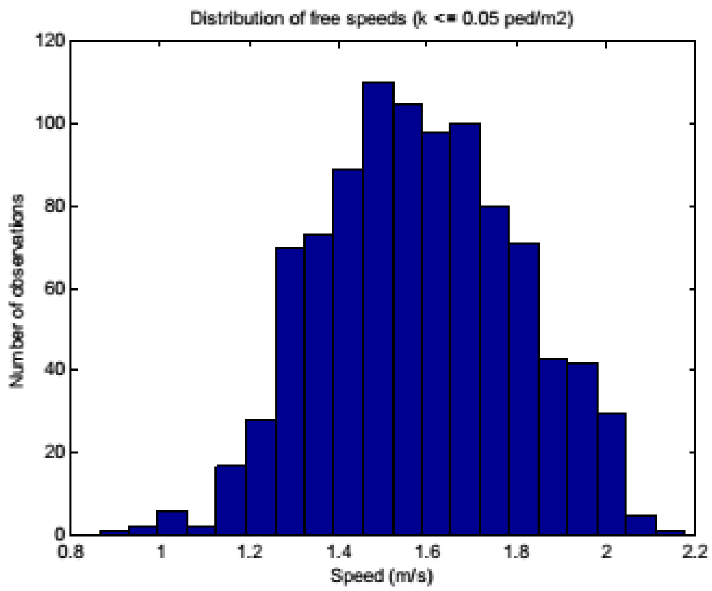


Figure 3-14 – Pedestrian Free Speed Distribution for Narrow Bottleneck Experiment (bottleneck width = 1.0m), with low density i.e. individuals are not constrained by other pedestrians (Daamen & Hoogendoorm, 2003) (Daamen & Hoogendoorm, 2003)

The study by Bosina & Weidmann (2017) has focused on a review of all available literature for walking speeds in the past 80 years. The study collected over 200 measurements from previous studies on walking speed, to quantify the important influences on walking speeds. This has been compiled into a series of findings (Figure 3-15 – Figure 3-18). The results as shown by the histogram of speeds (Figure 3-15) show that stairs slow walking speed. Without the presence of stairs there is a greater range of speeds demonstrated. The density of pedestrians affects the speed at which the pedestrians can travel, a greater density of pedestrians slows the walking speed. The density has a similar reduction in walking speed as when pedestrians encounter stairs. The Speed Density Relationship (Figure 3-16) shows that in general, as density increases walking speed decreases and that the range of speeds decreases with density. This study has considered a greater range of ages when researching walking speeds, from 0 – 100 years of age (Figure 3-17). The graph shows that speed increases until around 25 years old then decreases slowly until around age 60 then more steadily declines to 100 years old. When age 100 is reached, speeds decrease to lower than early age walking speeds. Between the ages of 25 and 60, there is not a large difference in walking speed, approx. 0.4 m/s. However, this will be noticeable over longer distances. The results also show that as group size increases, the group walking speed decreases. This is represented as walking speed and as a ratio (Figure 3-18). When there are fewer members in the group, there is a greater range of speeds experienced.

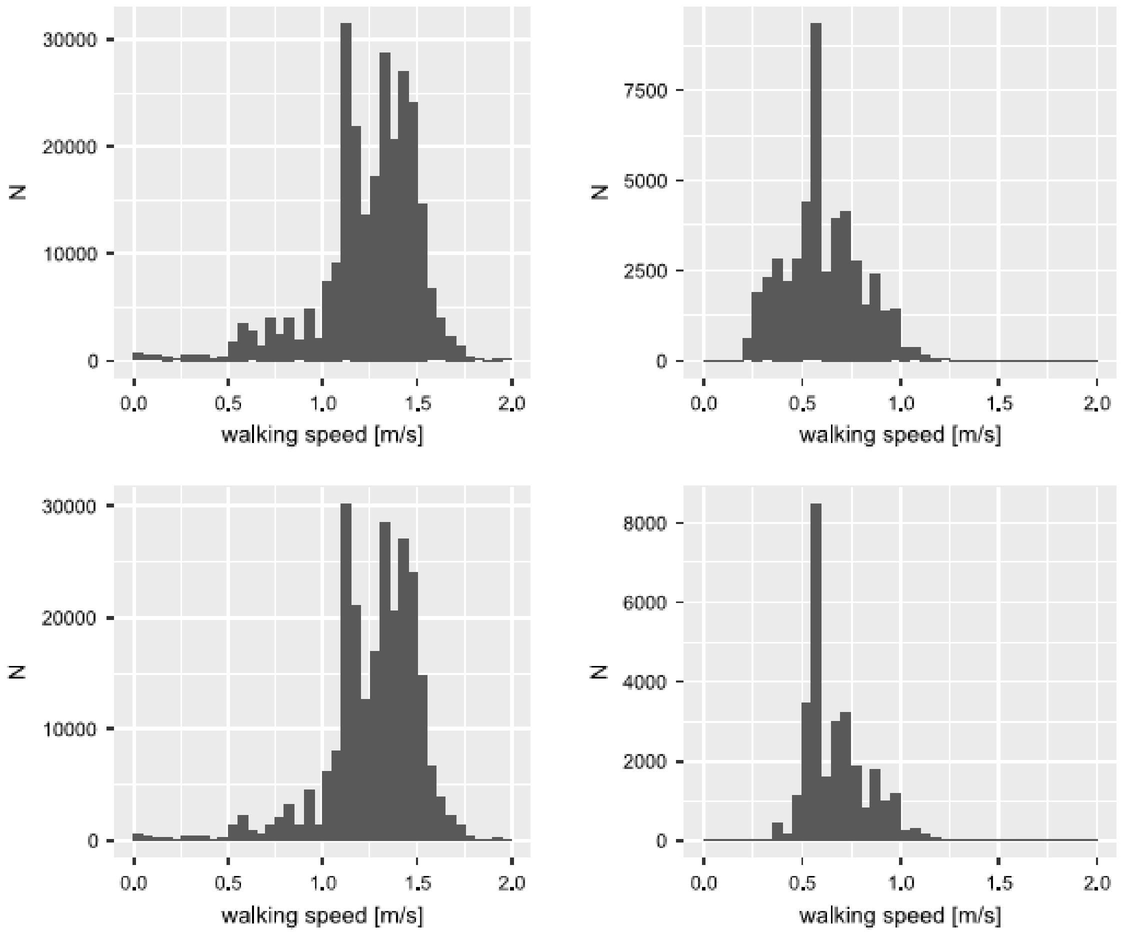


Figure 3-15 – Histogram of all speed measurements obtained from literature (Bosina & Weidmann, 2017) (left = non-stair facilities, right = stairs, top = all densities, bottom = densities ≤ 0.5 P/m²)

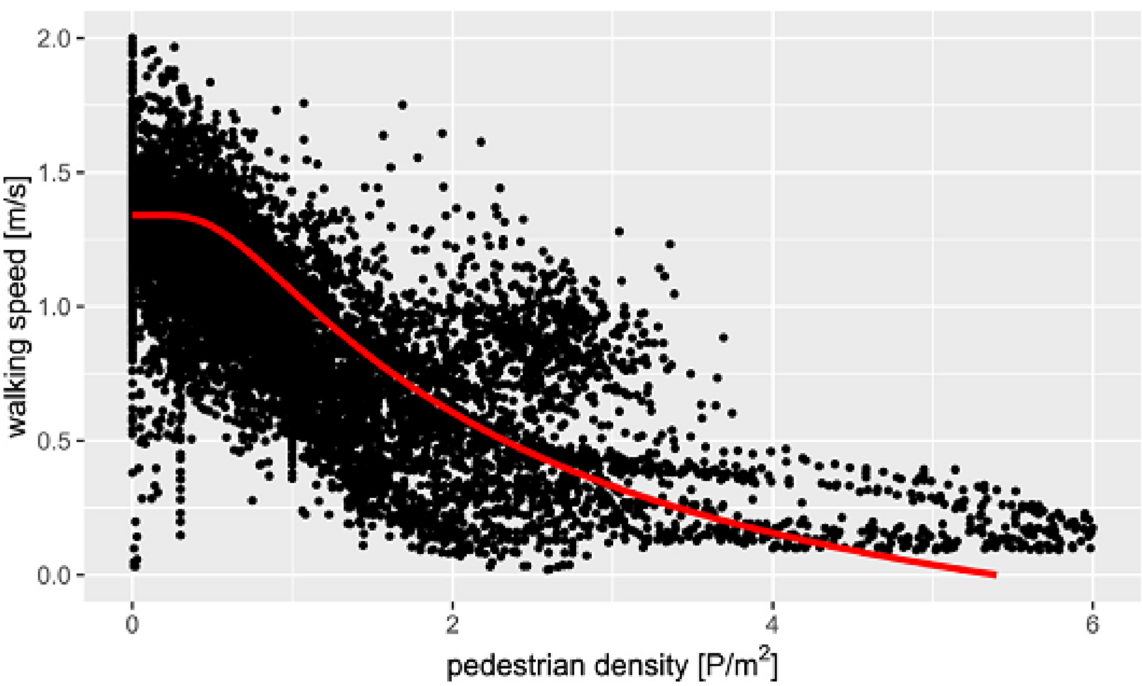


Figure 3-16 – Speed-Density Relation for all literature data except data from stairs used compared to Kladek Formula (Bosina & Weidmann, 2017) Note: the Kladek formula is used to describe the relation between average momentary speed and density of motorised urban road traffic (Kretz, et al., 2015)

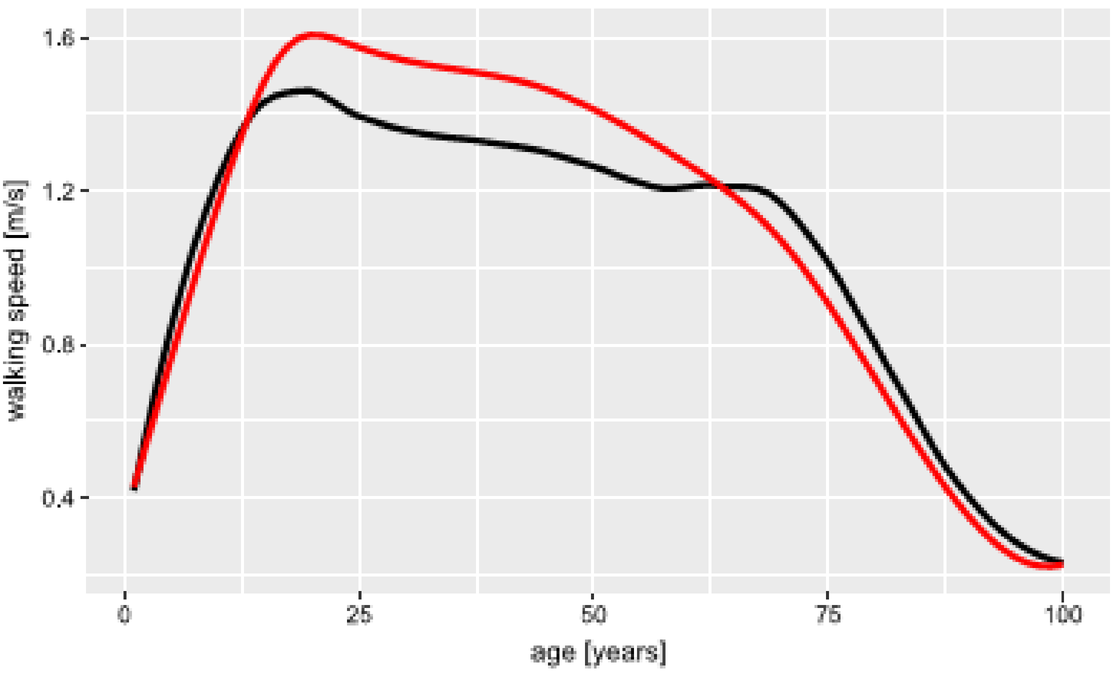


Figure 3-17 – Influence of Age on the Walking Speed (Bosina & Weidmann, 2017)

Group size	Ratio between group walking speed and single pedestrian walking speed
1	1
2	0.90
3	0.84
4	0.79
5	0.77
6	0.78

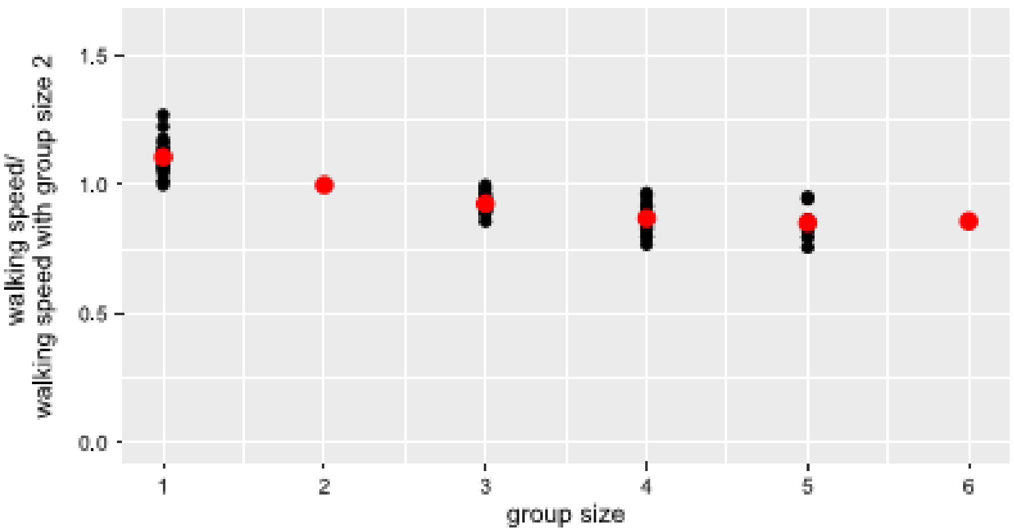


Figure 3-18 – Average Reduction in Group Walking Speed and Comparison of Group Walking Speed to Walking Speed of Groups of 2 People (Bosina & Weidmann, 2017)

The research by Moussaid et al (2010) concentrated on the movement of groups within crowds, as it has been claimed, "*up to 70% of people in a crowd are moving in groups*". The study analysed the movements of approximately 1500 pedestrian groups under natural conditions, to better understand the interactions of group members and to produce group-walking patterns that influence crowd dynamics (Moussaid, et al., 2010). The results show that walking speed declines with pedestrian density (Figure 3-19). It also decreases with group size. The walking speed is slowest when there is a larger group and the crowd is denser. The range of walking speeds is larger when there is a lower density or a larger group. The study also examined the formation of groups and found that when in low density situations, groups tend to walk side by side, but when density increases this formation changes to a V-like pattern. This allows social interactions to continue within the group but decreases the possible pedestrian flow. Hence, it can be assumed that as crowd density increases, a trade off must be sought between social interactions and walking speed (Moussaid, et al., 2010).

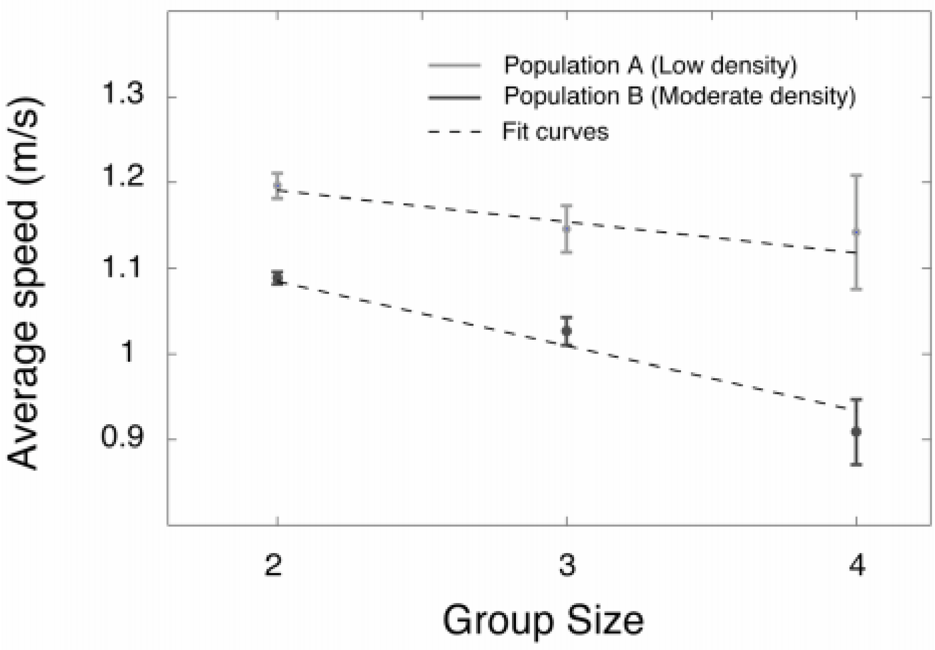


Figure 3-19 – Effects of Group Size on Walking Speed (Moussaid, et al., 2010)

The study by Shen et al (2014) was based on the requirement to include human movement characteristics with different visibility scenarios into fire-performance based designs and evacuation calculations. To accommodate this, an evacuation experiment was carried out in a classroom and recorded with video cameras, to analyse the effects of visibility and gender on walking speed. The results show that loss of visibility decreases the walking speed (Figure 3-20). The loss of visibility appears to affect females more than males in this study. There is a smaller range of walking speeds between good visibility conditions and poor visibility conditions for males (0.5 – 1.35 m/s – male) than females (0.25 – 1.38m/s – female). One limitation of this study is that the experiments were classroom based, so would only be appropriate to transfer to other evacuations with similar layouts to a classroom.

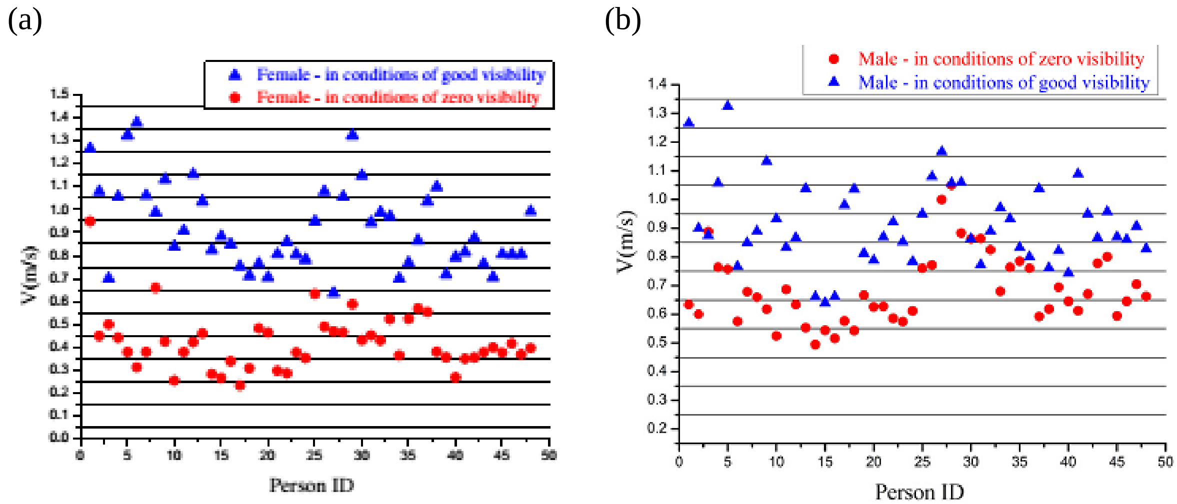


Figure 3-20 – (a) Mean Velocity of Female Participants in Different Visibility Conditions (Shen, et al., 2014) Note: female average in good visibility = 0.924m/s, and 0.422m/s in poor visibility (Shen, et al., 2014), (b) Mean Velocity of Male Participants in Different Visibility Conditions (Shen, et al., 2014) Note: male average in good visibility = 0.913m/s, and 0.687m/s in poor visibility (Shen, et al., 2014).

The study by Bae et al (2014) aimed to collect a human behaviour dataset in terms of travel times and interpersonal distance when using a corridor and stairs. An experiment was set up to simulate the Jungang-ro subway station in good and poor visibility conditions, whilst carrying out analysis on walking speed, density, travel time, plus interpersonal distance and angle distribution. The results show that the travel times are greater on stairs but that there are a smaller range of travel times when using stairs i.e. it takes participants similar times to walk upstairs (Figure 3-21). There is a decrease in walking speed on stairs and due to poor visibility. In poor visibility conditions, the walking speed decreases from 0.9m/s to 0.76m/s on the corridor and from 0.61m/s to 0.57m/s on the stairs (Bae, et al., 2014). The travel times are also affected by visibility, more so when in a corridor (9.75s to 8.75s) than a walking on stairs (18.75s to 18.25s) though.

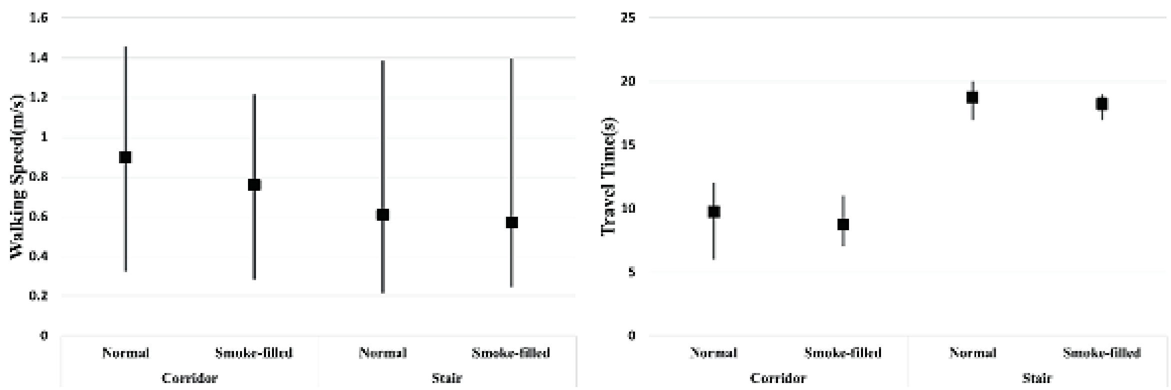


Figure 3-21 – Comparison of Walking Speed and Travel Time in Normal and Smoke-Filled Conditions (Bae, et al., 2014)

The study by Silva et al (2014) focused on the "*need for safe and efficient pedestrian infrastructure*". The aim was to create a mathematical model for estimating pedestrian walking speed based on several variables and multiple linear regression techniques. The results of their literature search and analyses suggests that an average walking speed of 1.25m/s (2.80mph) with a lower estimate of 0.68m/s (1.52mph) and a higher estimate at 1.92m/s (4.29mph) were appropriate figures. These average figures can be improved upon with their model predicting walking speeds based on gender and age. The model shows that walking speed declines with age, the variation between the 18-24 group and 25-34 group is relatively small, but a greater variation can be seen when compared to the elderly group (>65) (Figure 3-22). The model also shows that male pedestrians adopted higher walking speeds than females in all age categories (Figure 3-22).

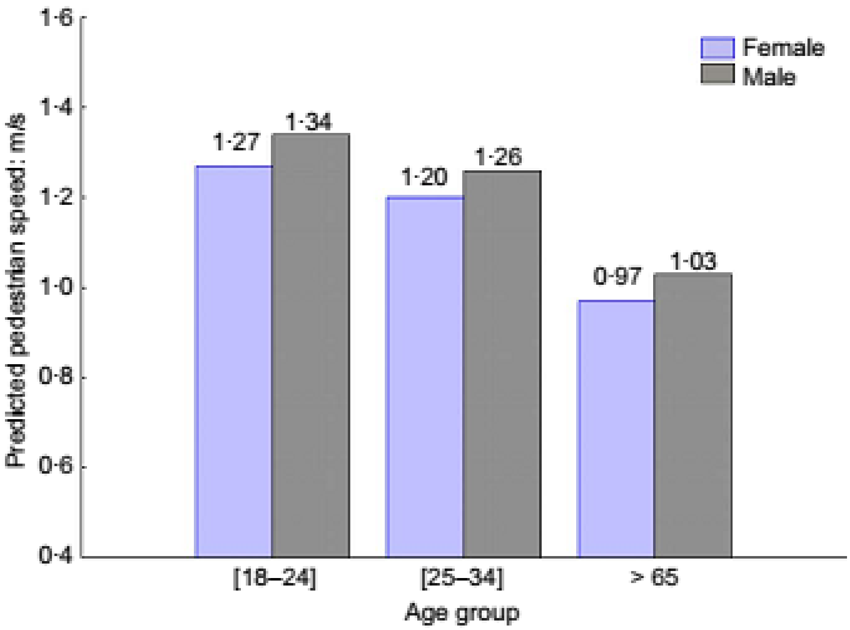


Figure 3-22 – Estimated Mean Walking Speed by Gender and Age Group (Silva, et al., 2014)

The research by Rastogi et al (2011) aimed to explore the design implications of walking speeds on pedestrian facilities. It is argued that walking speeds are affected by several variables such as age, gender, land use, temporal variations, mobile phone use, baggage and travelling in groups, but it is not anticipated that these factors are incorporated into pedestrian facility design. Therefore, eighteen locations in five cities in India were selected to be analysed in terms of sidewalks, wide-sidewalks and precincts and the walking speed factors. As part of the literature review of this study, walking speeds were compiled from previous studies from across the globe over a 30-year period (Table 3-3). This shows that literature places walking speed at approximately 1.34m/s (3mph) regardless of location. There are some obvious exceptions to this such as Saudi Arabia at 1.08m/s (2.42mph) and France at 1.50m/s (3.36mph) (Table 3-3).

The results of the study also show that pedestrians walk fastest when using sidewalks, compared to wide sidewalks and precincts (Table 3-4). In addition, male pedestrians consistently walk faster than female pedestrians regardless of the infrastructure (Table 3-4). Young adults exhibit the fastest walking speeds on each type of pedestrian facility, followed by middle-aged adults and children then older pedestrians (Table 3-4). The larger the group size, the slower the walking speed, regardless of the facility walked on (Table 3-4). Both baggage and mobile phone use decreased the walking speed of pedestrians; the greatest effect was when using sidewalks (Table 3-4).

Table 3-3 – Average Walking Speed in Different Countries (Rastogi, et al., 2011)

Author	Year	Country	Average Speed (m/s)
Fruin	1971	United States	1.35
Bornstein and Bornstein	1976	France	1.50
Bornstein	1979	Republic of Ireland	1.27
Polus et al.	1983	Israel	1.32
Tanaboriboon et al.	1986	Singapore	1.23
Koushki	1988	Saudi Arabia	1.08
Morrall et al.	1991	Sri Lanka	1.25
Morrall et al.	1991	Canada	1.40
Knoblach et al.	1996	United States	1.43
Lam and Cheung	2000	China	1.23
Tarawneh	2001	Jordan	1.33
Finnis and Walton	2008	New Zealand	1.47
Kotkar et al.	2010	India	1.20

Table 3-4 – Global Walking Speeds adapted from (Rastogi, et al., 2011)

	Category	Mean Walking Speed (m/s)			
		Sidewalks	Wide Sidewalks	Precincts	Overall
Sex	**Male**	1.22	1.17	1.07	1.15
	Female	1.15	1.12	1.05	1.11
Age	**Children**	1.23	1.21	1.08	1.17
	Young Adults	1.37	1.29	1.20	1.29
	Middle-Aged Adults	1.21	1.16	1.07	1.15
	Older Pedestrians	0.94	0.93	0.90	0.92
Group Size	**2 pedestrians**	1.19	1.13	1.09	1.13
	3 pedestrians	1.06	1.01	1.00	1.03
	4 pedestrians	0.91	0.98	1.00	0.97
	5 pedestrians	1.01	0.90	0.89	0.94
	More than 5	0.99	-	0.83	0.91
Activity	**With baggage**	1.03	1.09	1.10	1.07

	Without baggage	1.31	1.20	1.02	1.18
	With cell phone	1.05	1.04	0.99	1.02
	Without cell phone	1.31	1.26	1.13	1.23
Land Use	**Commercial**	1.11	1.26	-	1.18
	Educational	1.42	-	-	1.42
	Mixed	1.33	1.05	-	1.19
	Recreational	1.11	1.13	1.16	1.13
	Residential	1.08	-	-	1.08
	Shopping	-	1.09	0.92	1.00
Whole data		1.19	1.15	1.06	1.13

The study carried out by Costa (2010) examined the spatial organisation of 1020 groups of young people, observed in an urban environment whilst walking. The results showed that male groups of two or three preferred walking abreast less often than female groups. When there was a mixed group of two walking abreast was more common than for single sex groups. Males walked at higher speeds than females regardless of group size (Figure 3-23). The mixed groups walked at similar speeds as the female groups suggesting that groups will walk at the slowest speed to accommodate all group members (Figure 3-23). A V-shaped formation is the most frequently observed group construction, with the middle person slightly behind the other members to form the V. Observations also showed that groups over three tended to split down into smaller groups.

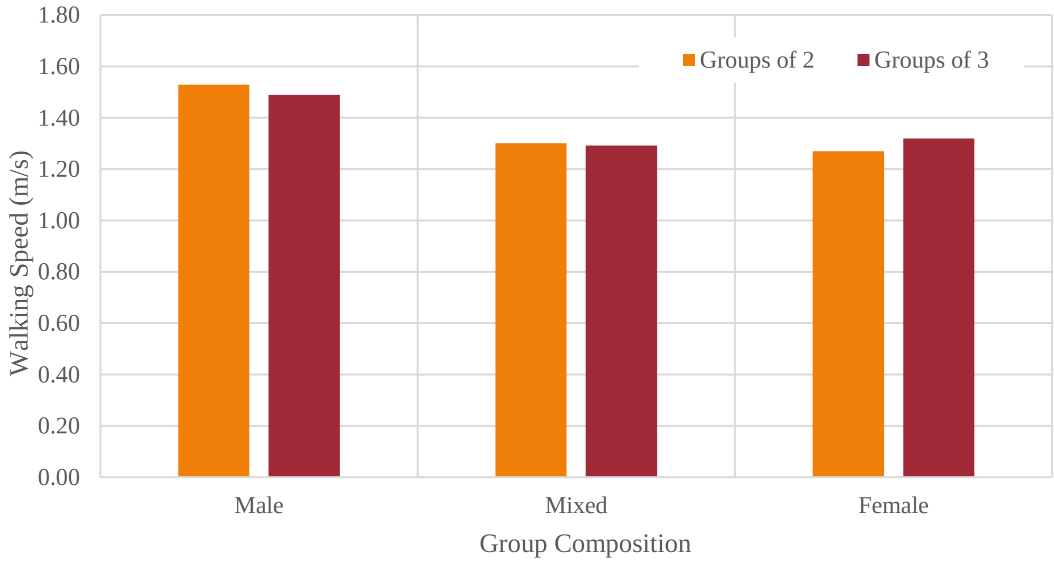


Figure 3-23 – Study of Group Size and Walking Speeds in Pescara and Bologna, Italy (Costa, 2010)

3.4.2 Flee Behaviour Literature Analysis

From the literature findings, it is possible to bring together datasets, to show whether there is a correlation amongst the literature and to draw conclusions. The literature can be split into three categories to aid comparison: (1) age & walking speed, (2) group size & walking speed, (3) influence of stairs and the influence of visibility.

Many of the studies were focused on walking speed and age, but it is important to understand whether there is agreement between the values. Five of the studies proposed walking speeds for different age groups and overall, all demonstrate that walking speed decreases with age (Figure 3-24). It can be seen that the one-mile walk test results, despite being the average fitness results, are estimating significantly greater walking speeds. It is anticipated that due to the nature of this test that the walking speeds are an overestimation for use in evacuation models. The other datasets show positive correlation though particular between the Bosina & Weidmann 2014 study and the Schimpl et al 2011 data. The results from Silva et al 2014 and Rastogi et al 2011 are not significantly different from the other datasets and correlate well together.

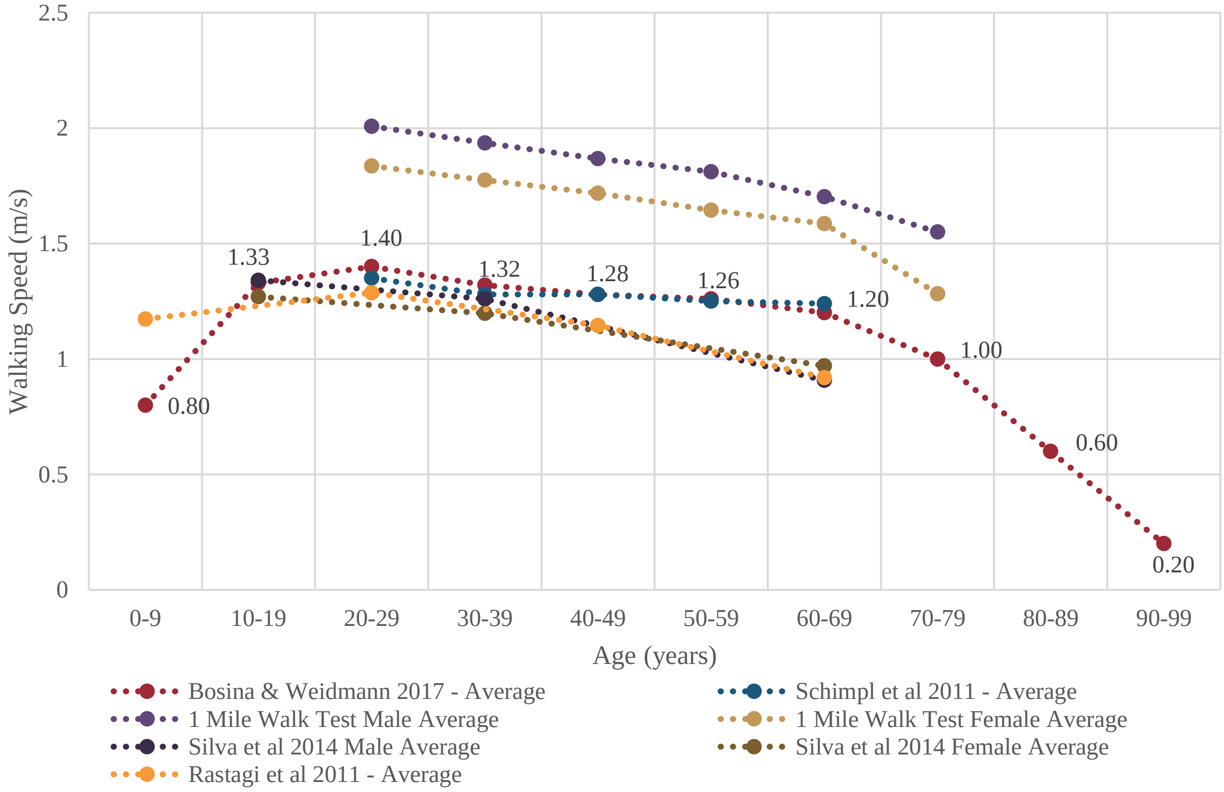


Figure 3-24 – Combined Age & Walking Speeds from Literature

Several studies considered the impact of group size on walking speed. The studies showed that in general as group size increases, walking speed decreases (Figure 3-25). However, as each study started with a different average walking speed for a single person it is difficult to determine whether there is any correlation. Therefore, a ratio was calculated from the walking speeds, to ascertain whether there is a similar decrease in walking speed with group size in each study (Figure 3-26). This demonstrated that there was a comparable decline in the ratio. From this, it was then possible to create a proposed ratio for a group size ruleset (Figure 3-27), using the Bosina & Weidmann 2014 ratio.

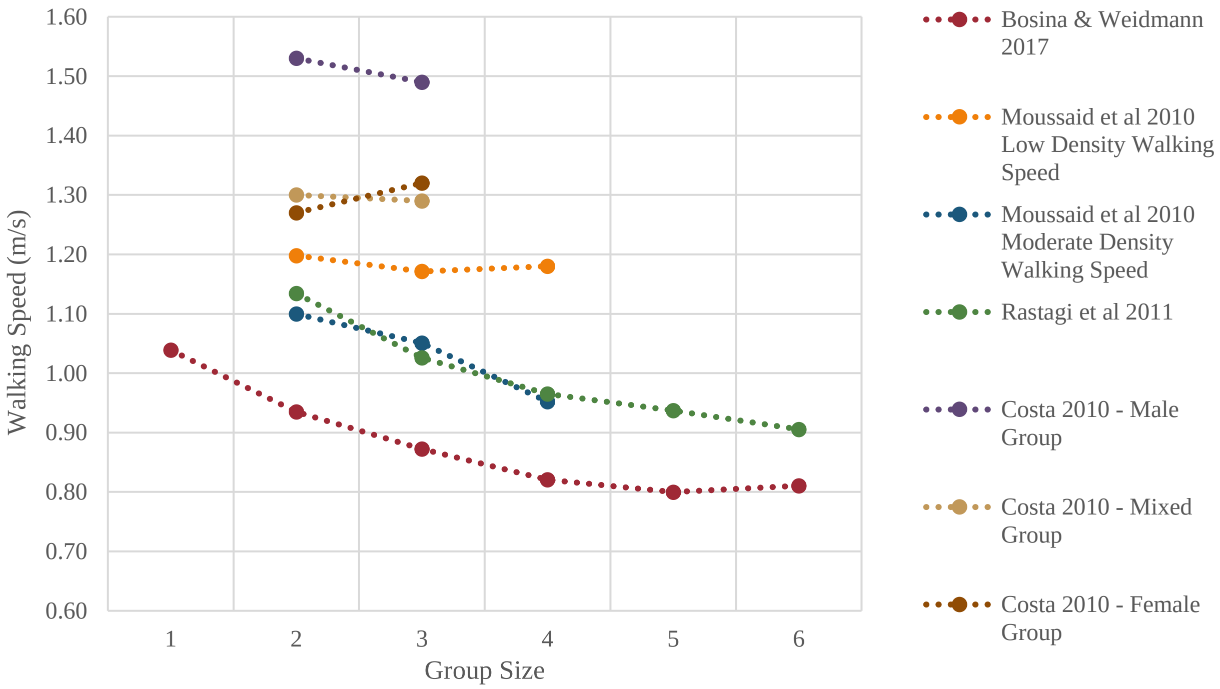


Figure 3-25 – Combined Group Size & Walking Speeds from Literature

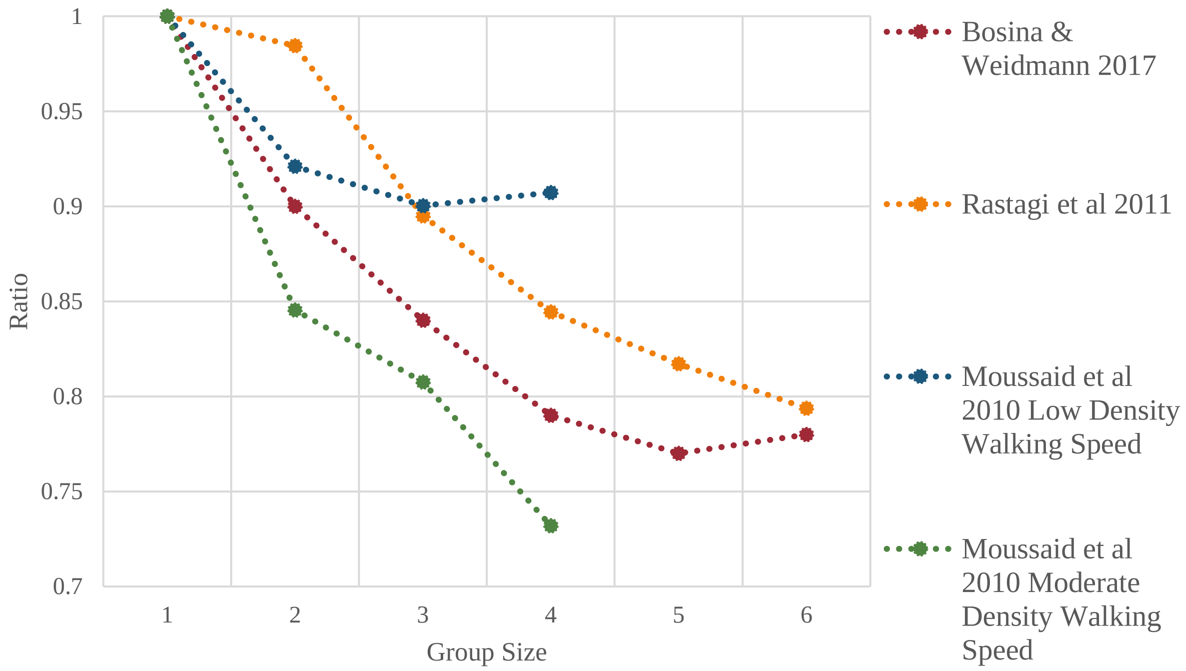


Figure 3-26 – Ratio of Change in Walking Speed with Group Size adapted from Literature Values

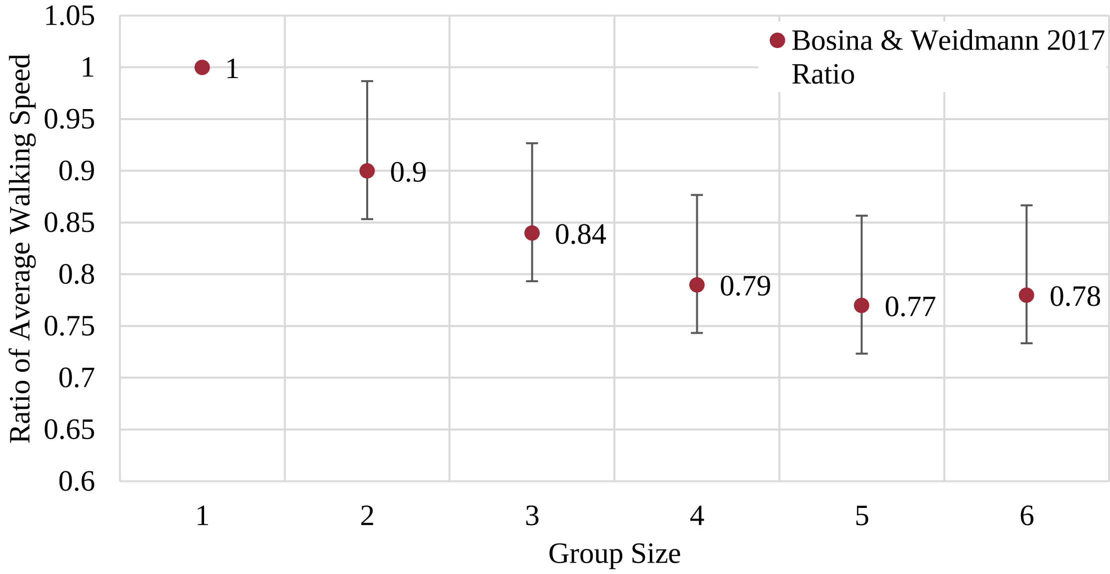


Figure 3-27 – Proposed Group Size Walking Ratio – Adapted from (Bosina & Weidmann, 2017), (Rastogi, et al., 2011), (Moussaid, et al., 2010)

Several of the studies focused on the impact of stairs on walking speed, the studies all showed that compared to walking on a corridor or pavement there was a decrease in walking speed (Figure 3-28). This is to be expected as additional energy and effort needs to be exerted to climb upstairs, which results in a reduce speed. The three studies featuring research on stairs correlate to show that walking speed is approximately half of the "normal" walking speed. The effect of visibility is not covered in many studies. However, two studies do include visibility, these show that the loss of visibility has a detrimental effect on walking speed (Figure 3-29). The study by Shen et al 2014 suggests this is more severe in females than males, as the walking speed is halved. The extent of the effect is not clear from the two studies, other than the agreement that there is a decline.

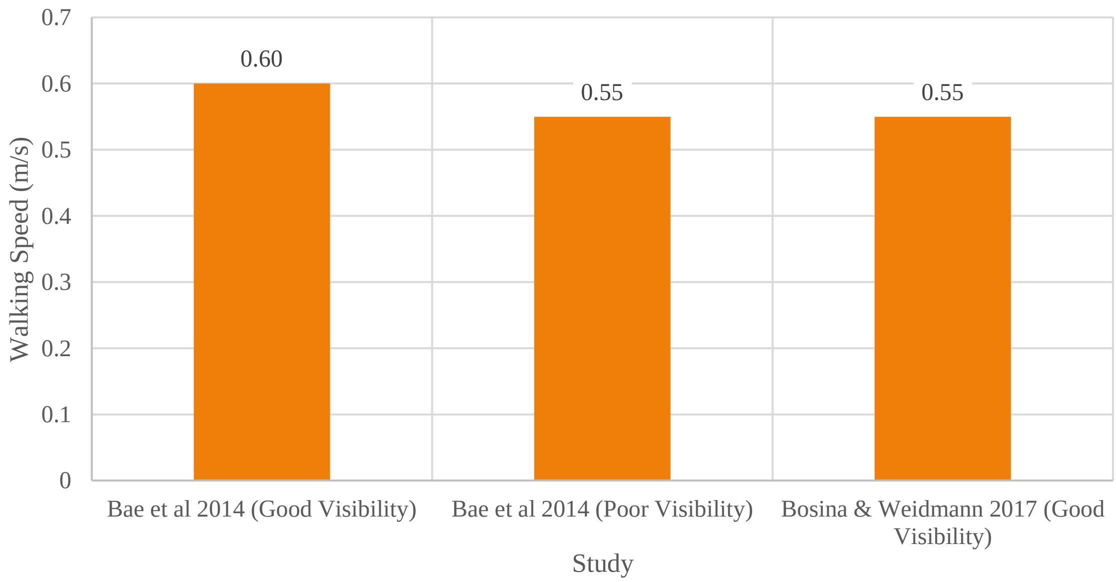


Figure 3-28 – Average Walking Speed on Stairs from Literature

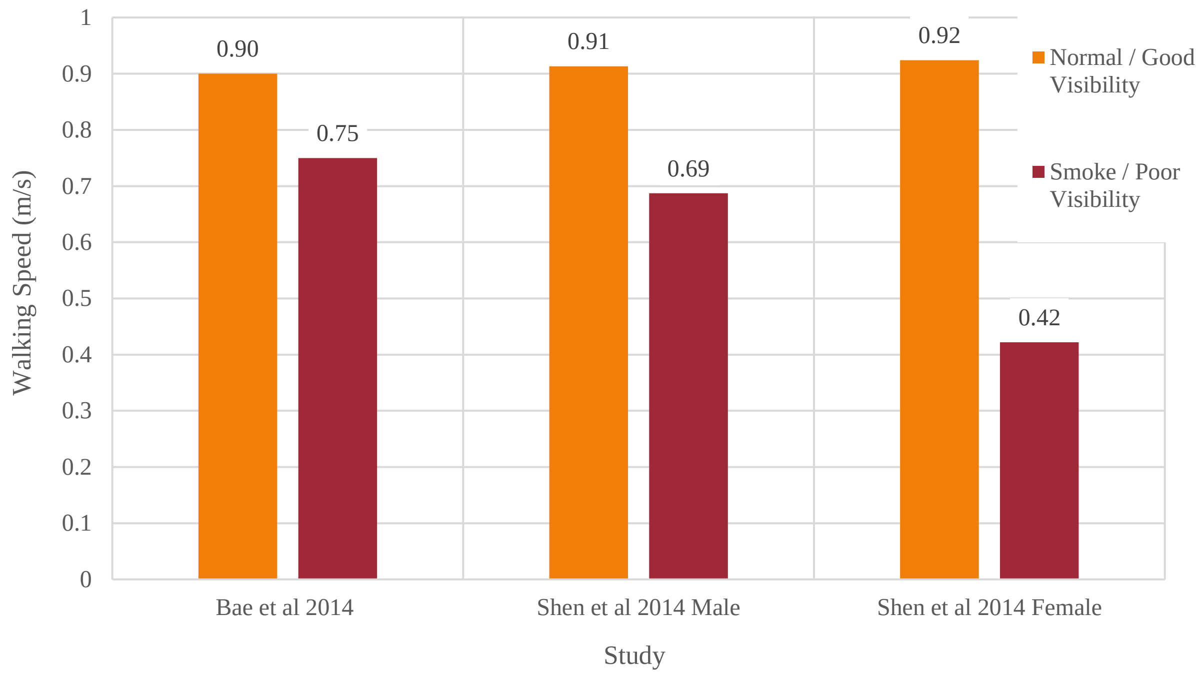


Figure 3-29 – Average Walking Speed in Different Visibility Conditions from Literature

3.4.3 Flee Behaviour Suggested Rulesets

The literature has demonstrated that there is quantifiable data available on which to formulate flee behaviour rulesets particularly with regards to demographics and walking speed. There are also several studies available on the effect of obstacles such as stairs and visibility, however it is not anticipated that in the initial model creation these behaviours will be as important when considering the evacuation of a city. Therefore, the proposed rulesets to be included based on flee behaviour are:

1. A range of walking speeds based on age (centred on Figure 3-24);
2. Allowance for fitness levels within each age bracket (as a spread of walking speeds for each age);
3. Decrease in walking speed based on group size (based on the proposed ratio in Figure 3-27);
4. Decrease in speed when crowds are denser (to be combined with findings on interpersonal distance).

From these suggested rules on flee behaviour, it is possible to specify parameters that need to be included in the agent-based model. Consideration also needs to be given to the parameters currently included in models (the models are discussed in detail in Chapter 2) (Table 3-5), and the capabilities of existing software to include the proposed rules (Table 3-6). This has shown that current models do not include all the required rules but that there is software available that has the capability to include the necessary parameters.

Table 3-5 – Existing Models Available Parameters for Flee Behaviour

Parameter	SimWalk (Bus Station & Fire)	SimWalk (Pedestrians in Train Station)	Flood Evacuation Model	Life Safety Model
Walking Speed	✓	✓	✓	✓
Age	×	×	×	×
Group Size	×	×	×	×
Sex / Gender	×	×	×	×
Stairs	×	✓	×	×
Other Obstacles e.g. street furniture	✓	✓	✓	×
Fitness levels	×	×	×	×
Population/Crowd Density	✓	×	✓	×
Pedestrian Constraints	✓	×	✓	×
Visibility Levels	×	×	×	×

Table 3-6 – Existing Software Available Parameters for Flee Behaviour

Parameter	NetLogo	Gamma	Miarmy	SimWalk
Walking Speed	✓	✓	✓	✓
Age	✓	✓	?	✓
Group Size	✓	✓	✓	✓
Sex / Gender	✓	✓	?	✓
Stairs	✓	✓	✓	✓
Other Obstacles e.g. street furniture	✓	✓	✓	✓
Fitness levels	✓	✓	?	?
Population/Crowd Density	✓	✓	✓	✓
Pedestrian Constraints	✓	✓	?	✓
Visibility Levels	✓	✓	✓	✓

From the rules proposed for a new agent-based model, it is important to understand if any of these are already included in existing models and to what extent. To do this several existing models identified in Chapter 2 are considered including; SimWalk, Flood Evacuation Model (Netlogo) and Life Safety Model. SimWalk has numerous pedestrian centred models on transport terminals, these models have a graphic representation similar to a simple computer game. In some cases, these agents have been given different walking speeds from 11 defined profiles, however this is then often applied to the whole crowd rather than individual agents. This results in agents walking at the same speed in rigid lines, without making full use of the available space. It is not clear whether a mix of the agent profiles can be applied to a scenario and the impact this may have. The flood evacuation model created in Netlogo contains agents moving at the same speed although in different directions depending on their evacuation location. The graphical representation is poor with agents marked only as dots. It does not appear that the agents have unique identifiers although this would not be impossible even with simplistic graphics. The Life Safety Model has begun the process of creating unique agents by colour coding agents based on whether they are deceased, safe or unaware. The graphical representation is again simplistic as agents are identified as dots which appear to move at the same speed, due to the scale it is also impossible to identify if agents are walking as individuals or in groups. These existing models show that there are improvements to be made when representing unique populations with demographic characteristics but there are software packages available that can include the necessary parameters.

3.5 Available Studies on Desired Behaviours – Interpersonal Distance

3.5.1 Interpersonal Distance Literature Review

Another important factor when considering crowds is the interpersonal distance between people. This can be classed as the zone or buffer around people, but this can be interrupted by people bumping into each other or dense crowds. There may also be cultural differences in the acceptable distances depending on whether countries are contact or non-contact. A literature review has been carried out to further the understanding on interpersonal distance and to identify suitable datasets for compiling rulesets in an agent-based model.

Interpersonal distance can be defined by several measurements taken during social interactions. Interpersonal distance was first described by Hall (1966) and can be classified into four types; Public: distance > 2.1m, voices tend to be at higher volume and eye contact is minimal, Social: distance 1.22 – 2.1m, sustained in more formal communications, Personal: distance 0.46 – 1.22m, usual behaviour when with friends) and Intimate: distance <0.46m, primarily in close relationships, vision is usually poor and blurred, additionally increased awareness of heat

(Sorokowska, et al., 2017) (Figure 3-30). The measures proposed by Hall in 1966 are still highly regarded but it is important to explore the comparison with recent studies too.

Intimate	Personal	Social	Public
0 – 0.46m	0.46 – 1.22m	1.22 – 2.10m	2.10m+

Figure 3-30 – Interpersonal Distance Preference as defined by (Hall, 1966), (Baldassare & Feller, 1975) & (Sorokowska, et al., 2017)

The study by Sorokawska et al (2017) focused on improving the interpersonal data collected from hundreds of previous studies. This was in the form of preferred interpersonal distances across the globe. The dataset included 8943 participants from 42 countries, preferred distances were related with the individual characteristics of participants and some elements of their culture. The study's main conclusion was that individual characteristics (e.g. age and gender) influence interpersonal distance preference, and that some variations can be attributed to the temperature of some regions (Sorokowska, et al., 2017).

From the study, it can be concluded that there is a big range in preferred interpersonal distances across the globe (Figure 3-31). It follows Hall's pattern in that social distance is greatest, followed by personal distance and then intimate distance as expected. The mean social distance is 80-130cm, the mean personal distance is 60 – 110cm and the mean intimate distance is 35-95cm. There are no clear indications in terms of patterns, but it could be argued that non-contact countries typically have larger interpersonal distances e.g. Saudi Arabia. The data is ranked based on social distance and this shows positive correlation with the preference for personal distance, in that the rank order would be similar. However, there is less of a correlation between social distance and intimate distance in terms of the rank order, which suggests a preferred social distance cannot accurately predict a preferred intimate distance (Sorokowska, et al., 2017).

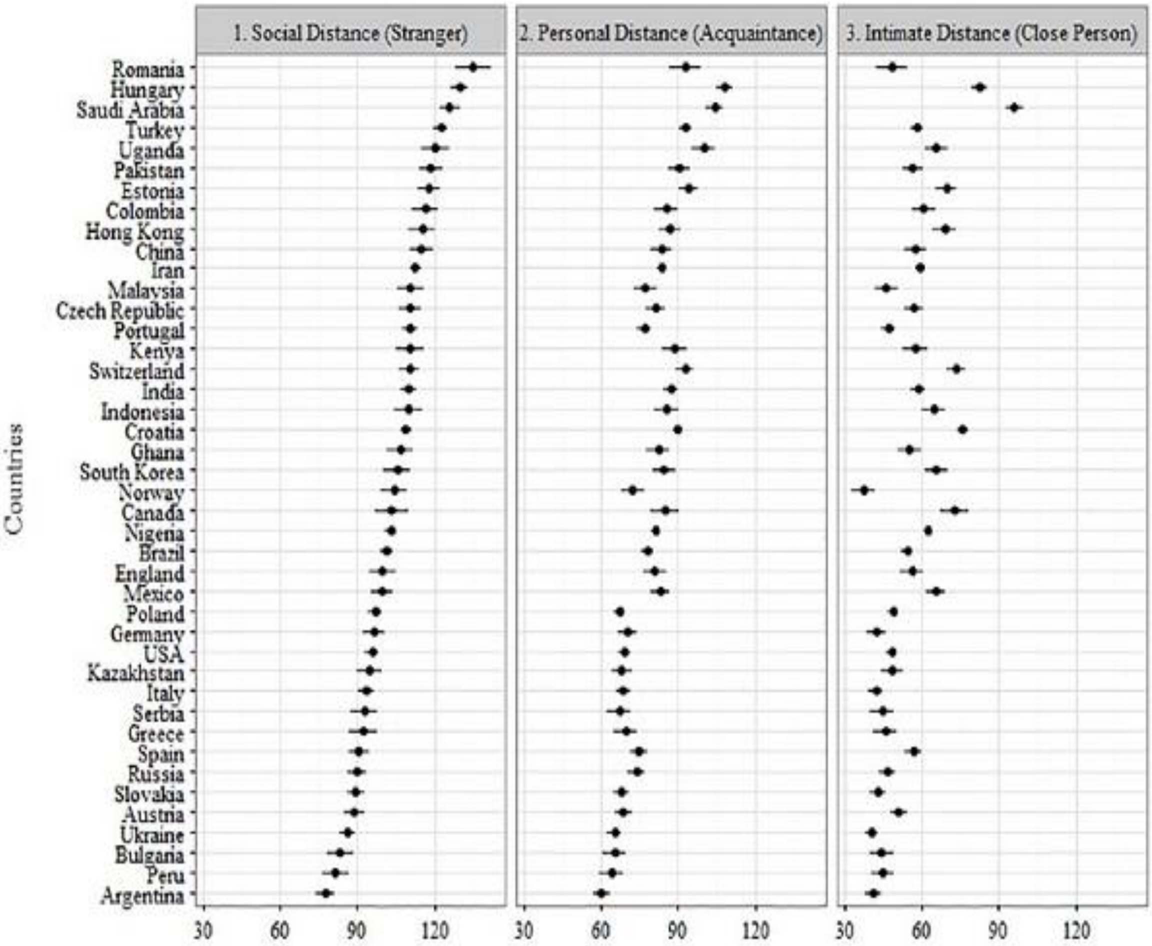


Figure 3-31 – Mean Values (cm) of social, personal and intimate distance across all nations in study (8943 participants from 42 countries) (Sorokowska, et al., 2017) Note: Nonoverlap of the confidence intervals between any two countries indicates significant mean differences. Means for interpersonal distance with strangers are rank ordered.

Two of the personal characteristics, age and gender, have been examined as part of this study (Figure 3-32). The results show that on average females prefer a greater distance with strangers. As people age, the preference for a larger personal distance increases, with women preferring a larger distance with friends. This study has ascertained that age and gender can be used as an indicator for preferred interpersonal distances. The study also found that the higher the annual temperature of a region, the larger the preferred personal distance to a friend.

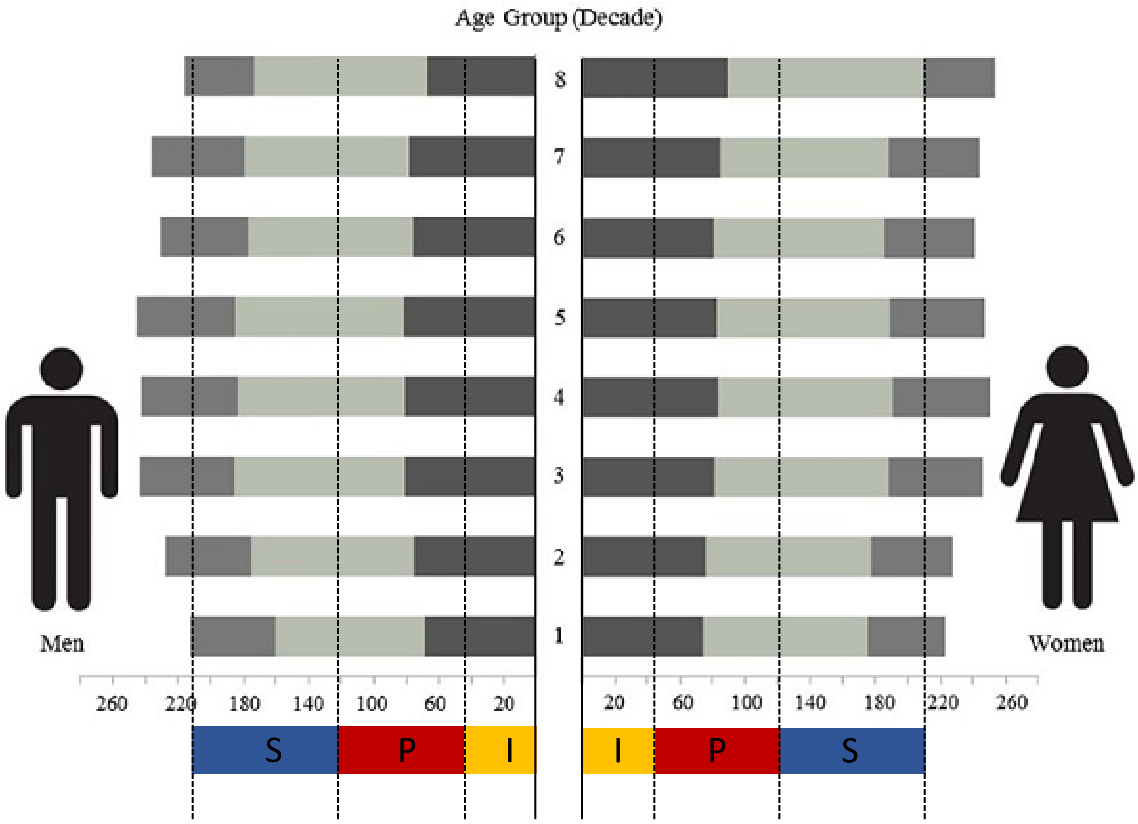


Figure 3-32 – Mean Values (cm) of Social (grey), personal (light grey) and intimate distance (dark grey) for men and women in different age groups summed for all nations (Sorokowska, et al., 2017) Note: Coloured bands indicate the intimate, personal and social interpersonal distances as defined by (Hall, 1966)

The study by Bae et al (2014) aimed to collect a human behaviour dataset in terms of travel times and interpersonal distance when using a corridor and stairs. An experiment was set up to simulate the Jungang-ro subway station in good and poor visibility conditions, whilst carrying out analysis on walking speed, density, travel time, plus interpersonal distance and angle distribution. Visibility can impact upon the density and interpersonal distance, the extent of which is considered in this study (Figure 3-33). When smoke is present, the interpersonal distance decreases whilst the density increases. This is to be expected as the loss of visibility encourages a change in pedestrian's behaviour, resulting in closer formations. The densities are greater when using stairs in good visibility, presumably as pedestrians have a smaller available space to pass slower walkers. The range of densities are larger when there is poor visibility. The range of interpersonal distances is largest when there is good visibility on a corridor, allowing pedestrians to maintain their preferred distance.

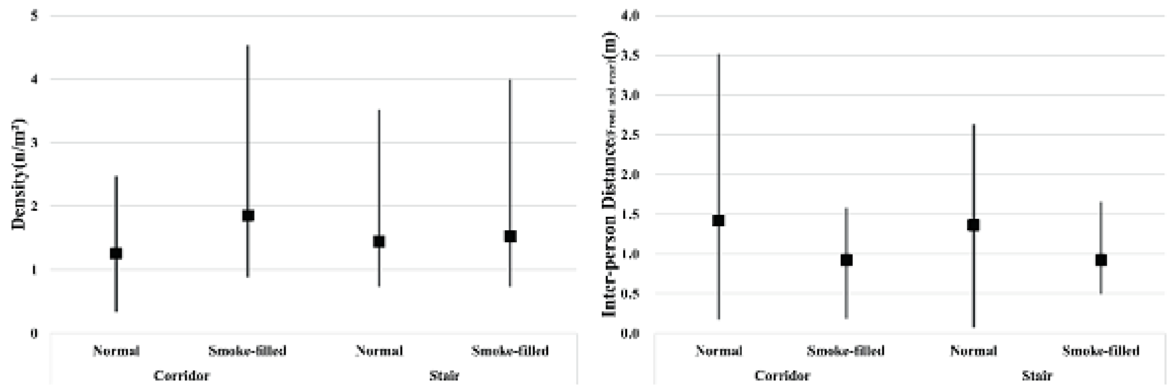


Figure 3-33 – Comparison of Density and Inter-Person Distance in Normal and Smoke-Filled Conditions (Bae, et al., 2014)

To further the study, the observations of interpersonal distance and angle were translated into percentage preference. This was produced for distances and angles to the front and rear, as well as the left and right. The largest range of interpersonal distances is exhibited at the front and back compared to the left and right. The average interpersonal distance is 1.027m (front and rear) compared to 0.473m (left and right) in good visibility (Figure 3-34). With poor visibility, the distances drop to 0.843m (front and rear) and 0.403m (left and right) (Figure 3-35). This shows a decrease in interpersonal distance in both directions, but it is greater to the front and rear. The range of interpersonal distances present during poor visibility is reduced.

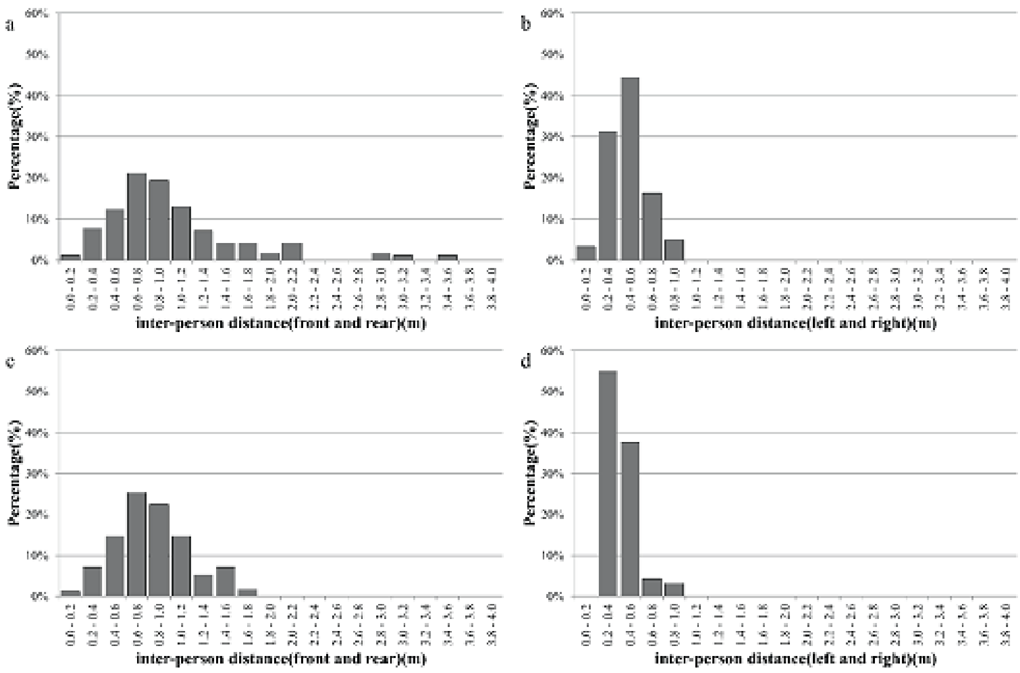


Figure 3-34 – The Distribution of Inter-Person Distance for each condition on the corridor, (a) inter-person distance (front and rear) in normal condition, (b) inter-person distance (left and right) in normal condition, (c) inter-person distance (front and rear) in smoke-filled condition, (d) inter-person distance (left and right) in smoke-filled condition (Bae, et al., 2014)

There is a large range of interpersonal angles for the visibility conditions. The average interpersonal angle is 17° (front and rear) and 68° (left and right) for good visibility. During smoke filled conditions, the average interpersonal angle is 16° (front and rear) and 75° (left and right), showing there is little change due to visibility conditions.

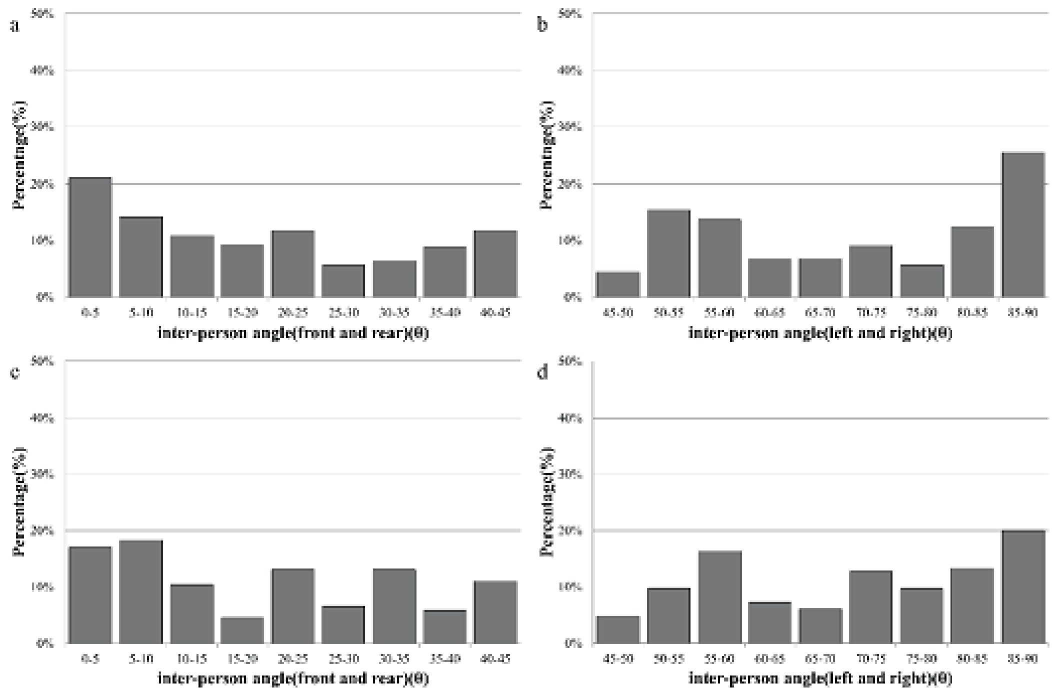


Figure 3-35 – The Distribution of Inter-Person Angle for each condition on the corridor, (a) inter-person angle (front and rear) in normal condition, (b) inter-person angle (left and right) in normal condition, (c) inter-person angle (front and rear) in smoke-filled condition, (d) inter-person angle (left and right) in smoke-filled condition (Bae, et al., 2014)

3.5.2 Interpersonal Distance Literature Analysis

On completion of the literature review, it is possible to bring together datasets to identify whether there is any comparison between values of interpersonal distance. This is important to understand where there is correlation and to determine appropriate rulesets for any future agent-based model.

The data from the study by Sorokawska et al (2017) is a large dataset for countries across the globe, for comparison this has been plotted against Hall's proposed interpersonal distances, to further aid understanding, the average from Sorokawska's data for the social, personal and intimate distance has been calculated (Figure 3-36). This shows that Hall's distances for intimate and social distance are an underestimate when compared to this dataset. The average for the personal distance and Hall's proposed value is closer and therefore more comparable.

The data can also be ranked; this has been done for each of the interpersonal distance components (Table 3-7). When ranked by social, personal and intimate distance there are similarities in the countries that are identified. It could be argued that there is a European preference for smaller intimate distances, as four of the five are European countries. However, there is also three European countries present in the greatest intimate distances, which suggests there is no European preference for similar intimate distances. Overall, there is no clear indication of a pattern of preference by continent or temperature from this dataset. However, it does demonstrate that there is a clear difference on a country by country basis, which should be expressed within models.

Table 3-7 – Ranking of Social, Personal and Intimate Interpersonal Distance interpreted from (Sorokowska, et al., 2017)

Smallest			Greatest		
Social	**Personal**	**Intimate**	**Social**	**Personal**	**Intimate**
Argentina	Argentina	Argentina	Saudi Arabia	Saudi Arabia	Saudi Arabia
Ukraine	Ukraine	Ukraine	Hungary	Hungary	Hungary
Peru	Peru	Norway	Romania	Romania	Croatia
Bulgaria	Bulgaria	Germany	Uganda	Uganda	Canada
Austria	Serbia	Italy	Turkey	Estonia	Switzerland

Based on these findings, the data has been divided into continents. The data has been split into Europe, Latin and South America, Asia and Africa. The dataset named as Europe also contains data from the USA and Canada, this was an inclusion for the original journal article and will be maintained for continuity. For the countries within Europe, the personal distance correlates positively with Hall's measure (Figure 3-37). Both the social and intimate distance are slightly higher when compared to Hall's values (Figure 3-37). This is to be expected though from the ranking, which exhibited European countries at both ends of the scale. For Latin and South America, there are only five countries in total, which show positive correlation with Hall on all the interpersonal distance components, there is only a small difference for each (Figure 3-38). There is a range of countries from across Asia; again, the personal distance correlates well with Hall's figure (Figure 3-39). However, the intimate and social distances are both greater than Hall's value (Figure 3-39). This could be a result of Asian countries at both ends of the ranking for each of the interpersonal distances. Finally, there are four African countries in the study; all three of the interpersonal distance components are higher than Hall's values (Figure 3-40). Based on these results it would be possible to provide an average social, personal and intimate distance for each continent for use in a ruleset for an agent-based model, which would be an update from Hall's 1966 figures.

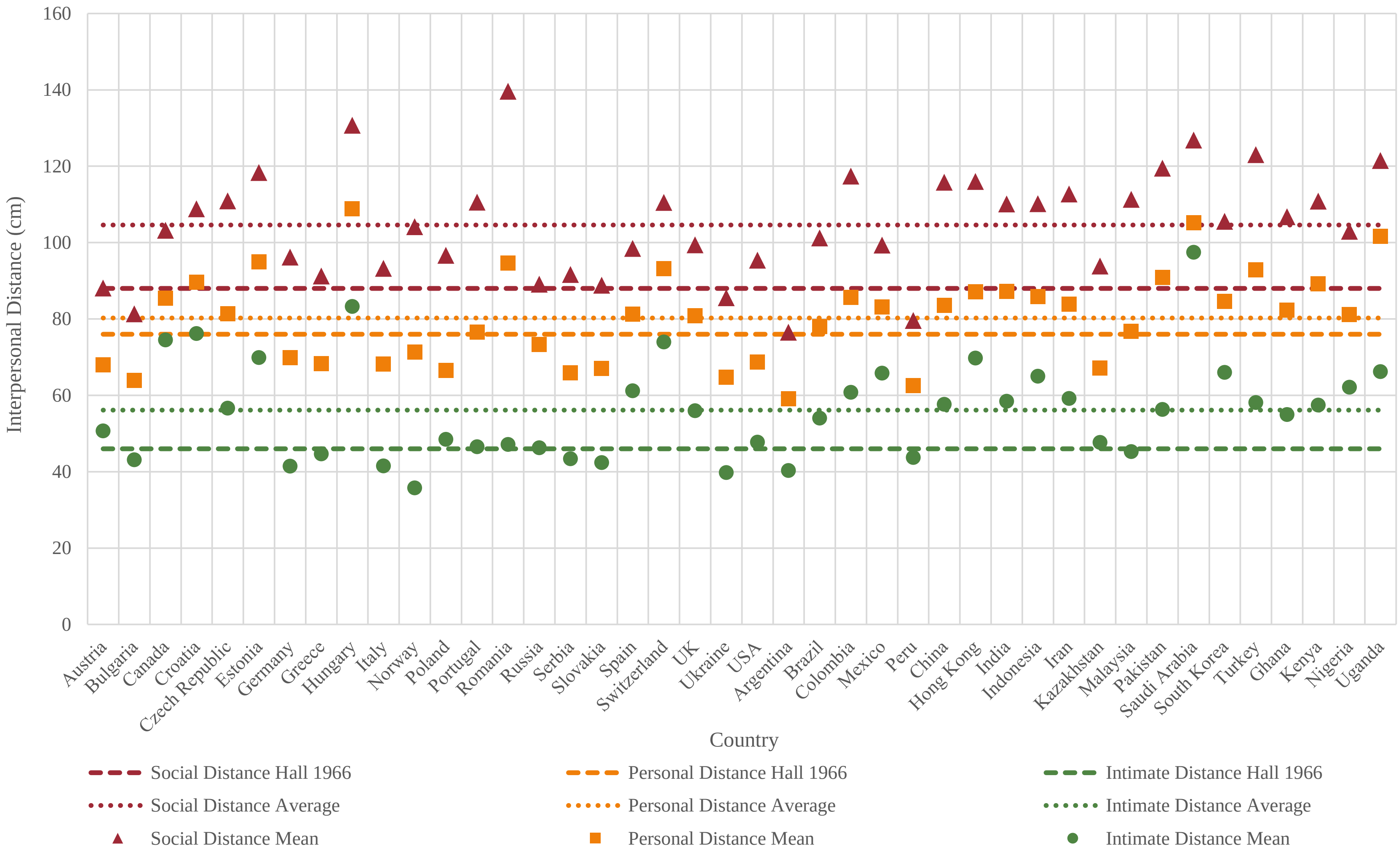


Figure 3-36 – Worldwide Interpersonal Distances compared with Hall 1966 Values for Interpersonal Distances, adapted from (Sorokowska, et al., 2017)

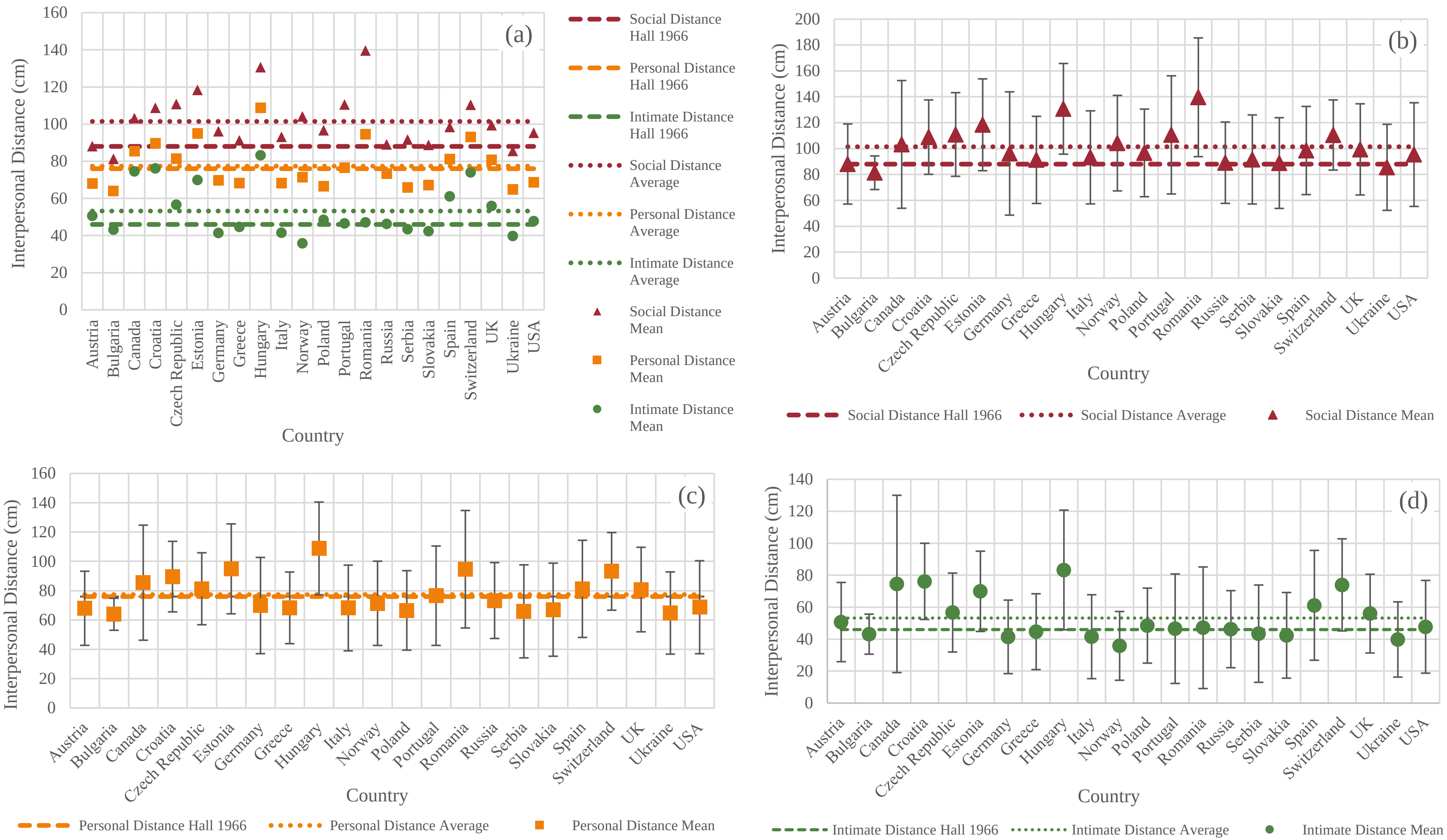


Figure 3-37 – European Interpersonal Distances adapted from (Sorokowska, et al., 2017) – (a) interpersonal distances, (b) social distances, (c) personal distances, (d) intimate distances

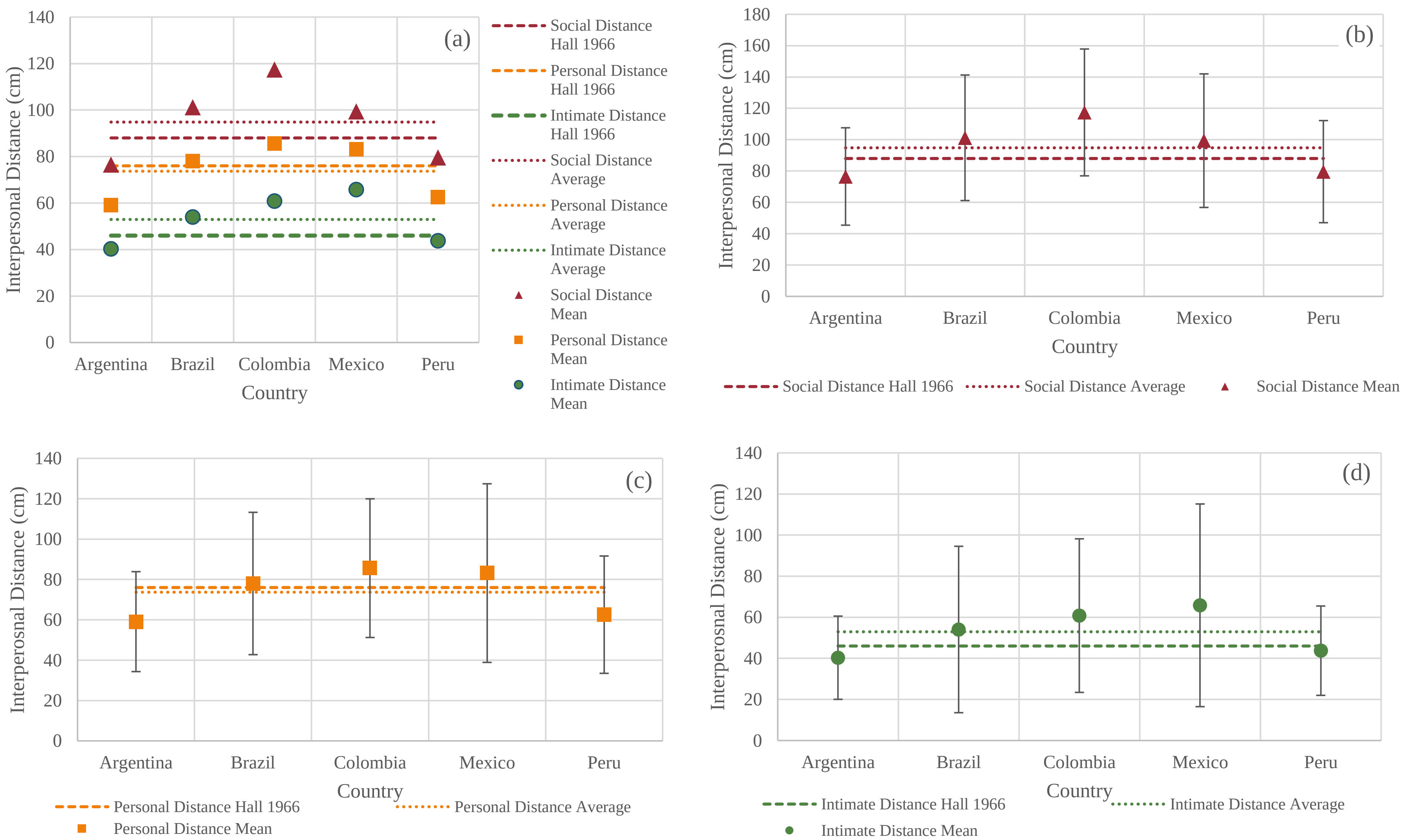


Figure 3-38 – Latin and South America Interpersonal Distances adapted from (Sorokowska, et al., 2017) – (a) interpersonal distances, (b) social distances, (c) personal distances, (d) intimate distances

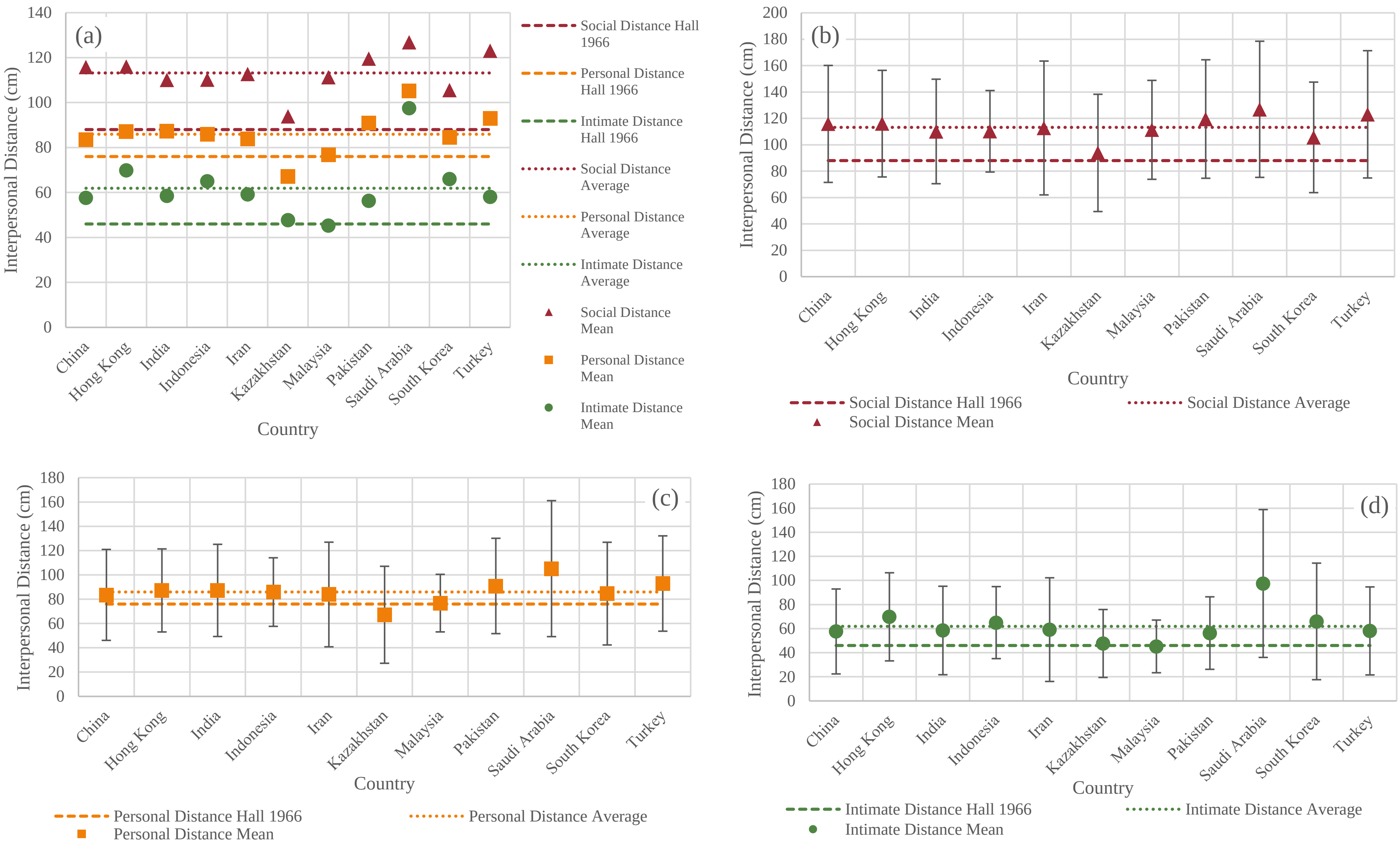


Figure 3-39 – Asia Interpersonal Distances adapted from (Sorokowska, et al., 2017) – (a) interpersonal distances, (b) social distances, (c) personal distances, (d) intimate distances

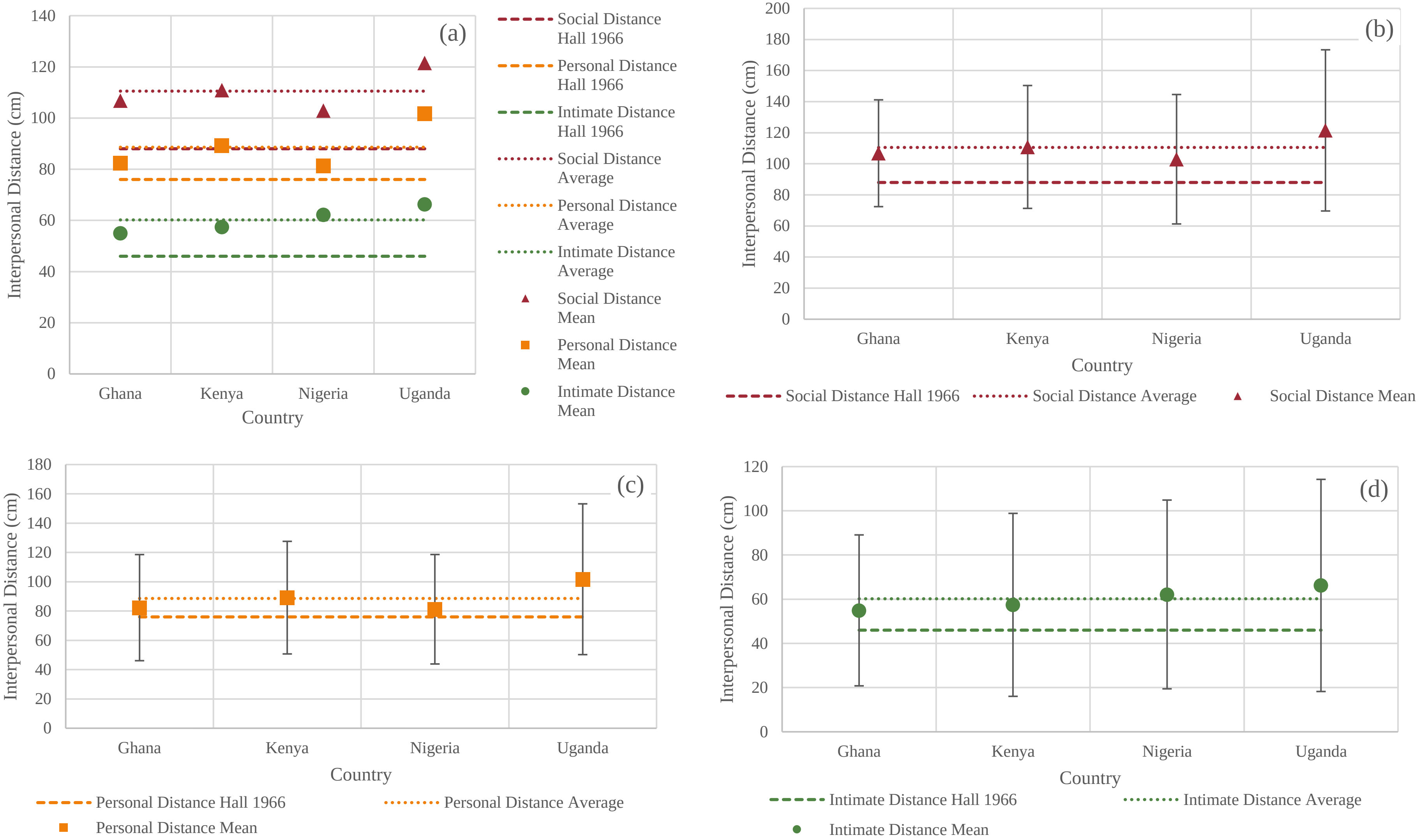


Figure 3-40 – Africa Interpersonal Distances adapted from (Sorokowska, et al., 2017) – (a) interpersonal distances, (b) social distances, (c) personal distances, (d) intimate distances

3.5.3 Interpersonal Distance Suggested Rules

From the literature findings, it is possible to draw several conclusions, to formulate a series of potential rulesets for the agent-based model to be created. These are based on the literature reviewed and include:

1. Initial interpersonal distance based on intimate, personal, social and public scale (based on oval shape rather than circle if possible) (can include age and male/female differences if required);
2. Initial interpersonal angle/crowd positioning can also be included;
3. Decrease interpersonal distance during danger or smoke being present;
4. Alter interpersonal angles based on danger/smoke presence;
5. Option in future to change interpersonal distance for different areas of the world.

From these suggested rules on interpersonal distance, it is possible to specify parameters that need to be included in the agent-based model. Consideration also needs to be given to the parameters currently included in models (Table 3-8), and the capabilities of existing software to include the proposed rules (Table 3-9). This has shown that current models do not include all the required rules but that there is software available that has the capability to include the necessary parameters.

Table 3-8 – Existing Agent Based Models

Parameter	SimWalk (Bus Station & Fire)	SimWalk (Pedestrians in Train Station)	Flood Evacuation Model	Life Safety Model
Interpersonal Distance (Front/Back)	✗	✗	✗	✗
Interpersonal Distance (Left/Right)	✗	✗	✗	✗
Interpersonal Angle	✗	✗	✗	✗
Visibility	✗	✗	✗	✗
Density of Crowd	✓	✗	✓	✗
Crowd Spacing	✗	✓	✗	✗
Gender	✗	✗	✗	✗

Age	✗	✗	✗	✗
Stairs/Corridor	✗	✓	✗	✗

Table 3-9 – Existing Agent Based Software

Parameter	NetLogo	Gamma	Miarmy	SimWalk
Interpersonal Distance (Front/Back)	✓	✓	✓	?
Interpersonal Distance (Left/Right)	✓	✓	✓	?
Interpersonal Angle	✓	✓	✓	?
Visibility	✓	✓	✓	?
Density of Crowd	✓	✓	✓	✓
Crowd Spacing	✓	✓	✓	✓
Gender	✓	✓	?	✓
Age	✓	✓	?	✓
Stairs/Corridor	✓	✓	✓	✓

From the rules proposed for a new agent-based model, it is important to understand if any of these are already included in existing models and to what extent, the models are discussed in detail in Chapter 2. The models considered are; SimWalk, Flood Evacuation Model (Netlogo) and Life Safety Model. For both the Flood Evacuation Model (Netlogo) and the Life Safety Model the scale of the models means that interpersonal distance and crowd spacing has not been included. In SimWalk the agent's height and breadth can be altered in the 11 agent profiles, unfortunately this does not appear to affect the interpersonal distance or crowd spacing. Visually crowds are very uniform and often agents form lines with no distance between agents, suggesting interpersonal distance is not a parameter within the existing model.

3.6 Available Studies on Desired Behaviours – Crowd Behaviour

Another important part of modelling a crowd is the dynamics of the crowd, this can be shown through the influence of direction, comparisons to flocking or herding, initial responses to hazards and the effect of what others do in the crowd. A literature review has been undertaken to assess crowd behaviour and to find suitable datasets to base rulesets on for an agent-based model.

3.6.1 Crowd Behaviour Literature Review

There are many studies available on crowd behaviour, one of which is Low (2000). The dynamics of a large crowd are important and result in the comfort and security of individuals, especially during stressful situations such as evacuations. When a crowd is particularly large there can be an increased risk of injury or loss of life due to the pressures that can be exerted by the crowd such as crushing, trampling and panic. Therefore, there is a need to be able to understand the likely movements of any crowd, to minimise the risks to individuals. Previous models have focused on treating crowds like fluids, i.e. the crowd moves as one continuous mass, this results in the crowd becoming "*identical unthinking elements*" (Low, 2000) (Low, 2000). This is untrue though, as crowds can experience fear, panic, different directions of travel, stumbles or falls. Hence, there is a need to improve modelling so that crowds are made up of individuals who can think and react to events.

Within this study, Low (2000) introduces the model created by (Helbing, et al., 2000). This model introduces the idea of individuals within a crowd, particularly during episodes of panic. The model includes reactions to crushing, panic and loss of visibility, as well as the preference for individuals to "*follow the crowd*", although there are elements of personal tactics. The model shows that when panic is prevalent in a smoke-filled room, individuals will speed up and herd, this results in the blocking of an exit (Figure 3-41). If a normal walking speed was assumed this exit could be easily passed. Also, if this scenario had been modelled as a fluid, it would have predicted an equal use of both exits, as the actions of individuals were not captured. Hence, a fluid model would not have reproduced the real behaviour of the crowd.

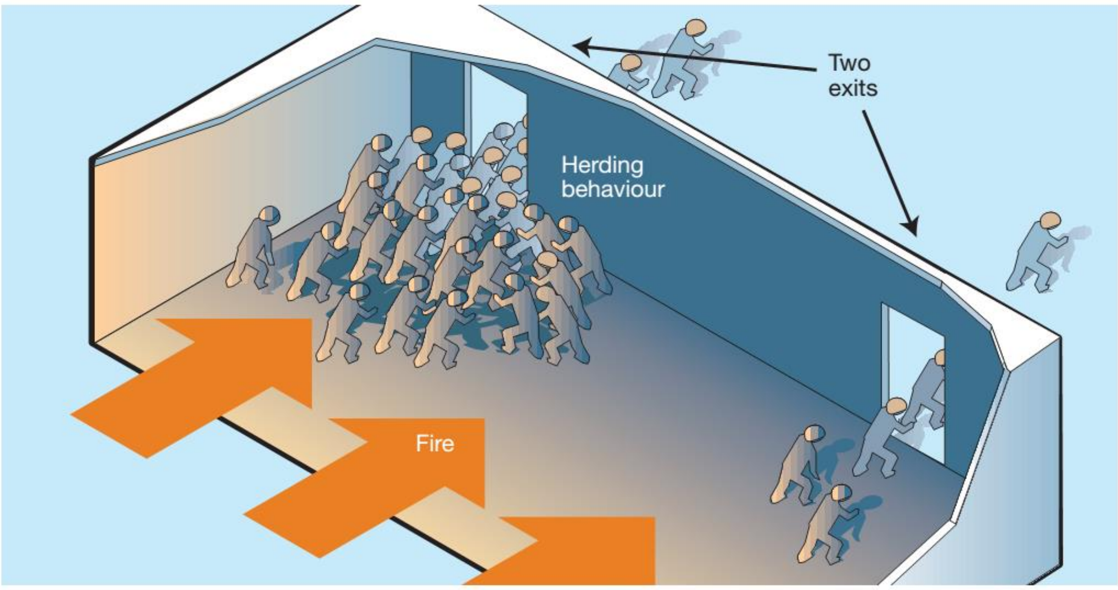


Figure 3-41 – How Crowd Behaviour Affects Escape from a Smoke Filled Room (Low, 2000) (Low, 2000)

The model also explored the idea of widening corridors, but again found this slowed the flow of the crowd, which is often not what would be assumed. This is believed to be due to the pedestrians who tried to overtake, which then must move back into the main flow at the end of the widening. Models like this can be utilised to produce low-risk designs and to explore the best evacuation strategies. The previous barrier of computer power to run the calculations for the model has been addressed. However, the obstacle remains on validating these types of models with the real world as data as data is often scarce or non-existent, meaning it is necessary to determine the difference between "real life" and attempts to model it (Low, 2000). Nevertheless, improved models of crowd behaviour can be effective in increasing safety in crowded scenarios.

Helbing et al (2000) also included a panic parameter with their model, to explore the mechanism of panic and to understand ways to reduce risks. As previously outlined, herding behaviour is exhibited within the model when there are two exits available, creating congestion at one exit. This is further considered with mass behaviour in the model. A scenario is created where pedestrians are attempting to exit a smoke-filled room but need to find an "invisible" exit first (Figure 3-42(a)). Agents can select an individual direction or follow an average direction of neighbouring agents within a certain radius or a mixture of both. The model results show that neither herding behaviour nor individual behaviour performs well (Figure 3-42(b)), as individuals only accidentally find the exit and herding results in everyone using the same blocked exit. A mix of the two behaviours is required for optimal survival.

The results show in general as the panic parameter is increased the number of people evacuating within 30 seconds decreases (Figure 3-42(b)). When exits are relatively narrow and the panic parameter is small or large, evacuation takes a long time, best strategy is a compromise between following others and individual problem solving and searching (Figure 3-42(c)). Groups normally perform better than individuals, but masses are inefficient at finding solutions. The difference in numbers of people leaving using the two exits provided, shows that when a high panic parameter is used that evacuees tend to jam at one of the exits rather than equally splitting between available exits (Figure 3-42(d)).

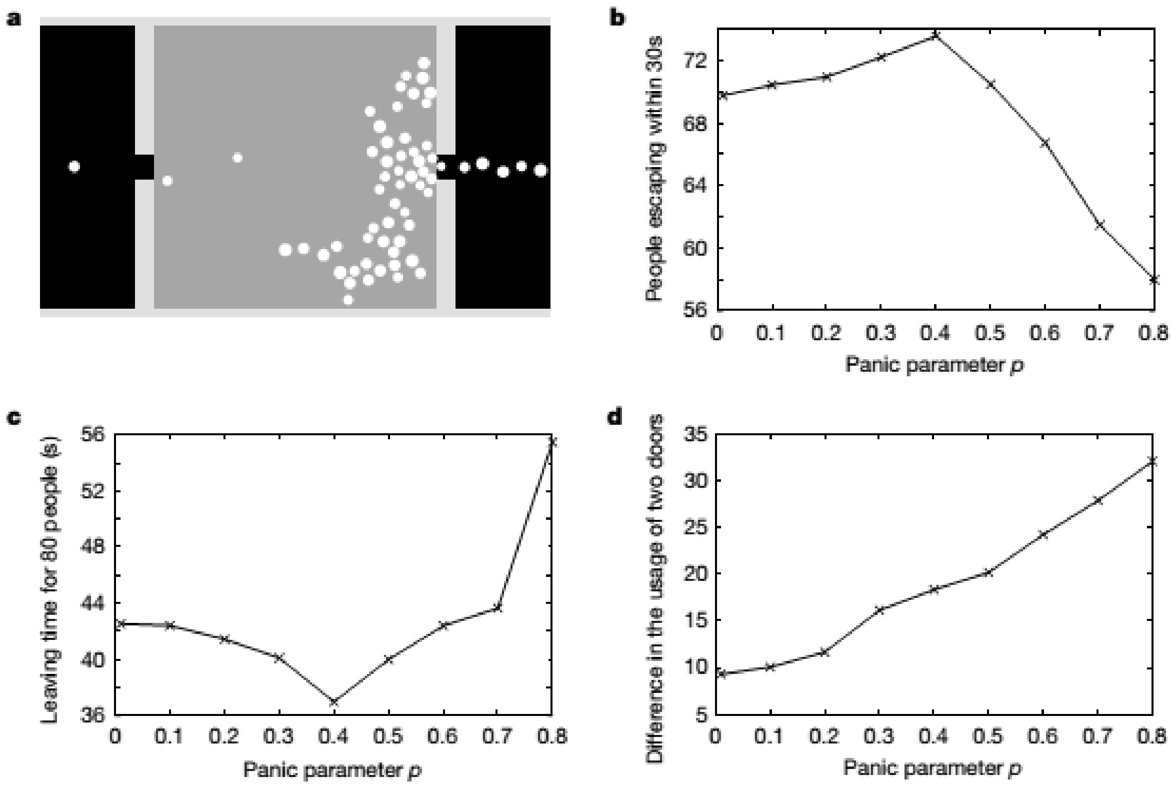


Figure 3-42 – Simulation of Evacuation with 2 Exits, (a) Snapshot of Evacuation, (b) Number of people who manage to escape within 30 seconds as a function of the panic parameter, (c) Time required for 80 individuals to leave a smoky room, (d) Absolute difference in numbers of people leaving through the left exit or the right exit as a function of the panic parameter (Helbing, et al., 2000)

Contrary to this, research carried out by Galea (2003) has shown there is a need to determine the difference between assumed behaviours and those actually exhibited in real-life. Panic is a good example of this. When studying aviation evacuations Galea noted that there had been a recurrent myth that those in an evacuation situation faced with a serious hazard who are untrained and inexperienced will panic and potentially act in a "*self-destructive manner*". However, he argued that this was not based on rational scientific investigation and it was necessary to clearly identify what types of behaviours are truly exhibited during high stress scenarios as "*panic was not necessarily the driving force behind the evacuation process*" and in fact should be labelled as a rare behaviour.

A study was carried out by Pelechano & Badler (2006), which aimed to explore the role of trained leaders during building evacuations on the effect of the whole crowd. The model simulated complex buildings with crowds who were unfamiliar with the building layout or found routes blocked. Two different scenarios were used; one where agents could communicate the known routes in the building and the alternative where agents take on roles such as leaders or followers. The crowds varied in size from 10 to 1000 agents, with simultaneous hazards in multiple locations in the building, with the measure taken as the time to successful evacuate.

The results show that without effective communication, it takes significantly longer to reach 100% safety of evacuees (Figure 3-44(a)). Approximately 40% of evacuees escape without any communication, in the same time 100% escape with communication, meaning the time to evacuate can be halved with communication. In addition, the larger the crowd, the shorter the evacuation takes in general, without any trained individuals (i.e. individuals are independent of each other) (Figure 3-44(b)). This is likely to be as with larger crowds there is more opportunity of meeting other individuals who know the correct route, so information passes more easily through the crowd, resulting in agents finding the correct path sooner. This is true if the crowd doesn't exceed the capacity, which then blocks the exits and creates congestion, which then increases the evacuation time. Hence, it can be argued that evacuation time can be constrained by the number of exits or safe locations and the flow rate of a crowd.

The evacuation time for a crowd decreases as the number of trained/informed individuals increases, as more individuals know the route to safety (Figure 3-44I). However, there is an optimal number of informed individuals (Figure 3-44I and Figure 3-44(d)). This research puts the optimal number of informed individuals at approximately 10%. If the number is lower than 10% then the time to evacuate at least doubles, but if greater than 10% and the evacuation time only decreases by 0.16 times at most (Pelechano & Badler, 2006). Finally, when there are fewer leaders, the size of groups formed to evacuate tend to be larger as individuals who are not informed will not leave a group to seek an alternative route (Figure 3-43). With more leaders present, the emergent behaviour is many smaller groups of people (Figure 3-43).

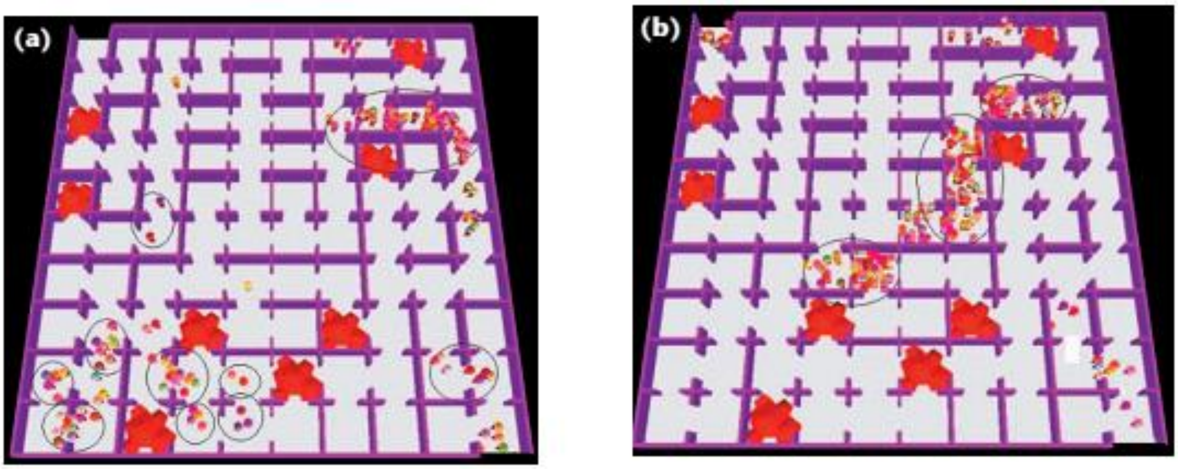


Figure 3-43 – Snapshot of Crowd Evacuation with (a) a high percentage of leaders and (b) a lower percentage of leaders (Pelechano & Badler, 2006) (Pelechano & Badler, 2006)

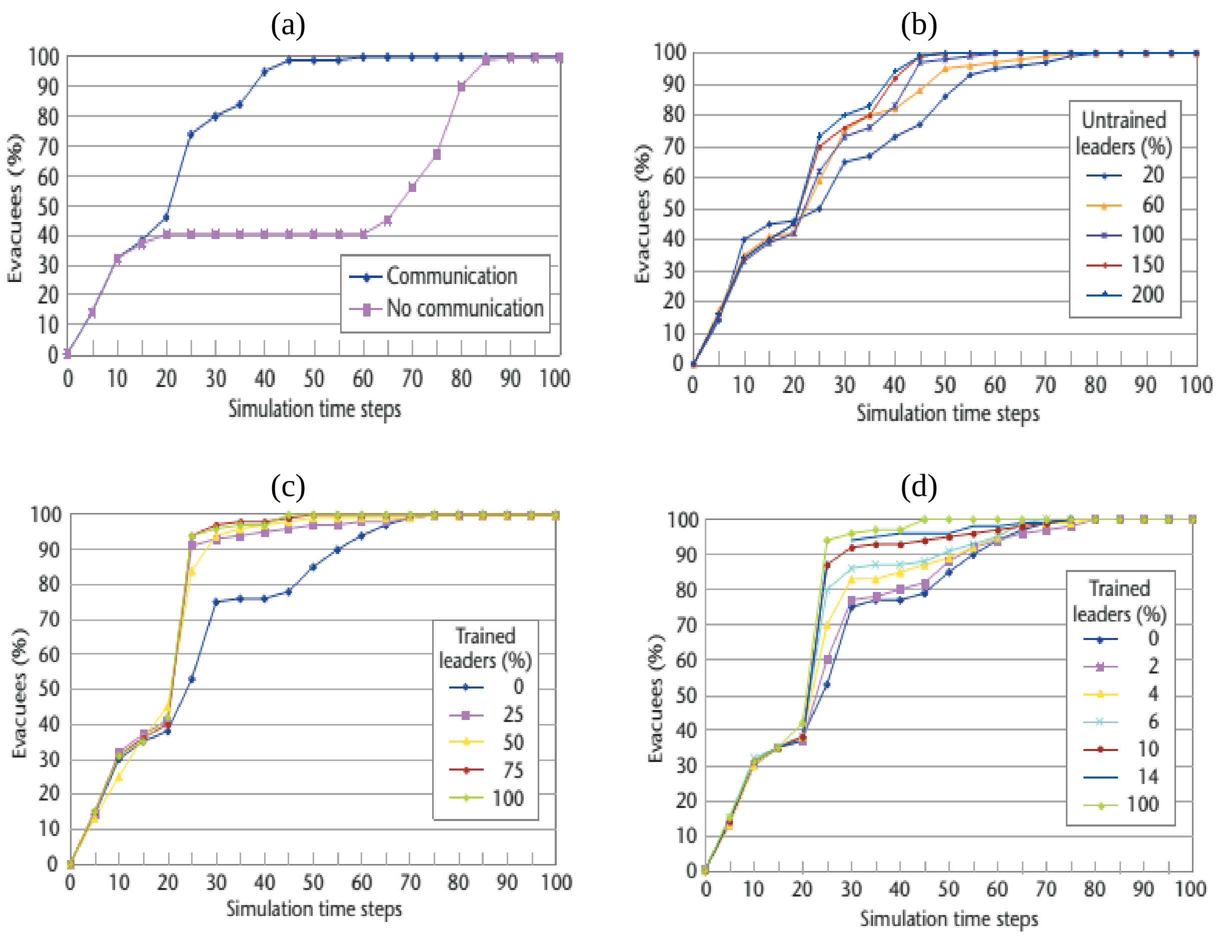


Figure 3-44 – (a) Communication vs. No Communication, (b) Evacuation Time for Different Crowd Sizes using Communication but no informed individuals / leaders, (c) Evacuation Times for Varied Levels of Trained Leaders in a Crowd, (d) Evacuation Times with Smaller Numbers of Trained Leaders (Pelechano & Badler, 2006) (Pelechano & Badler, 2006)

The study by Pelechano & Badler (2006) (2006) interlinks well with research at the University of Leeds which has found that "*it takes just a minority of 5% to influence a crowd's direction*" (Science Daily, 2008) (Science Daily, 2008), the remaining 95% will then follow without consciously recognising it. This is similar to the herd behaviour of animals such as sheep or cattle (Anitei, 2008). This focuses on direction only using 'informed individuals' and did not cover, for example, how family units move, the influence of walking speeds or the aggression within the group. The research did find that as the group size increased, the number of 'informed individuals' decreased (Univeristy of Leeds, 2008), which could be key in natural disaster scenarios where information availability can be scarce due to the impacts on infrastructure.

3.6.2 Crowd Behaviour Suggested Rules

From the literature findings, it is possible to draw several conclusions, to formulate a series of potential rulesets for the agent-based model. These are based on the literature reviewed and include:

1. Herding behaviour to be exhibited, need further exploration of parameters, could set others to follow each other therefore dependant agents during hazard scenarios.
2. Number of informed individuals or communication to be included to speed up safe evacuations, approximately 5 – 10%.
3. Crowd needs to be within capacity to ensure that congestion doesn't occur or explore what effects this will have on evacuation times.
4. Need to allow for inter-agent communication within the model to allow leaders and communication to occur.
5. Inclusion of grouping based on number of informed individuals.
6. Should consider including a panic parameter that affects the number of successful evacuees, group size and congestion at exits, maybe interlinked with the cognitive mechanism

From these suggested rules on crowd behaviour, it is possible to specify parameters that need to be included in models. Before that though, it is worth considering the parameters currently included in models (Table 3-10) and the capabilities of software to include the necessary rules (Table 3-11). This has shown that current models do not include all the required rules but that there is software available capable of included the parameters.

Table 3-10 – Existing Models Available Parameters for Crowd Behaviour

Parameter	SimWalk (Bus Station & Fire)	SimWalk (Pedestrians in Train Station)	Flood Evacuation Model	Life Safety Model
Communication	✗	✗	✓	✓
Leaders / Informed Individuals	✗	✗	✗	✗
Herding	✓	✗	✗	✗
Panic	?	✗	✗	✗
General crowd flows / behaviour	✓	✓	✓	✓

Table 3-11 – Existing Software Available Parameters for Crowd Behaviour

Parameter	NetLogo	Gamma	Miarmy	SimWalk
Communication	✓	✓	?	✓
Leaders / Informed Individuals	✓	✓	✓	✓

Herding	✓	✓	✓	✓
Panic	✓	✓	✓	✗
General crowd flows / behaviour	✓	✓	✓	✓

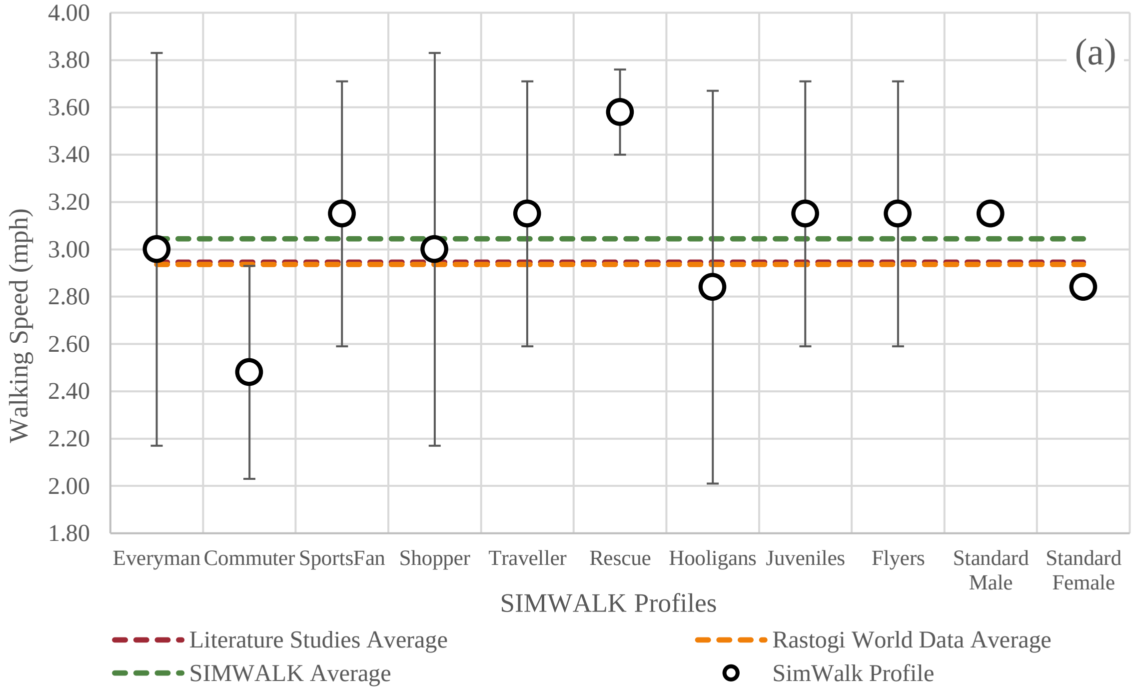
From the rules proposed for a new agent-based model, it is important to understand if any of these are already included in existing models and to what extent, the models are discussed in detail in Chapter 2. The models considered are; SimWalk, Flood Evacuation Model (Netlogo) and Life Safety Model. For the Flood Evacuation Model (Netlogo) and Life Safety Model the scale of the models again affects the visibility of crowd behaviours other than identifying pinch points for congestion, the up-close intricate human behaviours such as passing and giving way are not shown. In terms of SimWalk, there has been an attempt to model crowd behaviours, but it is hard to ascertain what the parameters are and responses to hazards seem unrealistic at times, suggesting further improvements could be made.

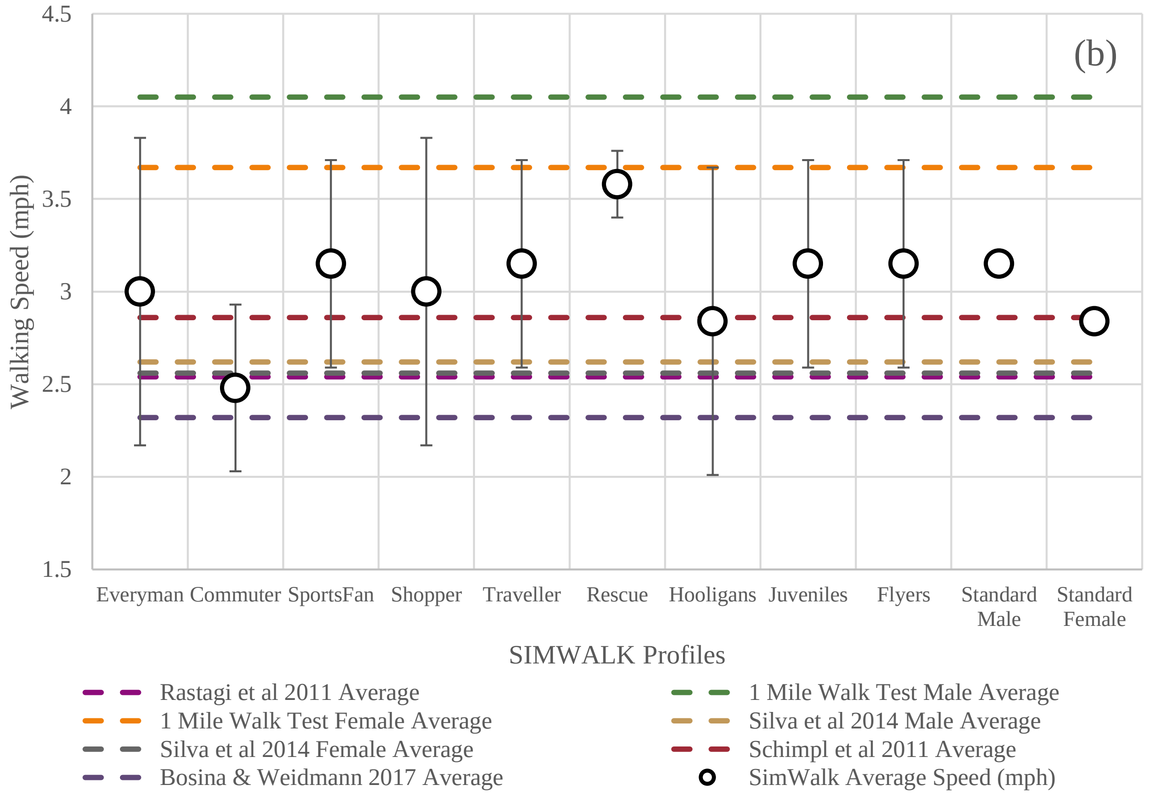
3.7 Available Software: SimWalk

SimWalk has been identified as one of the most comprehensive agent-based software packages currently available. Graphically it is superior to many of the other packages and although this is not the most important factor, it is another benefit. The main downsides of SimWalk are its primary focus on transport interchanges although it does have case studies of crowd flows at the Hajj Mecca pilgrimage (SimWalk, 2017 A) and the exiting of stadiums (SimWalk, 2017 B) (SimWalk, 2017 C), which are more focused on crowd behaviours. One of these stadium evacuations was a football stadium in Pennsylvania, USA which after creating a predicted evacuation time was validated against a real-life simulation of an evacuation, demonstrating that some of the case studies have been verified, calibrated and validated by SimWalk.

Within SimWalk, there are several agent profiles set up for modellers to use. The profiles included are; everyman, commuter, sports fan, shopper, traveller, rescue, hooligans, juveniles, flyers, standard male and standard female. These profiles have a range of pre-set parameters, which consist of; speed, breadth, height, age, gender and handicaps (e.g. baggage, disability or child). An initial analysis was carried out to compare the specified walking speeds from the profiles with the literature values previously found. This consisted of a comparison to all the literature values and to the specific study by Rastogi et al (2011) who featured several worldwide walking speeds from the past 50 years. Initially, to compare the studies and SimWalk profiles, the average walking speed was calculated. The average walking speed for the Rastogi et al study is 2.94mph and for the collection of literature studies is 2.95mph (Figure 3-45). The value for the SimWalk profiles is 3.04mph; this is higher than the other values, suggesting SimWalk may be over-estimating speeds (Figure 3-45).

A further comparison to literature values has shown that the walking speeds provided in the SimWalk profiles have large deviations but overall, are closer to the one-mile walking test study results than any of the other studies considered in this review (Figure 3-45). The exceptions to this are the commuter and standard female profiles, which are more in line with the other literature studies (Figure 3-45). The one-mile walk test results were deemed to be over-estimations of walking speeds since participants were aware that a test was being conducted and this meant that the results were thought to be higher when compared to other studies. It would therefore suggest that the SimWalk profiles are over-estimating walking speeds too. The Rastogi et al study contains a set of international walking speeds, which could also be compared to the SimWalk profiles (Figure 3-45). Overall this study agrees more with the SimWalk profile walking speeds. However, it should be noted that the Rastogi et al speeds are all below the one-mile walking test results, further demonstrating that the 1-mile walk test results are an over-estimation of walking speed.





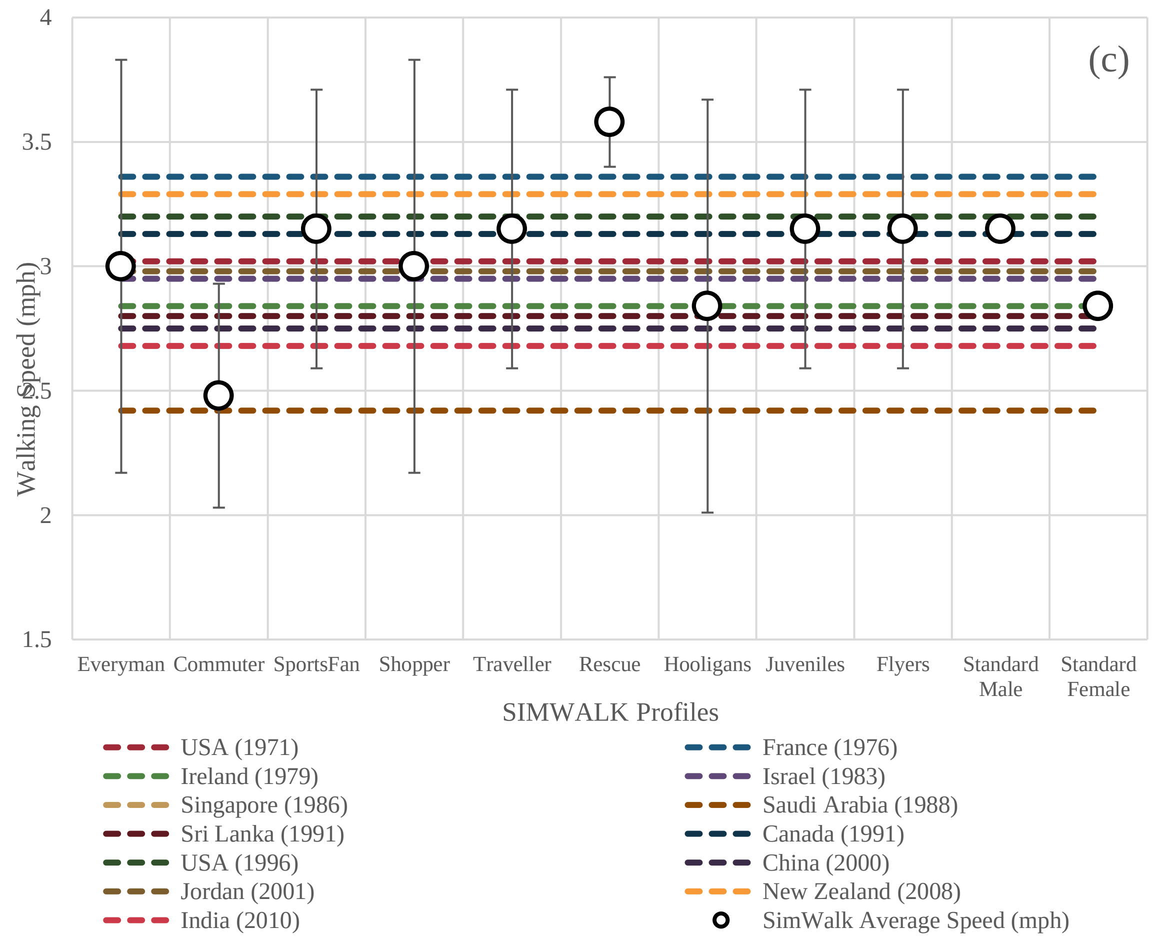


Figure 3-45 – (a) SimWalk Profiles compared with Average Literature Values and Average Rastogi et al 2011 Worldwide Values, (b) SimWalk Profiles compared with Literature Walking Speed Values, (c) SimWalk Profiles compared with Worldwide Walking Speed Values, adapted from (Rastogi, et al., 2011)

3.8 Rulesets Conclusion

Human behaviour is a vital component of any evacuation or crowd simulation. Three aspects of human behaviour have been explored in detail; walking speed, interpersonal distance and crowd behaviours. There are many other areas of human behaviour that could be explored but a basis has been formed from the three chosen areas. Dependant on modelling results, it may be necessary to explore further and to incorporate more behaviours in the future.

In terms of walking speeds, the literature has shown that there is a range of walking speeds dependant on age and sex. The location of a model can also have a variation on the walking speed. On top of this, the fitness of individuals can affect the overall walking speed. When walking in groups, there is evidence that this can also alter walking speed. Finally, poor visibility and the density of the crowd has been shown to decrease walking speeds. At present, these characteristics are not accurately captured in models and it is believed that this could have an overall effect on evacuation time, as well as the number of injuries and fatalities.

Interpersonal distance is another key feature of human behaviour and can dictate the density of a crowd. The scale created in the 1960s for interpersonal distance is still widely applicable today although there have been advances in terms of the angles of spacing. The literature has shown thought that there are differences in preference based on age and sex. There are also differences in interpersonal difference depending on location (e.g. non-contact countries). Interpersonal distance is shown to be affected by poor visibility, which is possible during an emergency scenario. The current models have shown little inclusion of interpersonal distance, but it is anticipated that this could have a large impact on crowd spacing and it needs to be more robustly modelled.

The third area was the behaviour within crowds, herding behaviour is often represented in models and is often exhibited by humans during emergency scenarios. This behaviour needs to be explored further in models to ensure the parameters are appropriate and representative. There has been some effort to capture leaders, group/following leaders and communication strategies in models, but again this needs to be examined as there tends to be 100% compliance, which may be unrealistic. The capacity of crowds is an important area and it can have a big impact on the flow of the crowd, this needs to be effectively captured. There is some evidence in literature of panic parameters but it is not anticipated at this stage that this will be included in any models due to the complexity, but the effects are likely to be seen in the number of successful evacuees, group sizes and congestion at exits, which will all be captured by one of the three behaviour types.

Hence, it is important that any models created to simulate crowds, in particular evacuations, capture human behaviour effectively. From literature, studies show the potential human behaviour that may occur, and it is necessary to robustly model this. To move forward, the suggested rules need to be incorporated into models either by editing existing code or writing new rules. To begin with, a simple evacuation model will be formed to test simplistic human behaviour (e.g. changes to walking speed). If this is successful, as a test base, the rules can then be transferred into more complex scenarios, additional behaviours added in and expanded further.

3.9 Agent-Based Model Expectations

Current agent-based models have begun to include a limited set of human behaviours during hazard events and evacuation scenarios as discussed. It has been documented that the inclusion to date has not been robust and in many cases limited. An improved representation of human behaviour will be a useful tool for emergency planners who need to prepare and plan for emergency scenarios, which presently cannot consider the full extent of possible behaviours.

Human behaviour is incredibly complex and can be both predictable and unpredictable at times. During hazards events, it is anticipated that behaviour will be less predictable than usual due to the extreme nature of the situation. However, it is possible to predict some common traits that have not previously been included within a model environment.

This literature review set out to find behaviour traits that are common in evacuations and where possible identify these in literature alongside quantifiable datasets. This resulted in the eleven potential behaviours set out earlier in the chapter, which are fleeing, crowd spacing, crowd behaviour, thinking time, the role of leaders, aggression, panic, stop and drop, route choice, capacity and the role of social media. It is plausible that all these behaviours could be present in an emergency scenario, but it is important to identify the most likely behaviours and those that can be quantified more readily as a starting point within the model environment. Hence, it was identified that the three priority behaviours should be considered as, fleeing, interpersonal distance, and crowd behaviour (Table 3-12). These were given priority for several reasons but primarily due to the ability to quantify these behaviour types through a large volume of available literature, which provided the possibility to calibrate, verify and validate the behaviour types. Initially, cognitive mechanisms were also identified as a priority however, after further investigation it was decided that the cognitive mechanisms currently in existence were not suitable to be combined within this anticipated agent based model environment and due to the complexity involved with creating a new robust mechanism, this trait would not be included in the initial models (Table 3-12). To compensate for the removal of the cognitive mechanism;

aggression, panic, route choice and capacity were identified to be included as alternative behaviours that could also influence evacuation timings (Table 3-12).

Table 3-12 – Desired Agent Based Model Inputs to Simulate Human Behaviour

Desired Model Inputs	Description	Included in Model (Model Type)	Variables
Flee Behaviour	Run from the hazard, varied walking speeds.	Yes	Population Distribution Walking Speed
Interpersonal Distance	Proximity of humans	Yes	Population Density
Crowd Behaviour	Crowd flows, following like sheep behaviour	Yes	No variables specifically assigned to create crowd behaviour, but rules introduced within the code.
Capacity	Of streets, roads, safe zones/shelters	Yes	No of Lanes Population Density
Routes	Shortest path, known routes, follow the leader	Yes	Shortest Path
Leader Behaviour	Influence of a leader on a crowd	No	N/A
Aggressive Behaviour	Aggression within a crowd	Partially	Patience Level
Panic Behaviour	Levels of panic, distress	Partially	Patience Level
Stop and Drop Behaviour	Due to panic/fear	No	N/A
Use of Social Media	Influence of route, causing panic	No	N/A
Cognitive Mechanism	The ability for agents to receive information, compute	No	N/A

	it then chose an action.		

The overall aim of this thesis is to create a modelling tool, which includes more robust human behaviour rulesets, to enhance the simulation of evacuations. The desire is to be able to do this on a macro scale i.e. city-wide scale, rather than on a small individual building or floor scale. The hope is that this tool will be beneficial for identifying larger scale issues such as congestion, route planning and positioning of shelters amongst other issues. Therefore, chapter 4 will outline the details of the initial agent-based model created at a city scale with the aim of identifying the evacuation time of a large area in a built-up environment and including the priority behaviours set out above.

Chapter 4. Modelling Techniques & Methodology

In Chapters 2 and 3, the need for agent-based modelling for hazard events was demonstrated and it has been identified that human behaviour is not robustly included with current agent-based models. This chapter will outline the macroscale city scale agent-based model and the human behaviour rulesets to be included as discussed previously in Chapter 3. With the aim that this can improve the representation of human traits in the model environment for emergency planning professionals to more robustly simulate evacuation scenarios. From the assessment carried out in previous chapters, it was identified that the Netlogo software would be the most appropriate tool to use for this project. Netlogo allows agent hierarchy, agent to agent communication, agent heterogeneity, feedback representation and is spatially explicit, which are all required for robustly simulate human behaviour.

The outcomes of the model will then be tested to ensure that the rulesets have reproduced appropriate behaviours. The proposed testing regime has been set out alongside the anticipated outcomes of each test. Validation, calibration, and verification of the model has also been considered to ensure the validity of the model proposed.

4.1 Macroscale Model (City Model)

The initial agent-based model was created at the macro scale and based on the city of Newcastle upon Tyne, UK, due to my familiarity of the area. It also holds major largescale sporting events at St James Park, in the past including the Olympics, Rugby World Cup as well as other large events such as music concerts, there is a large shopping centre, has two universities and a population of 314,366 (UK Population, 2020). Hence, there is a need to identify the most suitable evacuation routes across the city during an emergency scenario.

4.1.1 Initial Model Description

The model is based on a 3km x 2km area of Newcastle city centre, including the main shopping street (Northumberland Street & INTU Eldon Square), St James Park, Quayside and housing on the edge of the city centre (Figure 4-1). The model interface features a number of variables that can be set by the user (linking to population types, walking speed, and group size for example), as well as a GIS map background for the population to move around, with agents confined to the map's roads, population counters, a graphical output of the population change over time and a text output of the predicted evacuation time in minutes (Figure 4-2). The GIS map background was derived from the Ordnance Survey (OS) MasterMap topographic layer to provide some context of the urban environment and for the pedestrian network, which itself was created using OS Integrated Transport Network (ITN), a road network that provides a seamless pedestrian network for the agents. A safe zone is marked on the opposite side of the River Tyne in Gateshead and is identified by a green dot within the model. This safe zone has not necessarily been identified as the most suitable location in Newcastle but has been assigned as the population needs to cross the river to reach safety.

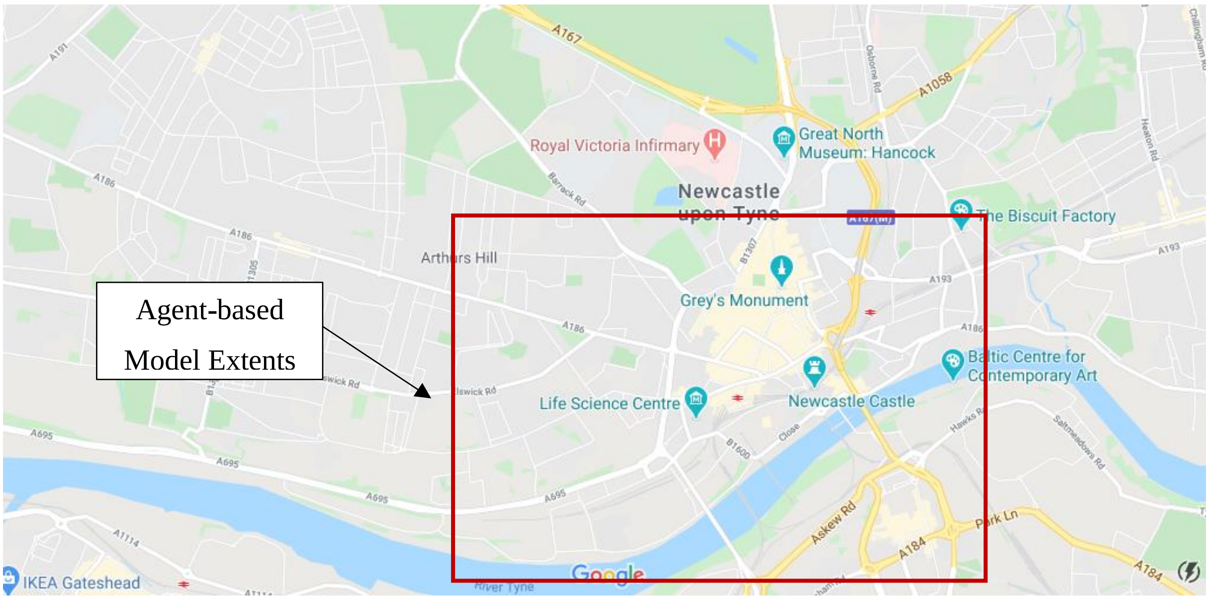


Figure 4-1 – Macroscale Agent-Based Model Extents (Google, 2018)

There are several variables for the user to input into the model such as population size and walking speeds (Figure 4-2). By altering the variables, it allows the user to simulate a variety of populations and walking speeds in an area. However, a series of suggested variable values have been provided to the user, these are based on UK data and literature (Table 4-1). It should be noted that the evacuation models have begun with an initial inclusion of walking speeds only and do not include running. It is acknowledged that there are studies which suggest children and young adults do run when in a panicked scenario, however this model is aiming to capture a worst-case scenario, therefore walking speeds have been used. The model area is also relatively large, with some evacuation routes shown to be 4km or longer, it is assumed in this case that even with panic included most humans could not run for such a prolonged period again supporting the use of walking speeds only in this thesis. Finally, there was a large volume of available literature to support the inclusion of varied walking speeds, allowing for quantification to occur, this was not necessarily available for running speeds over prolonged periods and in panicked scenarios.

Table 4-1 – First Iteration City Model Typical Values for User Variables

Typical Variable Values		
Variable	**Typical Value**	**Data Source**
Population Size	>1000	N/A – the population size of the model was limited to 10,000 agents due to computational power when running the simulations.
Population Types	Children = 18% Male Adults = 32% Female Adults = 33% Male OAPs = 8% Female OAPs = 9%	UK Average Population splits (Office for National Statistics, 2014)
Walking Speeds	Children = 0.8m/s (1.8mph) Male Adults = 1.34m/s (3mph) Female Adults = 1.12m/s (2.5mph) Male OAPs = 0.78m/s (1.74mph) Female OAPs = 0.76m/s (1.7mph)	Values combined from literature (Bosina & Weidmann, 2017) (Rastogi, et al., 2011) (Schimpl, et al., 2011) (Silva, et al., 2014)

For a user to operate the model, they must first set the variables (population size, distribution, walking speeds and precision) using the various buttons and sliders in the model (Figure 4-2 and Figure 4-3). Next the user presses the "load GIS" button, the mapping background is produced and then the "setup" button creates the variables and places the agents within the model. Agents are assigned to a random starting position in the model, but this will be onto one of the building patches (identified by their black colour in the model environment). During the setup process, the shortest paths from each available node in the model (nodes are identified as being where each roads join each other) to the single point of safety is calculated, the algorithm is run once during this phase and does not allow the agents to reroute during the simulation for example due to congestion on the roads. However, the model does allow faster agents to pass slower agents as if over-taking on a footpath. Once the setup of the model is complete, the user uses the "go" button to simulate the evacuation of the city centre. When this occurs, agents must first move from their building patch to their nearest road, when onto a road the agent searches the shortest path algorithm to find the route from their nearest node to the point of safety. Agents then travel at their assigned speeds to the point of safety using the pre-assigned shortest path. Once they reach the point of safety the evacuees “exit” the model (command used is the die command, so agents permanently exit) to simulate them entering an evacuation centre. A diagrammatic flowchart of the running procedure for the user (Figure 4-4) and an agent (Figure 4-5) in the model environment have been detailed.

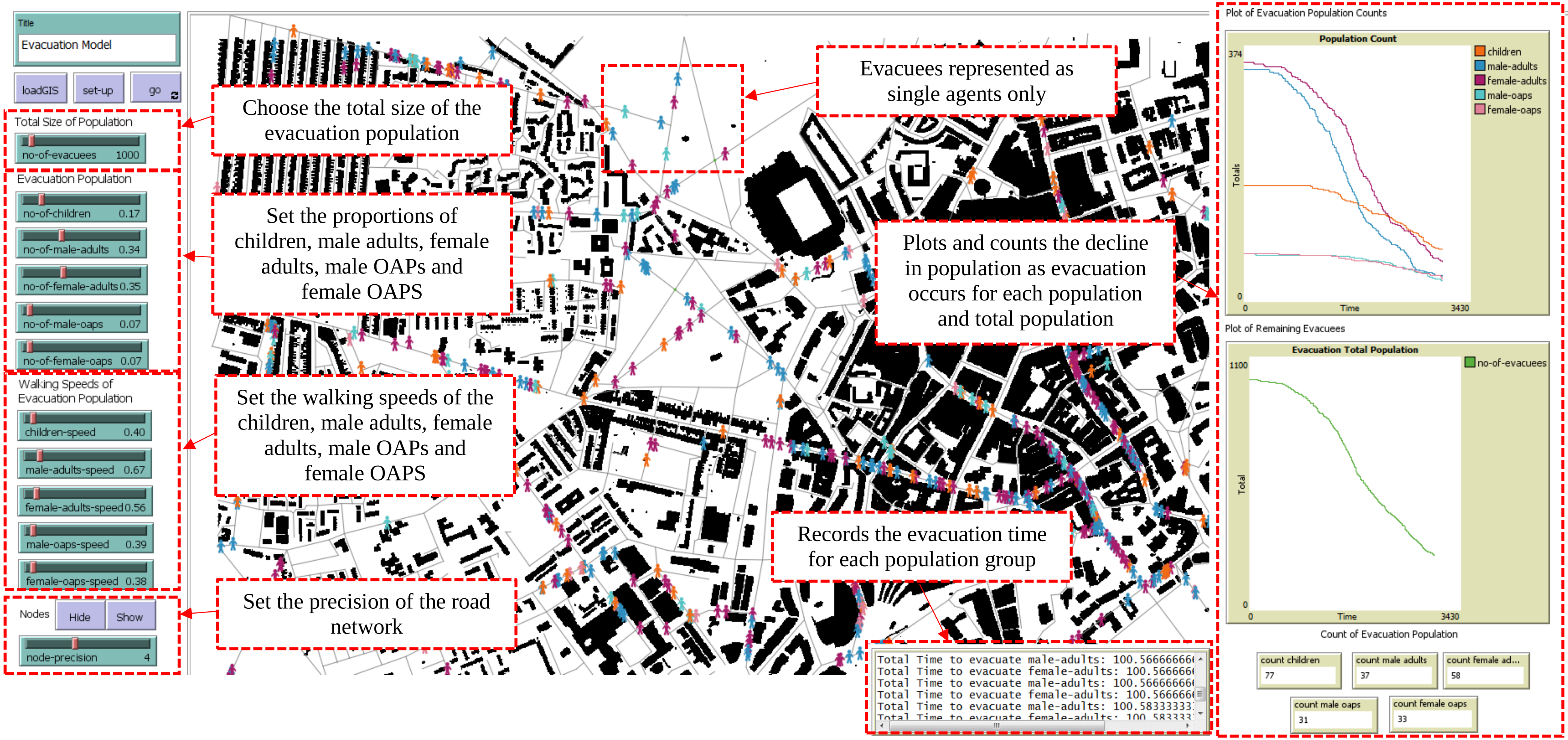


Figure 4-2 – Initial Evacuation Model User Interface Created by Barnes, Platform used is Netlogo (Wilensky, 1991)

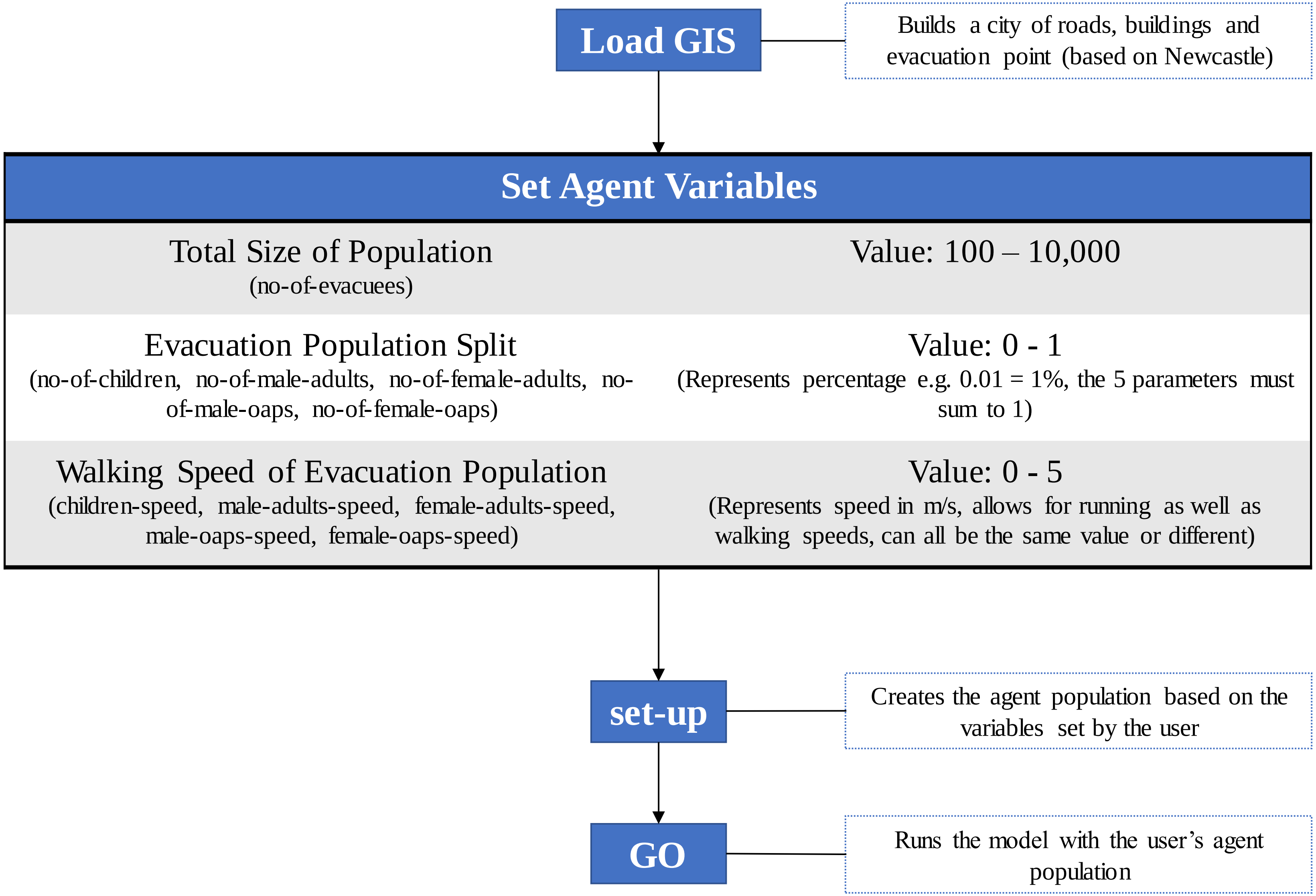


Figure 4-3 – Model Variables for User to Set in City Evacuation Model

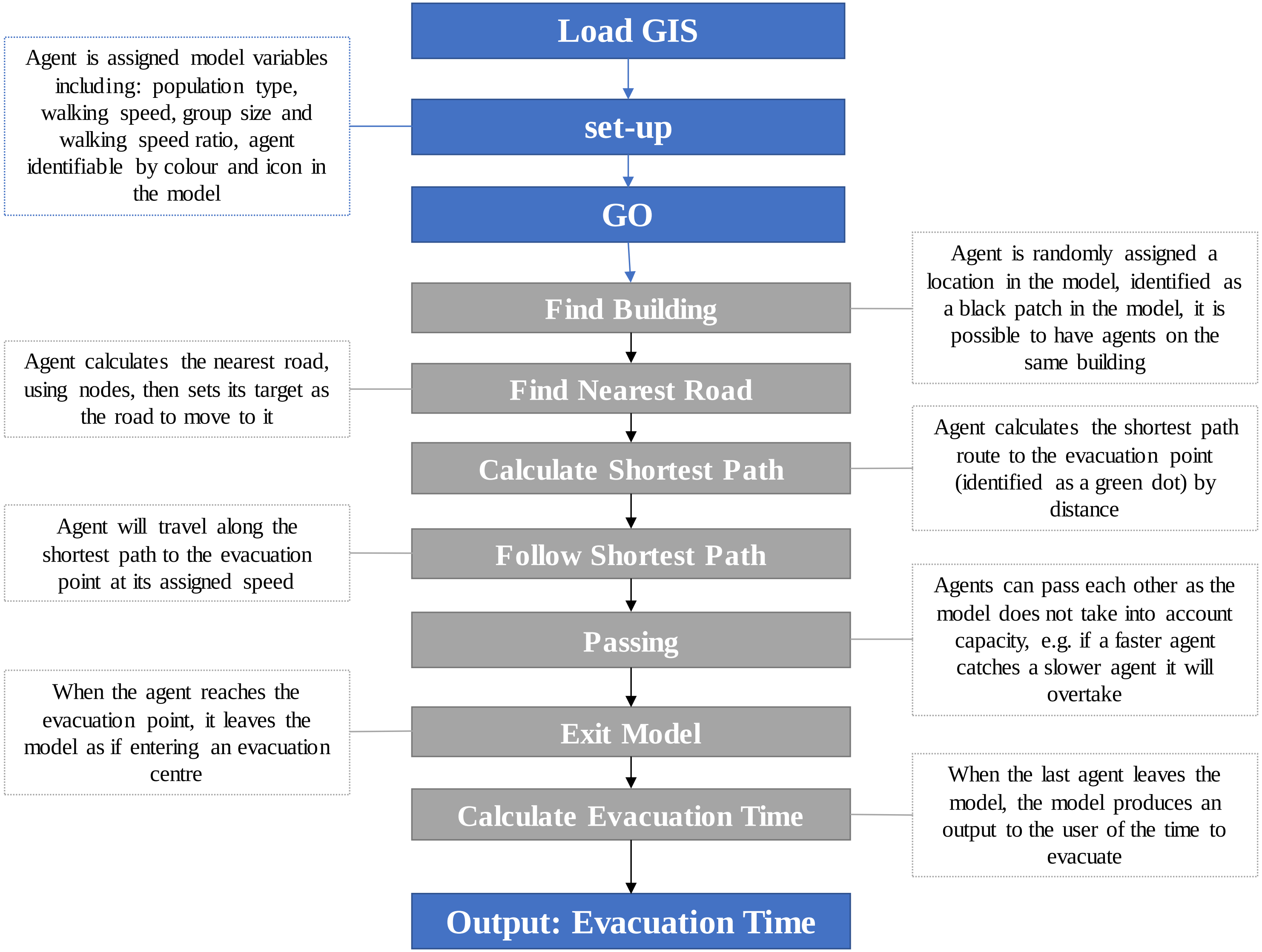


Figure 4-4 – City Evacuation Model Agent Running Procedure

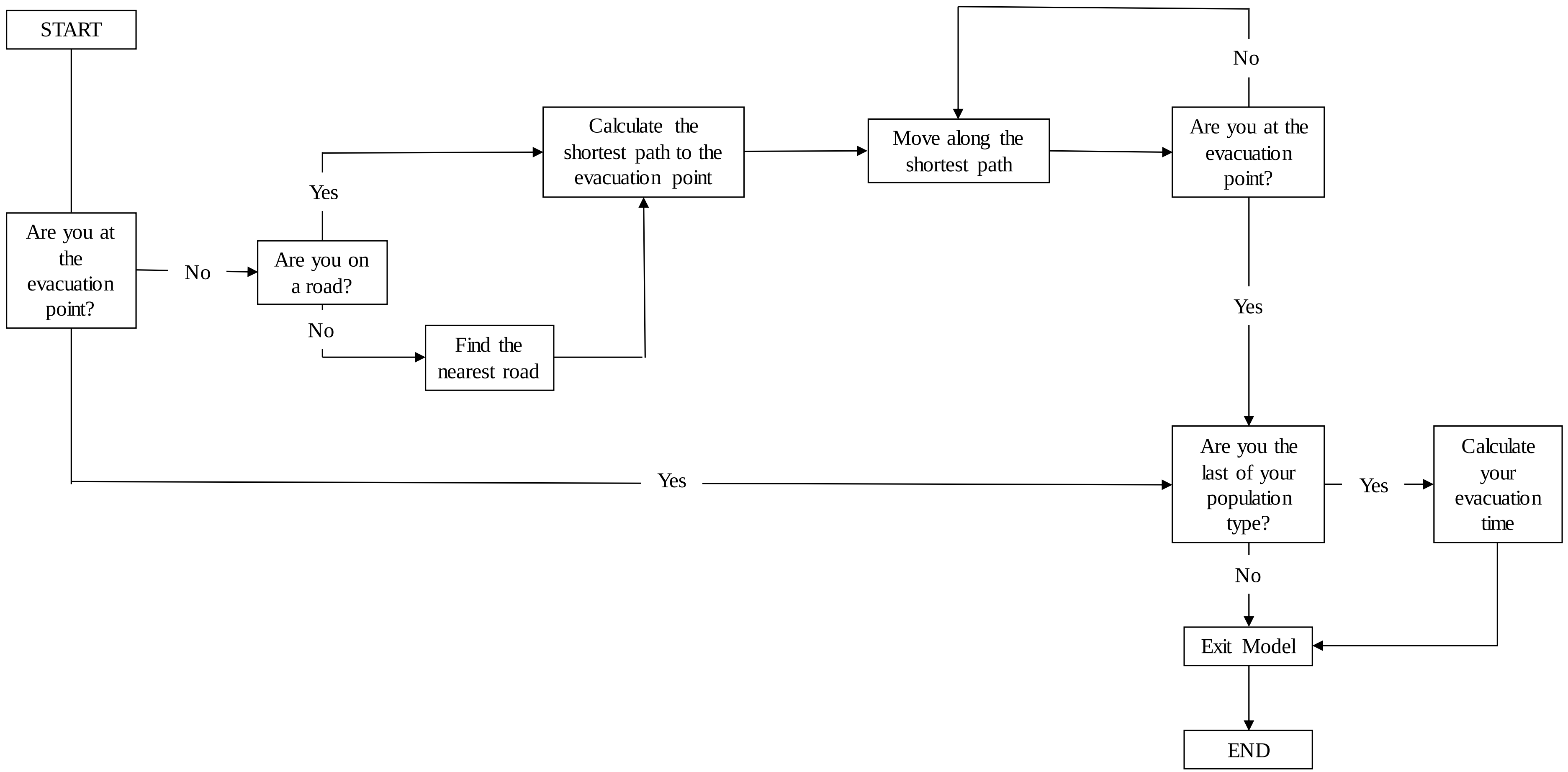


Figure 4-5 – Agent Thought Process for Macroscale Newcastle Model

4.1.2 *Second Iteration City Model Description*

From the initial model, a second iteration of the city scale model was produced. The area covered remained the same as did the initial variables included. Additional variables were added into the model, this was to allow the user to include groups within the model of between one and four in size (Figure 4-6 and Figure 4-7). To reflect the fact that walking speed decreases with group size, the user can also set a walking speed ratio variable for each group size (Figure 4-6 and Figure 4-7). This allows the user to include a more varied population based on age, sex and group size. As with the first iteration, the user must input the variables into the model to create their desired population. A series of suggested user variables have been produced for the user, based on UK data and literature (Table 4-2).

Table 4-2 – Second Iteration City Model Additional Typical Values for User Variables

Typical Variable Values		
Variable	**Typical Value**	**Data Source**
Group Sizes	Individuals = 28% Couples = 35% Groups of Three = 16% Groups of Four = 21%	UK household size data (Office for National Statistics, 2017)
Group Walking Speed Ratio	Individuals = 1 or 100% Couples = 0.9 or 90% Groups of Three = 0.84 or 84% Groups of Four = 0.76 or 76%	Values combined from literature (Bosina & Weidmann, 2017) (Moussaid, et al., 2010) (Rastogi, et al., 2011)

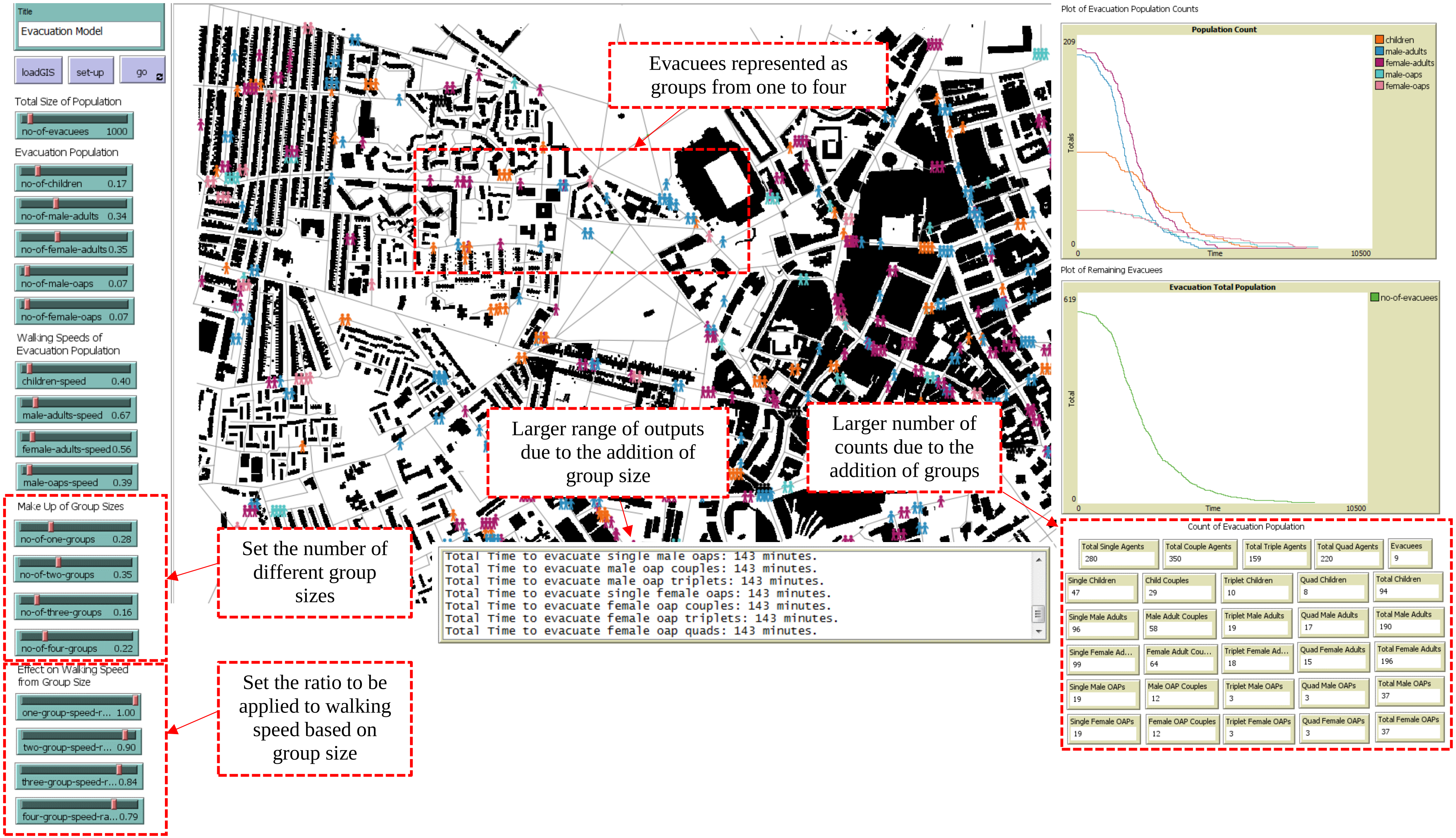


Figure 4-6 – Second Iteration Evacuation Model

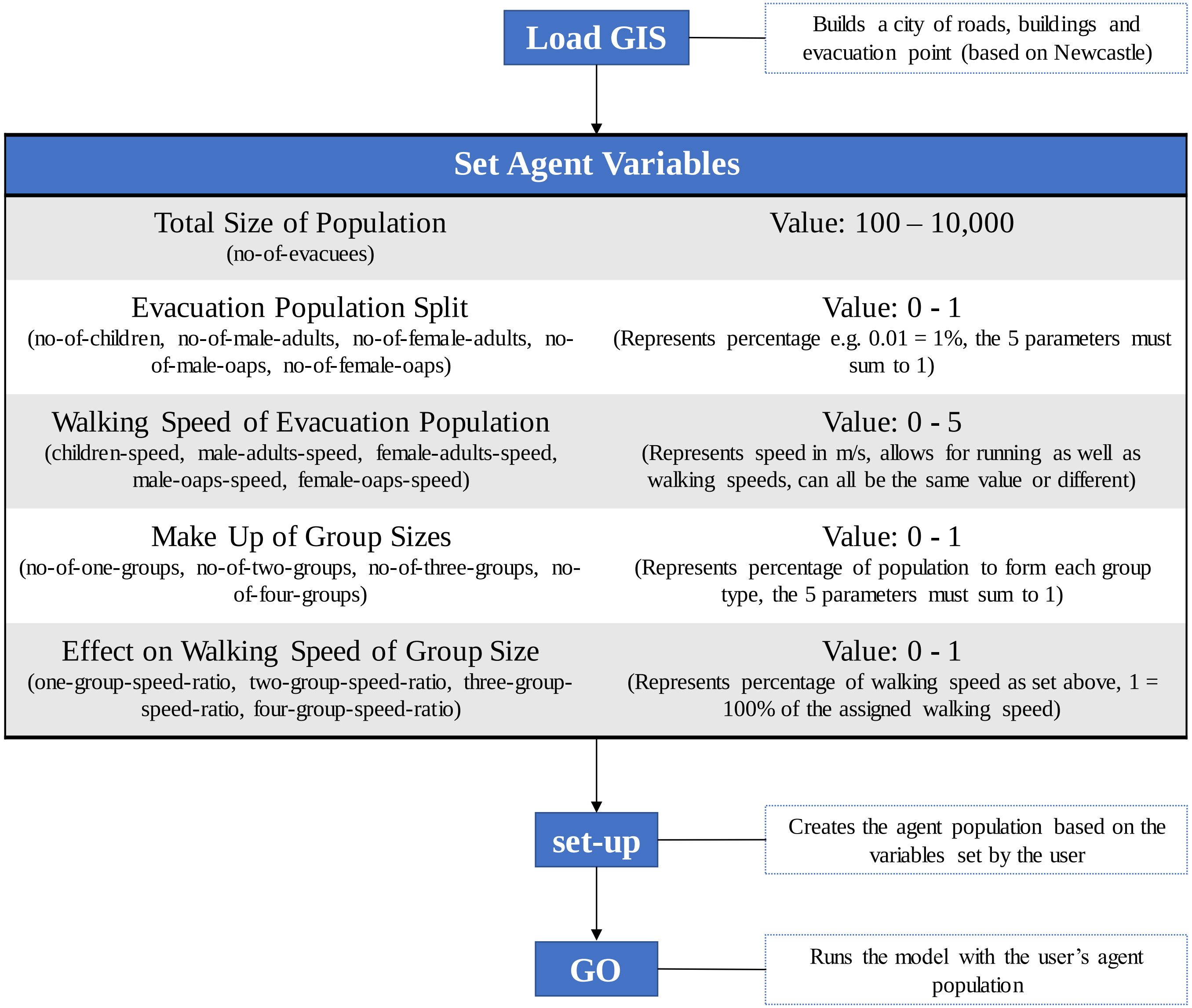


Figure 4-7 – Model Variables for User to Set in City Evacuation Model

4.2 Calibration, Verification & Validation

It is important with any model that efforts are made to calibrate, validate and verify the intended outcomes. Calibration is the process of checking the model's quantitative measurements to optimise them, in this case ensuring that the evacuation time is realistic, and the shortest path is robust. Verification of the model is comparing the model to a body of evidence to confirm its accuracy or truth. The model "*is checked to see if it behaves as it should*" (Ngo & See, 2011). This may be carried out using video footage of evacuations, comparing the displayed behaviours with descriptions of known behaviours or examining the evacuation times of previous events and checking if the model can replicate this.

Validation can be described as the "*process for determining if a model is able to produce valid and robust results such that they can serve as the basis for decision makers*." (Ngo & See, 2011) (d'Aquino, et al., 2001). Validation is used to determine how the model fits the real-world and the original design objectives. There have been many methods set out for validating agent-based models including: empirical, statistical, conceptual, internal, operational, external, structural and process validation (Ngo & See, 2011) (d'Aquino, et al., 2001) (Carley, 1996) (Klugl, 2008) (Parker, et al., 2002) (Troitzsch, 2004) (Windrum, et al., 2007).

It is necessary to consider all these aspects and methods when testing a model to ensure that it is robust and an accurate representation of the intended scenarios, although it remains a challenge to complete effectively. There will be some level of inaccuracy within the model as a result of including several assumptions and it is vital that checks are performed to ensure this does not result in a flawed model. No single validation, calibration and verification method has been used within this thesis and instead a series of tests will be completed on the Netlogo models to calibrate, verify and validate the model where possible as set out in Section 4.3.

4.3 Proposed Testing

It is important that the models created are robustly tested to identify limitations and to ensure the human behaviours included are in line with expectations. A series of tests have been proposed for the city scale model to include calibration against route planners, varied population size, varied population parameters, walking speeds and grouping factors.

Initially, a calibration check will be carried out of the macroscale city model with several route planners, to ensure that the model produces realistic evacuation time estimates and the routes taken are the shortest paths. Secondly, an observational check of the number of evacuees in the model and walking speeds will be carried out, to understand the spatial variability in the model and to check the model can compute different evacuation times for different walking speeds.

Once it is ascertained that the model can produce reasonable time estimates for travelling in the model, a series of tests will be undertaken to understand how population characteristics effect the model evacuation time, this can be classed as sensitivity analysis. Firstly, data from the UK will be assessed, this will include the average UK population make up but also the extremes e.g. areas where there are increased numbers of children or OAPs as these are the slowest agents in the model. Secondly, population data from across the world will be included within the model, where there are even greater population extremes e.g. the large OAP population in Japan. These tests will be carried out before the grouping has been included within the model.

After exploring the population characteristics, a test will be carried out to include the groups of agents within the model environment and to understand the possible effect on evacuation timing. Finally, the walking speed ratio will be tested to assess if this influences evacuation timing. The population will be based on Newcastle during these tests, which is similar to the UK average population make up.

Throughout all these tests a comparison will be made to existing agent-based evacuation models, which include fewer population characteristics and variables. This will allow an assessment to be made as to whether the inclusion of new variables is having a positive impact on evacuation timings.

4.4 Model Calibration – Using Route Planners

Before exploring the impact of including a wider range of population characteristics and groups of agents, as is set out in the proposed testing, it is necessary to check the model is calibrated correctly to produce realistic evacuation times and the routes taken are the shortest path. Hence, the aim of this test is to examine whether the model has been setup correctly by allowing an agent to walk from one point to another and comparing this with the outputs from several route planners. This will test: (1) the shortest path algorithm, (2) the evacuation time output, (3) Netlogo outputs and (4) Netlogo graphics.

To carry out the test, the model creates a single evacuee, placed at a varied starting location, who must evacuate to a known point of safety, which is kept consistent throughout the test. The variables were set within the model to reduce the evacuation model to one evacuee and set the walking speed to the approximated speed of the route planners, which is 1.34m/s (3mph).

The evacuee's location is randomly generated in the model each time, but its location can be used to produce a postcode location. This postcode can then be used within a route planner to compare the journey time and route taken.

The route planners used are Google Maps (Google, 2018), Bing Maps (Bing, 2018), Walkit (Walkit, 2018) and RAC (RAC, 2018). The route planners were chosen for a variety of reasons (as outlined below), but it was important to use a range of tools as most tools do not advertise their chosen walking speed so by using several, a range of speeds can be included. Google Maps was chosen as it is one of the most popular route planning tools on the market and Bing Maps is Google's closest rival. Walkit is an urban walking journey planner which allows the user to set the walking pace and RAC is a common route planner used for vehicles although it allows for a walking route to be calculated. Despite the walking speed being difficult to ascertain from route planners, it is believed the approximate walking speed in the route planners is 1.34m/s (3mph) (Ro, et al., 2011) (Walkit The Urban Route Planner, 2018) and hence the agent's speed was also set to 1.34m/s (3mph) to mirror this.

The main test carried out was to compare the Netlogo model to other route planners, this meant an assessment could be made between the evacuation times and distances calculated. Twenty-five simulations were run from a randomly generated starting point on Netlogo, a postcode was then produced of the same location, which was then inputted in the route planners. The route planners then all completed the route using their shortest path and walking algorithms.

A range of evacuation times were produced due to the spatial variability of the starting point. Analysis of the evacuation times shows that 62% of the time other route planners (Google Maps (Google, 2018), Bing Maps (Bing, 2018), Walkit (Walkit, 2018) or RAC (RAC, 2018)) were faster than the model and 38% of the time the route planners were slower (Table 4-3 and Table 4-4). The average difference in time was approximately 2% between the Netlogo model and other route planners (Table 4-4).

Table 4-3 – Evacuation Times from Netlogo and Route Planners (minutes)

No.	Start	Location	Netlogo	Google	Bing	Walkit (med)	RAC
1	NE4 6QX	St Michaels Church RC	49.18	42	37	40	40
2	NE1 2HF	One Trinity Gardens	16.73	15	15	19	17
3	NE1 5AG	95 Grainger Street	22.33	24	21	25	24
4	NE4 6AQ	Westgate Road	32.48	31	29	34	32

5	NE4 7JU	St Pauls C of E School	40.68	34	33	33	33
6	NE1 7AE	Northumberland Street	23.5	25	23	25	26
7	NE1 4SE	St James Park	39.42	33	31	32	38
8	NE4 7EH	Cambridge Street	42.48	40	39	44	42
9	NE4 5JQ	Beaconsfield Street	42.68	42	40	45	42
10	NE2 1AN	Petrol Station, Stoddart St	23.53	23	22	25	25
11	NE4 5NP	414 Westgate Road	60.6	42	42	43	42
12	NE1 4LY	37 Leazes Terrace	29.37	33	31	33	33
13	NE1 1EE	30 Cloth Market	20.73	22	20	20	22
14	NE2 1XS	2 Coppice Way	27.97	28	25	25	28
15	NE4 7AL	62 Dunn St	34.85	36	34	34	36
16	NE4 5RJ	5 Tindal Close	38.28	36	35	34	36
17	NE1 6UW	9 Worswick Street	20.23	24	22	22	24
18	NE4 6RJ	3 Hawthorn Terrace	43.28	39	37	37	39
19	NE4 7SE	2 Maple Terrace	35.98	38	35	38	38
20	NE1 5PN	39B Clayton Street	23.97	26	24	23	26
21	NE4 7BG	57 -71 Penn St	37.17	37	36	38	37
22	NE1 3JE	5 – 9 Side	14.52	17	16	15	17
23	NE1 8BS	3 Oxford Street	24.8	29	21	21	29
24	NE2 1AP	10 – 16 Boyd Street	23.32	24	22	23	24
25	NE8 2BA	9 Brandling Street	7.1	8	7	5	8

Table 4-4 – Comparison of Route Planners with Predicted Model Evacuation Time (minutes) in Netlogo (in terms of % difference)

No.	Start	Location	% G	% B	% W	% R	AVG
1	NE4 6QX	St Michaels Church RC	15%	25%	19%	19%	19%
2	NE1 2HF	One Trinity Gardens	10%	10%	-14%	-2%	1%
3	NE1 5AG	95 Grainger Street	-7%	6%	-12%	-7%	-5%
4	NE4 6AQ	Westgate Road	5%	11%	-5%	1%	3%
5	NE4 7JU	St Pauls C of E School	16%	19%	19%	19%	18%
6	NE1 7AE	Northumberland Street	-6%	2%	-6%	-11%	-5%
7	NE1 4SE	St James Park	16%	21%	19%	4%	15%
8	NE4 7EH	Cambridge Street	6%	8%	-4%	1%	3%
9	NE4 5JQ	Beaconsfield Street	2%	6%	-5%	2%	1%
10	NE2 1AN	Petrol Station, Stoddart St	2%	7%	-6%	-6%	-1%

11	NE4 5NP	414 Westgate Road	31%	31%	29%	31%	30%
12	NE1 4LY	37 Leazes Terrace	-12%	-6%	-12%	-12%	-11%
13	NE1 1EE	30 Cloth Market	-6%	4%	4%	-6%	-1%
14	NE2 1XS	2 Coppice Way	0%	11%	11%	0%	5%
15	NE4 7AL	62 Dunn St	-3%	2%	2%	-3%	0%
16	NE4 5RJ	5 Tindal Close	6%	9%	11%	6%	8%
17	NE1 6UW	9 Worswick Street	-19%	-9%	-9%	-19%	-14%
18	NE4 6RJ	3 Hawthorn Terrace	10%	15%	15%	10%	12%
19	NE4 7SE	2 Maple Terrace	-6%	3%	-6%	-6%	-4%
20	NE1 5PN	39B Clayton Street	-8%	0%	4%	-8%	-3%
21	NE4 7BG	57 -71 Penn St	0%	3%	-2%	0%	0%
22	NE1 3JE	5 – 9 Side	-17%	-10%	-3%	-17%	-12%
23	NE1 8BS	3 Oxford Street	-17%	15%	15%	-17%	-1%
24	NE2 1AP	10 – 16 Boyd Street	-3%	6%	1%	-3%	0%
25	NE8 2BA	9 Brandling Street	-13%	1%	30%	-13%	1%
		AVERAGE	0%	8%	4%	-2%	2%

KEY:		**Split**	**Average**
Faster	Other route planners are:	62%	2%
Slower	Other route planners are:	38%	
N = Netlogo, G = Google Maps, W = Walkit (medium), B = Bing Maps, R = RAC Route Planner			

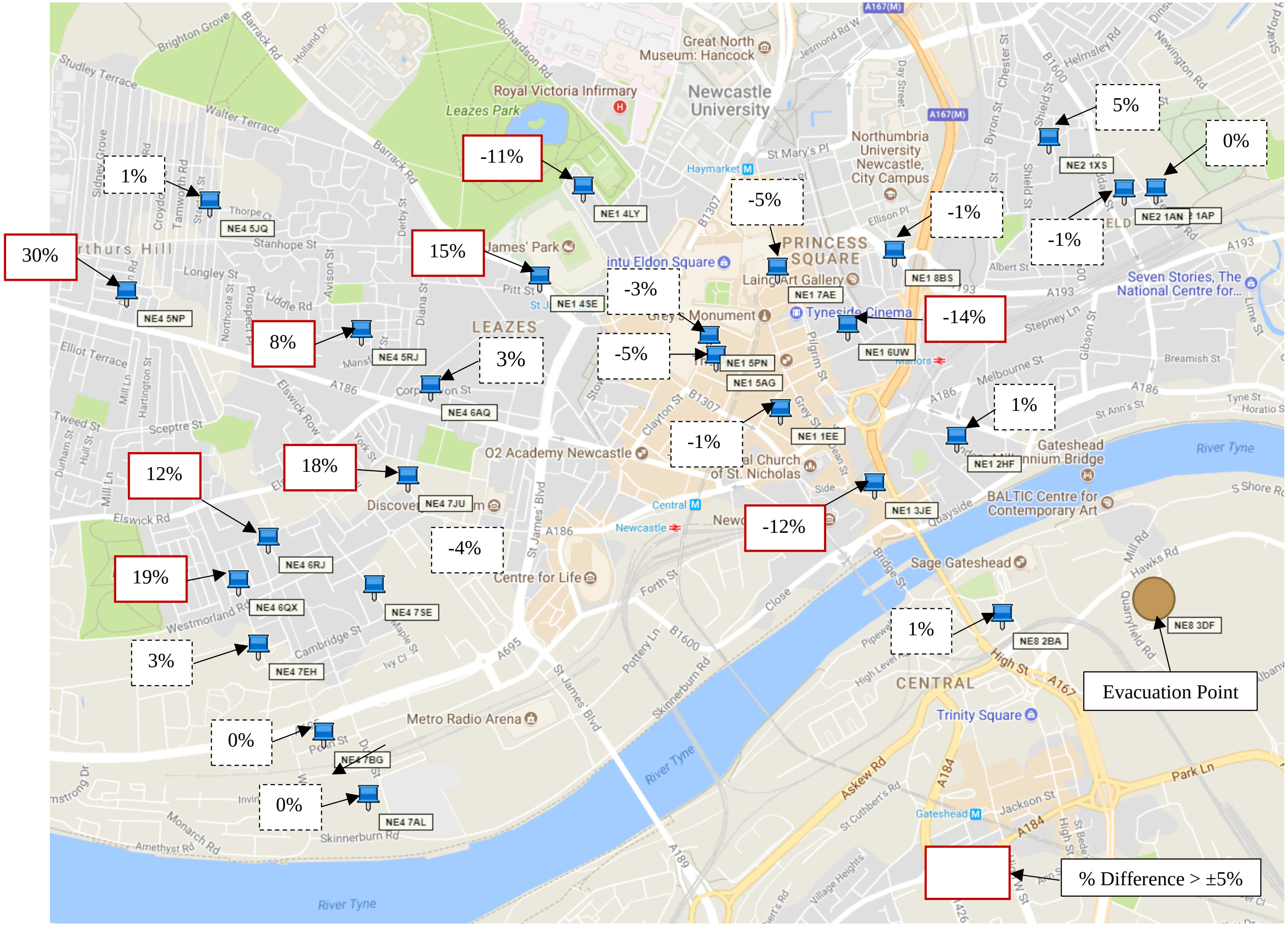


Figure 4-8 – Locations of Postcodes Used and the % Difference between the Netlogo Model and Route Planners in terms of Evacuation Time (minutes) (Google, 2018)

In terms of the evacuation distances, there were again differences between the Netlogo model and the other route planners. The distances calculated from Netlogo also need to be considered with care as it is not possible to accurately compute the agent's distance from a gridded cell system, instead distance is calculated from the speed and time taken, meaning the comparison with route planners may not be correct. In this instance, 31% of the evacuation distances were longer than other route planners and in 69% of cases, the other route planners took a shorter distance route (Table 4-5 and Table 4-6). This resulted in approximately 6% difference in distance (underestimate); the average route was 2.33km meaning the difference on average would be around 0.14km or 140m (Table 4-6). It is expected that the differences in evacuation distance is a result of the route choice and it demonstrates that the level of detail within the Netlogo model may need refining to include additional information such as steps climbed, capacity or no access for pedestrians, which could all affect the route taken.

Table 4-5 – Evacuation Distances from Netlogo and Route Planners (kilometres)

No.	Start	Location	Netlogo	Google	Bing	Walkit	RAC
1	NE4 6QX	St Michaels Church RC	3.92	3.35	2.95	3.19	3.04
2	NE1 2HF	One Trinity Gardens	1.34	1.20	1.20	1.52	1.29
3	NE1 5AG	95 Grainger Street	1.78	1.92	1.68	2.00	1.85
4	NE4 6AQ	Westgate Road	2.59	2.47	2.31	2.71	2.46
5	NE4 7JU	St Pauls C of E School	3.25	2.71	2.63	2.63	2.53
6	NE1 7AE	Northumberland Street	1.88	2.00	1.84	2.00	2.03
7	NE1 4SE	St James Park	3.15	2.63	2.47	2.55	2.41
8	NE4 7EH	Cambridge Street	3.39	3.19	3.11	3.51	3.28
9	NE4 5JQ	Beaconsfield Street	3.41	3.35	3.19	3.59	3.41
10	NE2 1AN	Petrol Station, Stoddart St	1.88	1.84	1.76	2.00	1.87
11	NE4 5NP	414 Westgate Road	4.84	3.35	3.35	3.43	3.40
12	NE1 4LY	37 Leazes Terrace	2.34	2.63	2.47	2.63	2.57
13	NE1 1EE	30 Cloth Market	1.65	1.76	1.60	1.60	1.68
14	NE2 1XS	2 Coppice Way	2.23	2.23	2.00	2.00	2.16
15	NE4 7AL	62 Dunn St	2.78	2.87	2.71	2.71	2.81
16	NE4 5RJ	5 Tindal Close	3.05	2.87	2.79	2.71	2.82
17	NE1 6UW	9 Worswick Street	1.61	1.92	1.76	1.76	1.83
18	NE4 6RJ	3 Hawthorn Terrace	3.45	3.11	2.95	2.95	3.03
19	NE4 7SE	2 Maple Terrace	2.87	3.03	2.79	3.03	2.87

20	NE1 5PN	39B Clayton Street	1.91	2.07	1.92	1.84	1.95
21	NE4 7BG	57 -71 Penn St	2.97	2.95	2.87	3.03	2.92
22	NE1 3JE	5 – 9 Side	1.16	1.36	1.28	1.20	1.27
23	NE1 8BS	3 Oxford Street	1.98	2.31	1.68	1.68	2.24
24	NE2 1AP	10 – 16 Boyd Street	1.86	1.92	1.76	1.84	1.83
25	NE8 2BA	9 Brandling Street	0.57	0.64	0.56	0.40	0.61

Table 4-6 – Comparison of Route Planners with Predicted Evacuation Distances (km) in Netlogo (in terms of % difference)

No.	Start	Location	%G	%B	%W	%R	AVG
1	NE4 6QX	St Michaels Church RC	-22%	-22%	-30%	-22%	-24%
2	NE1 2HF	One Trinity Gardens	-4%	-4%	-28%	-4%	-10%
3	NE1 5AG	95 Grainger Street	-1%	8%	-10%	4%	0%
4	NE4 6AQ	Westgate Road	-7%	-1%	-13%	-5%	-6%
5	NE4 7JU	St Pauls C of E School	-26%	-16%	-31%	-22%	-24%
6	NE1 7AE	Northumberland Street	3%	3%	-14%	8%	0%
7	NE1 4SE	St James Park	-23%	-23%	-28%	-23%	-25%
8	NE4 7EH	Cambridge Street	-5%	-5%	-10%	-3%	-6%
9	NE4 5JQ	Beaconsfield Street	-1%	-1%	-1%	0%	-1%
10	NE2 1AN	Petrol Station, Stoddart St	-6%	3%	-23%	-1%	-7%
11	NE4 5NP	414 Westgate Road	-30%	-28%	-32%	-30%	-30%
12	NE1 4LY	37 Leazes Terrace	11%	11%	7%	10%	10%
13	NE1 1EE	30 Cloth Market	3%	-3%	-9%	2%	-2%
14	NE2 1XS	2 Coppice Way	-1%	-6%	-15%	-3%	-6%
15	NE4 7AL	62 Dunn St	1%	1%	-10%	1%	-2%
16	NE4 5RJ	5 Tindal Close	-8%	-5%	-15%	-8%	-9%
17	NE1 6UW	9 Worswick Street	11%	11%	-7%	13%	7%
18	NE4 6RJ	3 Hawthorn Terrace	-13%	-13%	-22%	-12%	-15%
19	NE4 7SE	2 Maple Terrace	1%	1%	-6%	0%	-1%
20	NE1 5PN	39B Clayton Street	-1%	5%	-11%	2%	-1%
21	NE4 7BG	57 -71 Penn St	-2%	1%	-6%	-2%	-2%
22	NE1 3JE	5 – 9 Side	12%	12%	-14%	10%	5%
23	NE1 8BS	3 Oxford Street	11%	-9%	-19%	13%	-1%
24	NE2 1AP	10 – 16 Boyd Street	-3%	-3%	-14%	-2%	-6%

25	NE8 2BA	9 Brandling Street	6%	6%	-29%	8%	-2%
		AVERAGE	-4%	-3%	-16%	-3%	-6%

KEY:		**Split**	**Average**
Longer Route	Other route planners are:	31%	-6%
Shorter Route	Other route planners are:	69%	
N = Netlogo, G = Google Maps, W = Walkit (medium), B = Bing Maps, R = RAC Route Planner			

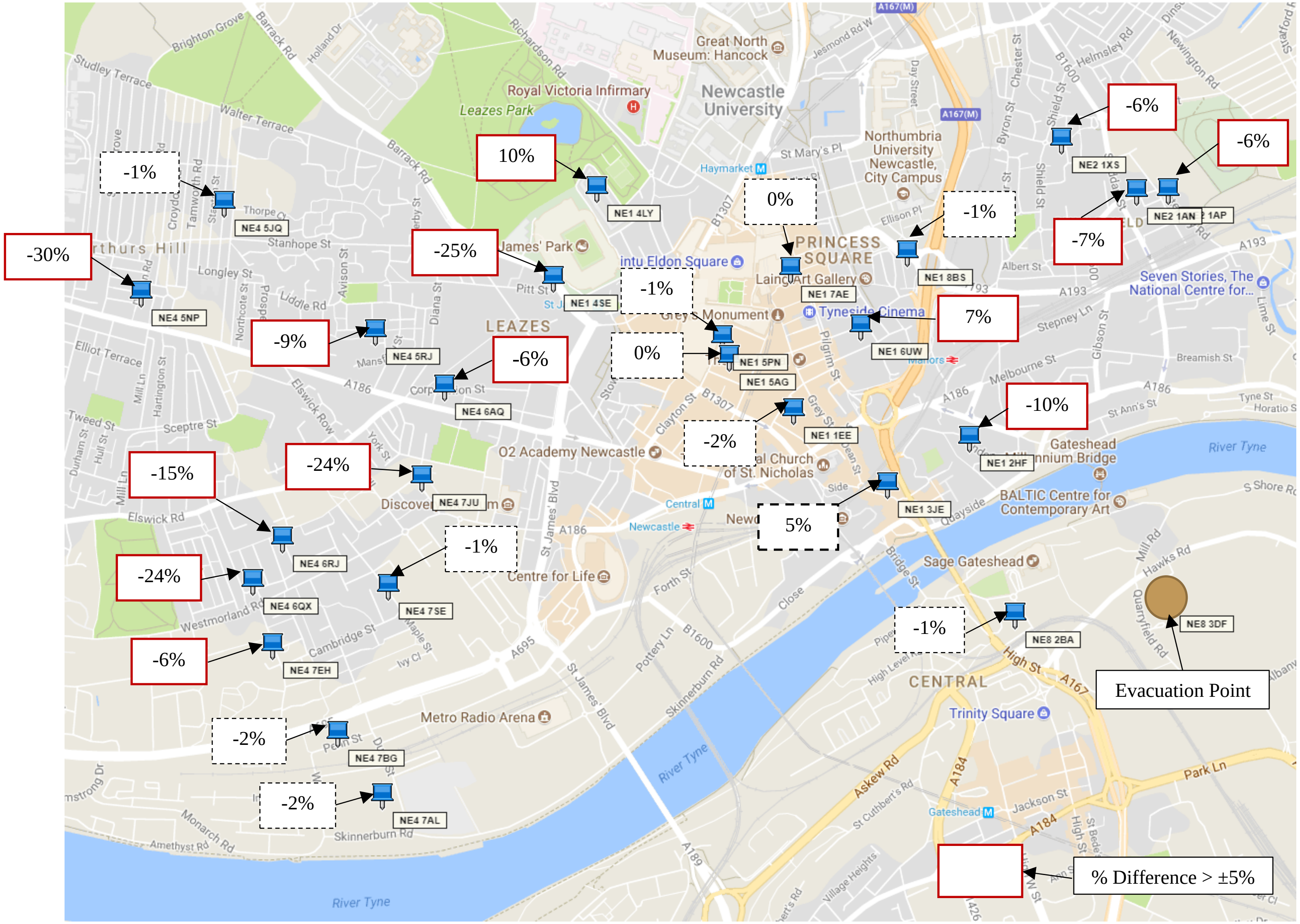


Figure 4-9 – Locations of Postcodes and the % Difference between the Netlogo Model and Route Planners in terms of Evacuation Distance (km) (Google, 2018)

There are routes that are slower, faster, shorter or longer for all route planners (Figure 4-8 and Figure 4-9), which suggests that the difference lies with the route taken, this is especially noticeable for the NE4 and NE1 postcode, Figure 4-10 shows their location. The NE4 postcodes tended to be furthest from the evacuation point, whilst the NE1 postcodes are concentrated within the city centre, it is likely that there are alternative routes available or there are missing links in the Netlogo model, to result in the large differences in time. For example, it was viewed that for the St James Park (NE1 4SE) start point, the agents in the model did not take the preferred routes of the route planner. This is because the agents are free to choose where they exit the stadium and this did not necessarily agree with the exit location of the route planners, this resulted in differences of between 4 and 21%. Alternatively, on Westgate Road (NE4 5NP), the shortest route suggested by Google Maps was 42 minutes whilst an alternative route took 48 minutes, this would change the percentage difference from 31% to 21%. There were other instances where agents utilised bridges such as the Tyne Bridge from the Quayside, which would result in a lengthy climb of stairs, at present this is not considered within Netlogo. Small differences such as this can then result in differences in the evacuation times.

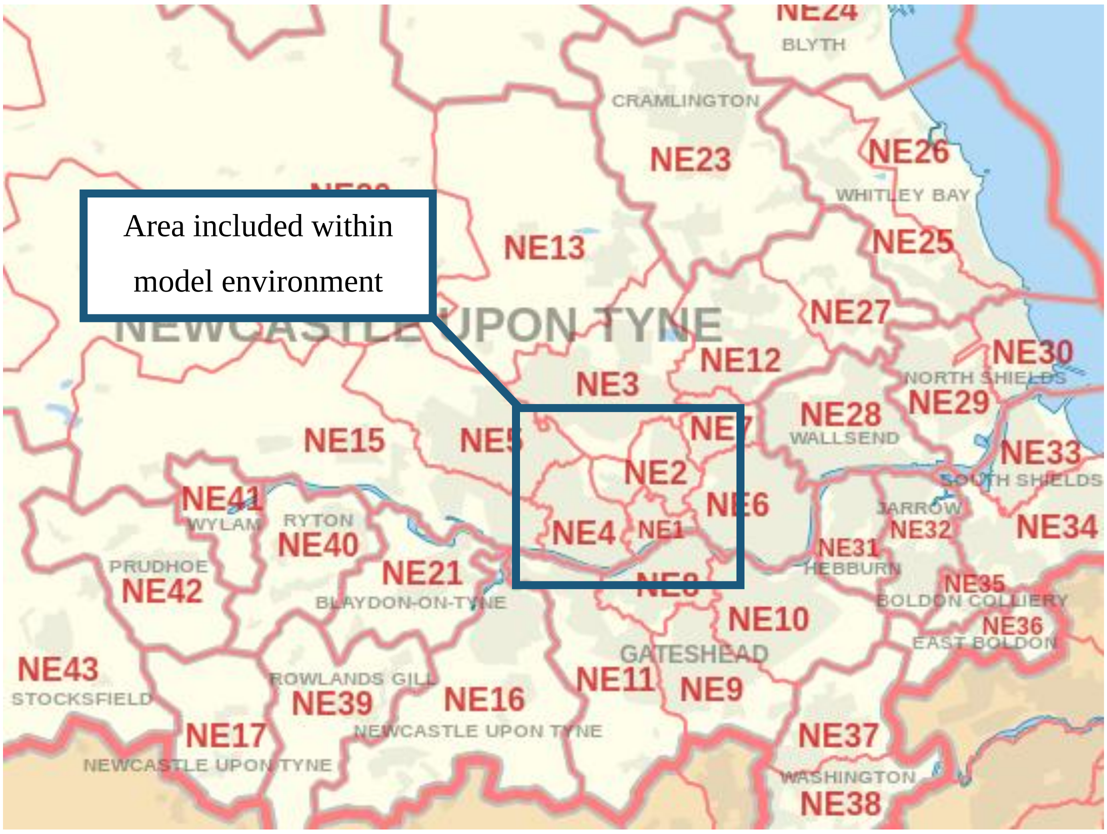


Figure 4-10 – Postcode Map of Newcastle upon Tyne, marking area used within city evacuation model (derived from Ordnance Survey OS OpenData) (Ordnance Survey, 2020)

The times and distances were plotted for the 25 locations to determine if there were any other general trends (Figure 4-11). The plot shows that as evacuation distance increases, the time to evacuate increases too. There is some variability in the predicted distance and times of the route planners, suggesting either the walking speed throughout the route does not always maintain approximately 1.34m/s (3mph), or external factors can be considered to decrease walking speed e.g. hills or congestion. The speed of each route planner and the Netlogo model can be calculated from the trendline gradients on Figure 4-11 (Table 4-7). These calculated speeds can be used to explain the average time difference values. For Google and RAC the slower walking speed of the route planner is counteracted by the shorter distance travelled resulting in a good match between the evacuation times. The 8% faster times using Bing Maps can be explained by a combination of the 3% shorter distances travelled and a 2% faster walking speed. The route planner Walkit is operating at a 5% slower walking speed than anticipated and is shown to repeatedly underestimate the route distance (on average by 16%), therefore comparisons should not be drawn between Walkit and the Netlogo model. The strong correlation between the evacuation times produced by Netlogo and those of Google and RAC show that the Netlogo model is well calibrated and producing accurate evacuation times.

Table 4-7 – Calculated Netlogo and Route Planner Speeds

Route Planner	Trendline Equation	Calculated Speed
Netlogo	y = 0.0798x – 3E-15	1.34m/s 2.99mph
Google	y = 0.0782x – 0.036	1.31 m/s 2.93mph
RAC	y = 0.0784 – 0.0513	1.31m/s 2.94mph
Walkit	y = 0.0816x + 0.052	1.27m/s 2.84mph
Bing Maps	y = 0.0757x – 0.1456	1.37m/s 3.06mph

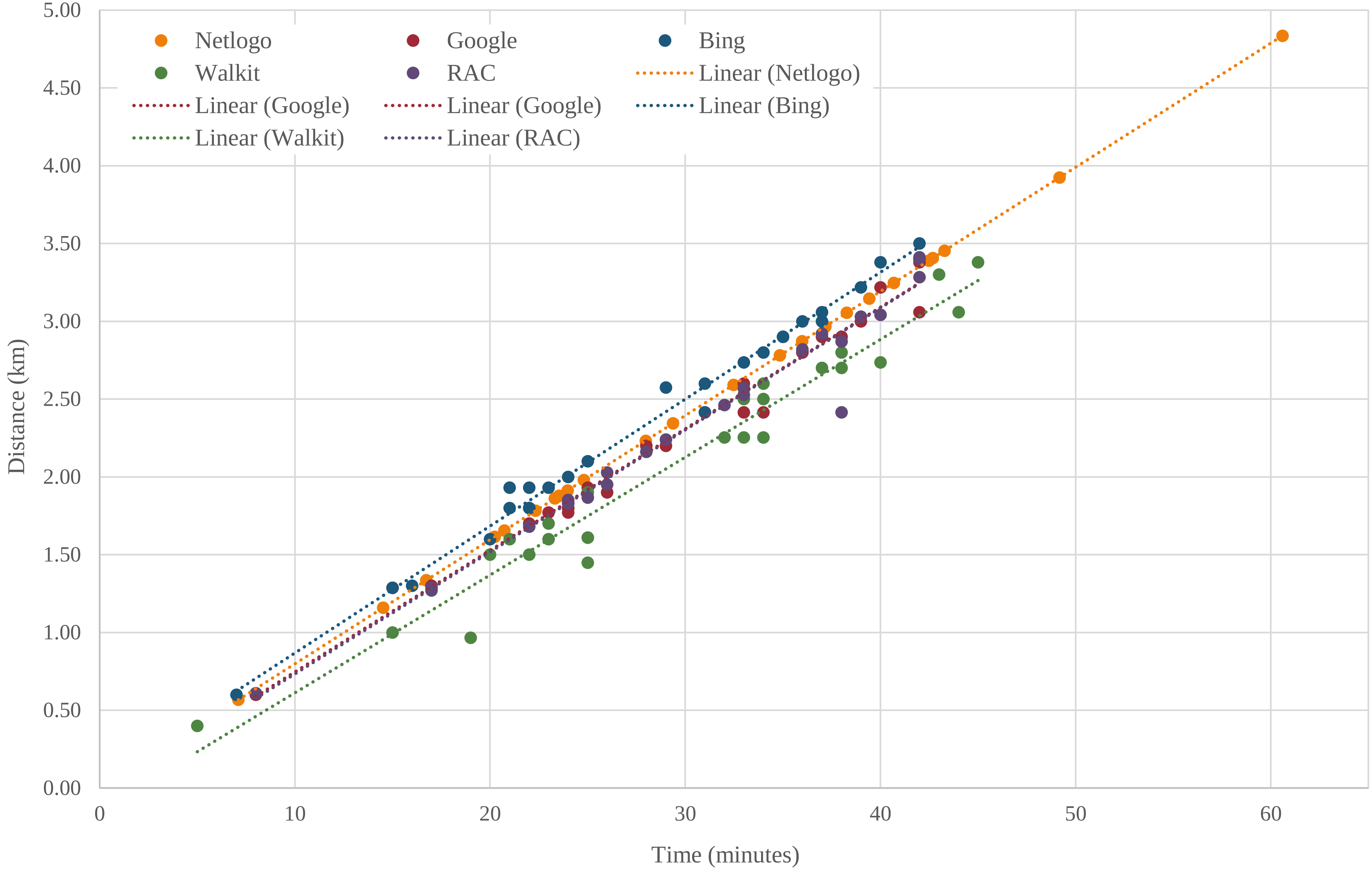


Figure 4-11 – Plot of Distance vs. Time for Route Planners and Netlogo Evacuation Model at 25 Different Locations

4.5 Conclusion

An initial macroscale city scale model has been created based on the city of Newcastle upon Tyne, UK. The model features several variables that can be set by the user linking to population size, population types, walking speed, group size and walking speed ratio, with the aim of reproducing realistic human behaviour traits. Calibration, validation, and verification is key to ensure the model is robust. The macroscale model has been successfully calibrated using existing route planners such as Google Maps, RAC and Walkit, which has shown that the time estimates produced are realistic and the shortest path algorithm employed is appropriate. A visual inspection of the simulations was also carried out to ensure that the agents moved as expected in the model environment. A final observational check was completed using a varied number of evacuees and walking speeds to understand the spatial variability in the model. The proposed testing regime for the macroscale has been set out; (1) utilise UK population data and walking speeds, (2) employ World population data and walking speeds and (3) include grouping of agents and ratio of walking speed applied to groups. Throughout all these tests, comparison will be made to existing agent-based models to understand the impact of including additional population characteristics and variables on evacuations timings. The test results will be explored comprehensively in Chapter 5.

Chapter 5. Macroscale Model (City scale) Testing

In chapter 4, the macroscale model was created and the human behaviour rulesets to be included detailed. In this chapter, the macroscale model will be tested to understand the implications of including a more robust representation of human behaviour within a city scale evacuation model. The testing will involve the inclusion of a range of population data from across the UK and internationally, to highlight the effect of considering slower agents (such as, children and OAPs) in the model. The macroscale model will also create groups of agents and explore the effect of this, including a factor to reduce walking speed based on the group size. This information is supported by the literature review in chapter 3, which includes the varied walking speeds, grouping of agents and the walking speed ratio, as summarised in section 3.4.2 and 3.5.2. Finally, conclusions will be drawn as to the benefits of incorporating these additional behaviours in the agent-based model, with the inclusion of quantification where possible.

5.1 Testing Schedule

The model has been calibrated using the route planners and the spatial variability assessed (see Chapter 4), it was then necessary to test the agent-based evacuation model to understand the effects of including a more robust representation of human behaviour. These tests were focused on the addition of population characteristics into the model environment as well as groups of agents and a walking speed ratio (Table 5-1). A range of population data was applied to the model environment to simulate UK and International populations, including population extremes such as a high proportion of children or OAPs, who are the slowest agents.

Table 5-1 – Testing Schedule for Macroscale City Evacuation Model

Test No.	Test Description	Test Aim
1 (Section 5.2)	UK Population Data & Walking Speeds	Understand: - The relationship between walking speed and evacuation time of a city (i.e. are they proportional) - How the evacuation times are affected by populations consisting of different demographics (e.g. age and sex)

		- How demographic composition affects evacuation times (e.g. proportion of slow agents in model)
2 (Appendix A)	World Population Data & Walking Speeds	Understand: - If the model needs to be calibrated for different locations (e.g. do locations with large numbers of children or OAPs need to input their own walking speeds) - To repeat test 1 (section 5.2) for different locations to understand how evacuation times may vary globally
3 (Section 5.4)	Grouping of Agents & Ratio for Walking Speed Applied to Groups	Understand: - If the inclusion of groups of between 1 and 4 agents affects the evacuation time of a city - If the application of a walking ratio is required to be applied to groups to affect the evacuation time of a city

5.2 Test 1 – UK Population & Walking Speeds

5.2.1 Test Aim & Variables

To begin with, the model was tested based on the information gathered in the literature review regarding varied walking speeds by age and sex of the population. To gain information regarding the proportion of different agent types, the walking speed data was combined with UK population data to ensure that the population used was realistic. The aim of this test, was to ascertain whether using varied walking speeds had any effect on the evacuation time of the case study area, including whether the population data needed to include the age and sex of the population or just the age. Within the test, three different scenarios were conducted to gauge the overall effect on evacuation time: (1) all agents have the same walking speed (2) varied walking speeds by age only, and (3) varied walking speeds by age and sex. These scenarios were run with a range of total population sizes (1000, 2000, 5000 and 10000) and population distributions based on different UK locations (Table 5-2), the test variations have been set out in Figure 5-1. The five different population distributions are the UK average, Newcastle, East Devon which has a larger OAP population, Slough which has a larger number of children and Tower Hamlets which has a larger adult population (Office for National Statistics (ONS), 2016) (Figure 5-2).

Table 5-2 – Macroscale City Evacuation Model Variables for Test 1 (For the walking speeds: C = Children, MA = Male Adults, FA = Female Adults, MO = Male OAPs and FO = Female OAPs)

Variables	1.34m/s (3mph) Walking Speed	Varied Walking Speed by age only	Varied Walking Speed by age and sex
No of Evacuees	1000, 2000, 5000, 10000		
Population Makeup	See Figure 5-2		
Walking Speed (Bosina & Weidmann, 2017)	All = 1.34 m/s (3mph)	C = 0.8m/s (1.79mph) MA & FA = 1.34 m/s (3mph) MO & FO = 0.78 m/s (1.74mph)	C = 0.8 m/s (1.79mph) MA = 1.34 m/s (3mph) FA = 1.12 m/s (2.5mph) MO = 0.78 m/s (1.74mph) FO = 0.76 m/s (1.70mph)

To get an indication on variability in the results, each set of variables and walking speed scenarios will have five realisations; this will result in 300 sets of evacuation times for this test, which equates to 60 results per location (Table 5-3). It was also necessary to understand the computational power required to run simulations in the model environment and whether reducing the number of variables had any effect on computational efficiency. The computational power was not easily quantified, instead this was reported anecdotally from the user's perspective.

Table 5-3 – Total Number of Results Expected from Test 1

	All Walking Speeds the Same					
evacuees	**Newcastle**	**UK Average**	**East Devon**	**Slough**	**Tower Hamlets**	**Total Tests**
1000	5	5	5	5	5	100
2000	5	5	5	5	5	
5000	5	5	5	5	5	
10000	5	5	5	5	5	
	Varied Walking Speeds by age only					
1000	5	5	5	5	5	100
2000	5	5	5	5	5	
5000	5	5	5	5	5	
10000	5	5	5	5	5	
	Varied Walking Speeds by age and sex					
1000	5	5	5	5	5	100
2000	5	5	5	5	5	
5000	5	5	5	5	5	
10000	5	5	5	5	5	

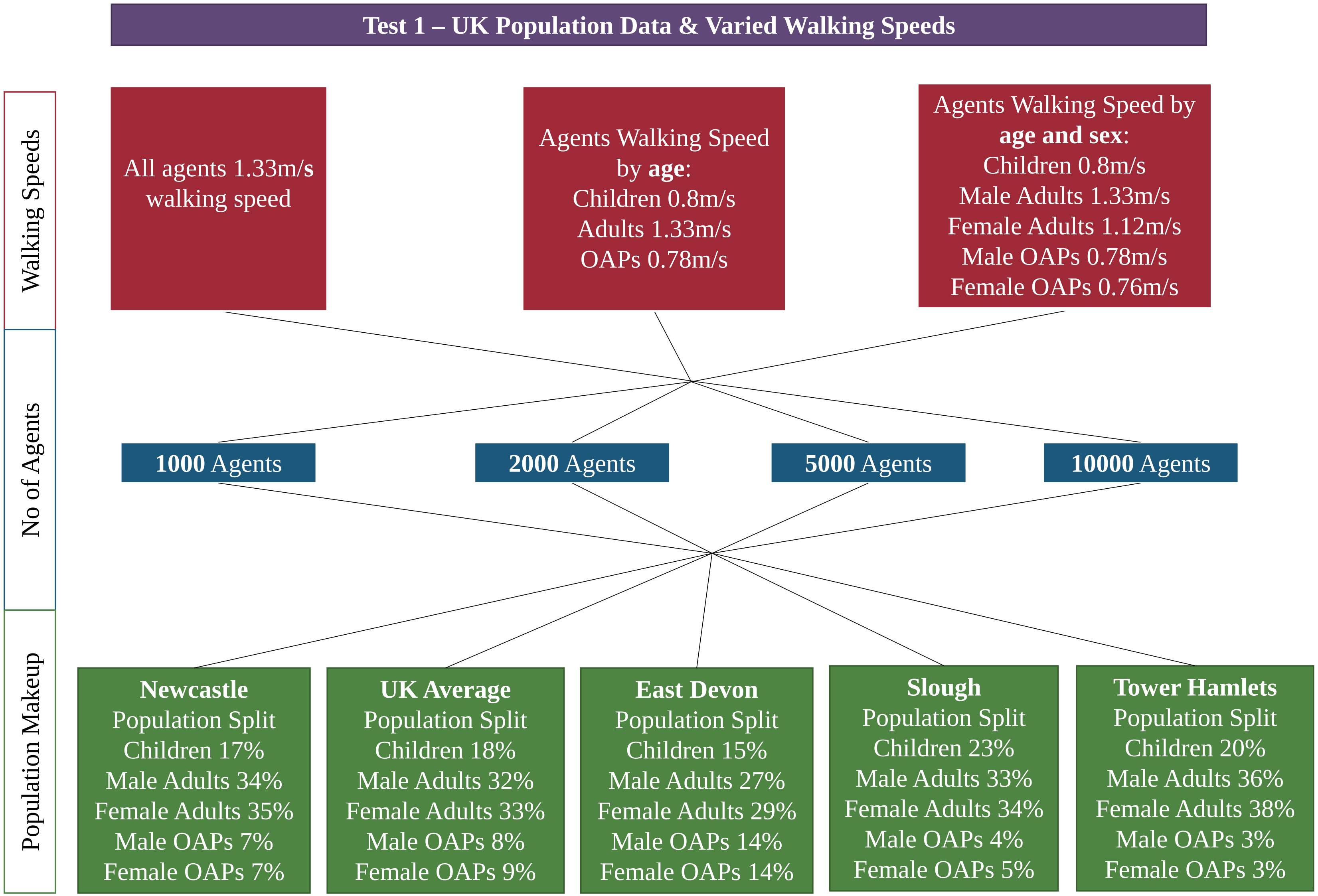


Figure 5-1 – Testing Regime for Test 1

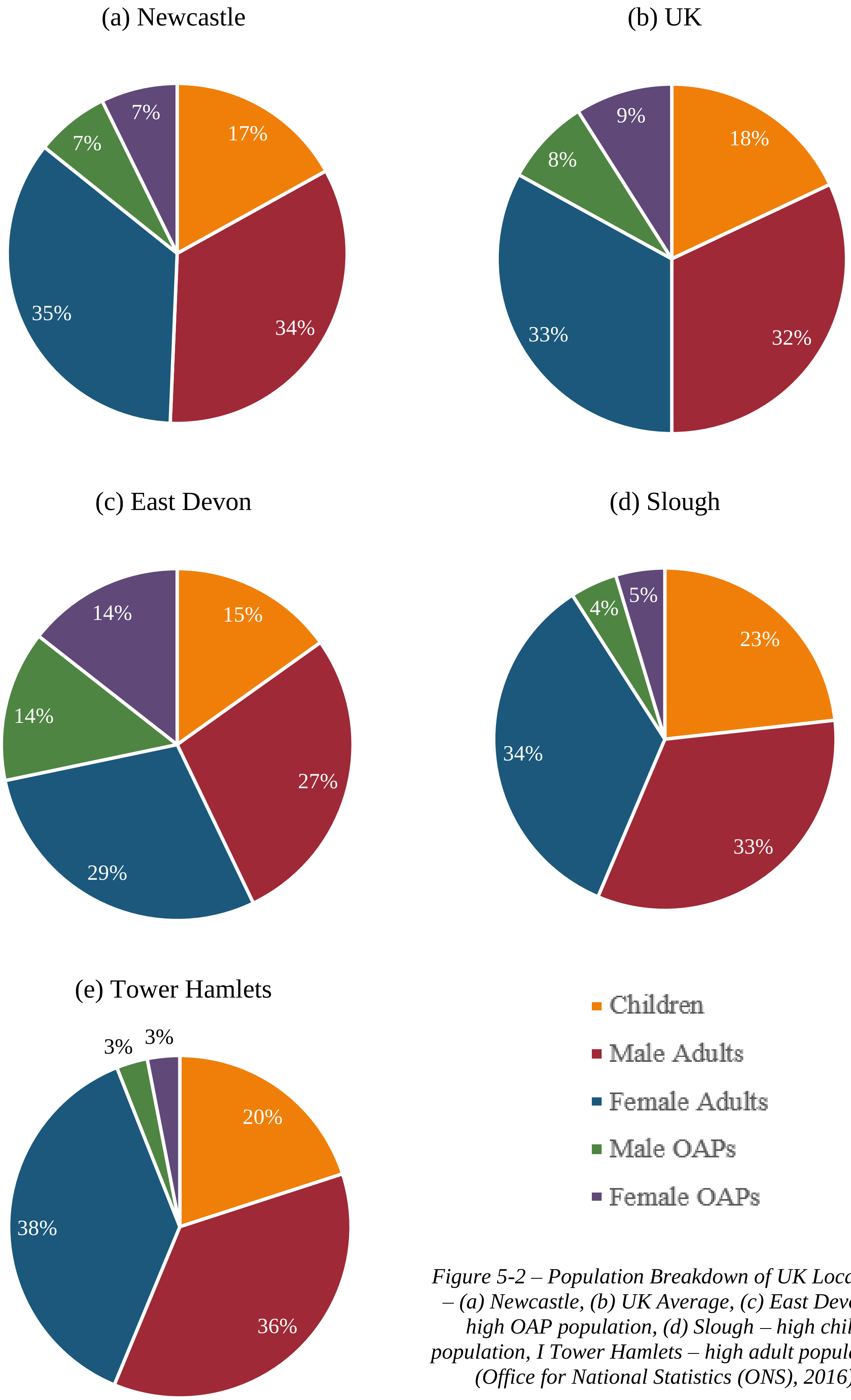


Figure 5-2 – Population Breakdown of UK Locations – (a) Newcastle, (b) UK Average, (c) East Devon – high OAP population, (d) Slough – high child population, I Tower Hamlets – high adult population, (Office for National Statistics (ONS), 2016)

5.2.2 *Initial Evacuation Times*

After completing the simulations for the different population make-ups with varied walking speeds, the averaged evacuation times for each population type were compiled (Table 5-4). This showed that there were a range of evacuation times produced when the demographics of the crowd was considered, demonstrating that there may be an impact of including population characteristics. However, it was important to understand whether this was a factor of the total population size, the inclusion of varied population characteristics (by age and/or sex) and the proportion of these different agents, or a combination of these factors. When walking speed was the same for all population types, there was little variation seen in the averaged evacuation times for the different regions (i.e. Newcastle, East Devon, etc.) (Table 5-4). The introduction of varied walking speed by age only, showed that the slowest agent types (OAPs and children) have an increased average evacuation time compared with the adults, approximately 60% slower, whereas adults slowed by only 3% (Table 5-4). Finally, the introduction of varied walking speed by age and sex demonstrated that the average evacuation times for adult females increased (by approximately 25%) whereas all other agents had similar evacuation times to the previous example (Table 5-4).

Table 5-4 – Average UK Evacuation Times (minutes) for different regions in the UK, showing (in the third column) average evacuation times when all agents walk at 1.34m/s, (in the fourth column) when agents of different age have different walking speeds and (in the fifth column) when both age and sex are considered in walking speeds

Variables		**Evacuation Time (minutes)**		
	Population	**1.34m/s (3mph) Walking Speed (minutes)**	**Varied Walking Speed by age only (minutes)**	**Varied Walking Speed by age and sex (minutes)**
Newcastle	Children	68.5	112.8	113.9
	M Adults		70.6	69.8
	F Adults			85.4
	M OAPs		114.6	113.7
	F OAPs			117.6
East Devon (Large OAP population	Children	68.7	114.3	114.7
	M Adults		70.7	68.5
	F Adults			83.8
	M OAPs		116.7	116.4
	F OAPs			121.5
Slough (Large	Children	67.4	113.8	118.8
	M Adults		70.9	70.8
	F Adults			83.8

Child population)	M OAPs		112.9	109.9
	F OAPs			117.4
Tower Hamlets (Large Adult population)	Children	67.3	116.6	115.2
	M Adults		70.8	68.3
	F Adults			86.5
	M OAPs		109.1	107.8
	F OAPs			112
UK	Children	69.2	114.9	115.6
	M Adults		71.2	70.5
	F Adults			83.4
	M OAPs		115.1	116.2
	F OAPs			117.8

To understand how evacuation times and simulation size (the total number of agents from a minimum of 1000 to a maximum of 10000) may vary between similar simulations, a plot of all the simulation results for each walking speed variant has been plotted (100 results for each variant) in Figure 5-3, Figure 5-4 and Figure 5-5. These figures show that there was a variation in evacuation times between the 100 results, which resulted from the initial random placing of agents. When all agents walk at the same speed (1.34m/s), the averaged evacuation time in Table 5-4 showed little variation between regions, as indicated by the small difference in standard variation of 1.63 minutes. However, overall, the plot of the 100 simulations has a standard deviation of 3.01 minutes, showing that there is variation between the evacuation times produced (Figure 5-3); this is likely to have been caused by the initial starting positions.

In Figure 5-4, the simulations where walking speeds were varied by age are plotted. In this figure it is clear to see the difference between the adult population and the children or OAPs. It is also possible to see that the children and OAPs have an increased variation compared to the adults, the standard deviation for adults is 4.38 minutes whereas children is 6.47 minutes and OAPs is 9.11 minutes (Figure 5-4). It is likely that this is a result of the random starting locations of agents, which means a greater or smaller number of slower agents were placed at the model boundary, this in turn effects the evacuation times produced.

Finally, when walking speed was varied by age and sex, there is now a difference between the male and female adult evacuation times produced, but the variation is small, the standard deviation for the male adults is 3.87 minutes and for female adults it is 4.93 minutes. There is greater variation for the slower agent types (children with a standard deviation of 6.87 minutes and OAPs with a standard deviation of 7.37 minutes (Male) and 7.56 minutes (Female)), as previously stated it is argued that this is a result of their initial random placement in the model (Figure 5-5).

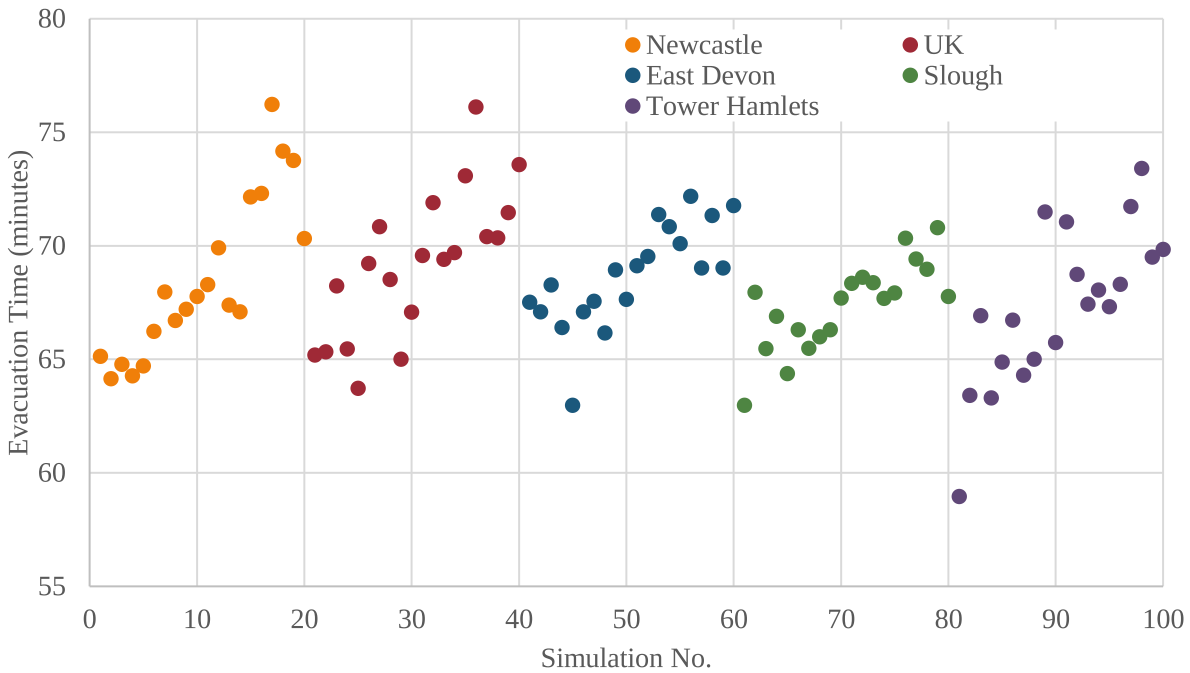


Figure 5-3 – All Evacuation Times Produced in Test 1 when Walking Speeds are the Same (1.34m/s or 3mph) mean of 68.22 minutes and Standard Deviation of 3.01 minutes (note the Simulation No. plotting position is arbitrary)

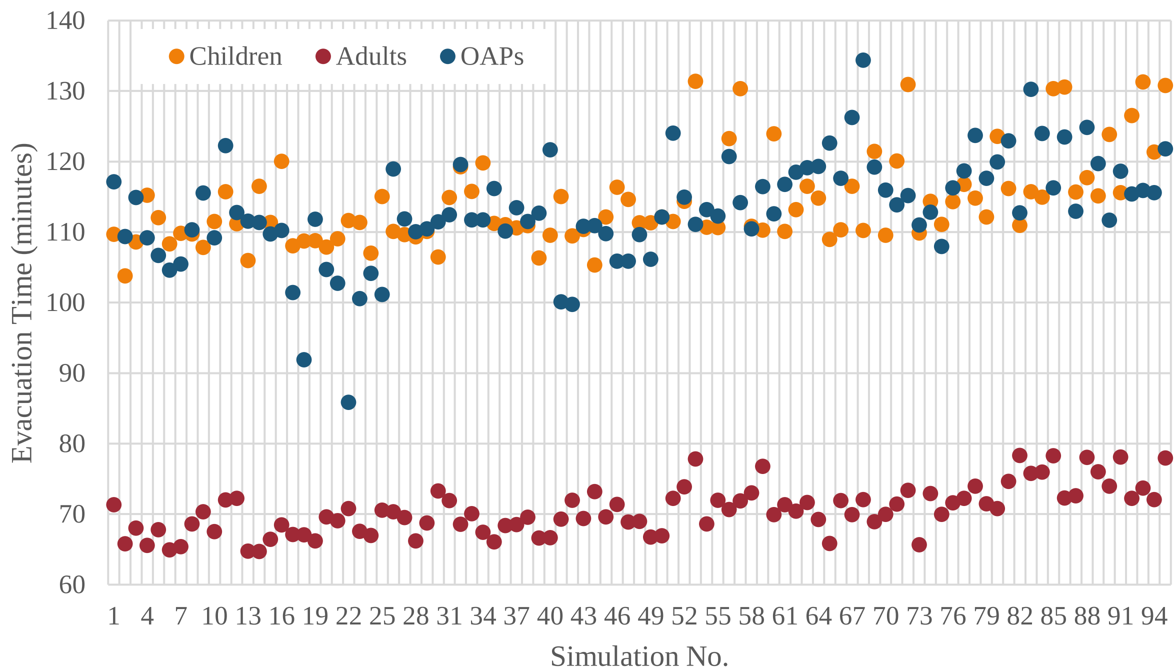


Figure 5-4 – All Evacuation Times Produced in Test 1 when Walking Speeds are Varied by Age only, for each population type: mean (standard deviation), Children: 114.23 minutes (6.47 minutes), Adults: 70.51 minutes (3.39 minutes) and OAPs: 113.29 minutes (7.49 minutes)

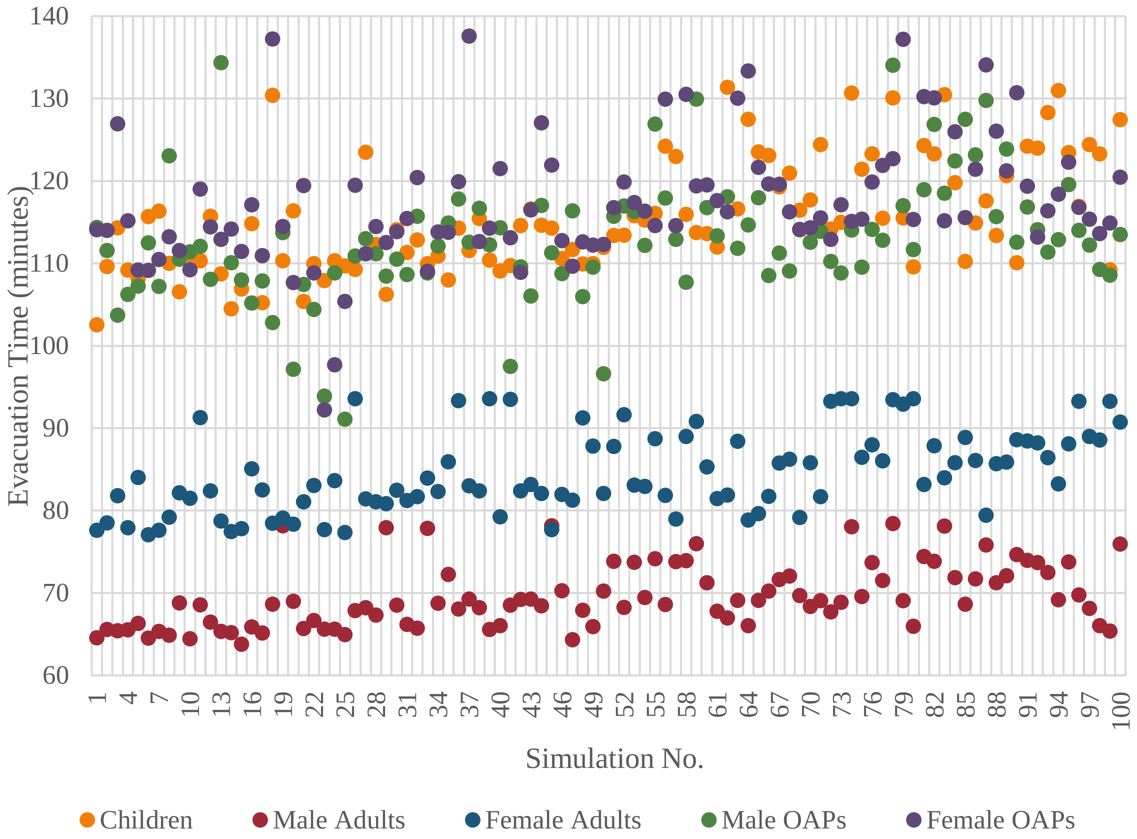


Figure 5-5 – All Evacuation Times Produced in Test 1 when Walking Speeds are Varied by Age and Sex, for each population type: mean (standard deviation), Children: 115.62 minutes (6.87 minutes), Male Adults: 69.57 minutes (3.87 minutes), Female Adults: 84.57 minutes (4.93 minutes), Male OAPs: 112.82 minutes (7.37 minutes) and Female OAPs 117.29 minutes (7.56 minutes)

5.2.3 Effect of Total Population Size

In the previous simulations it was demonstrated that total population size did effect evacuation times. In this section, the effect of this is explored in more detail. In Figure 5-6, Figure 5-7 and Figure 5-8 the data from the previous simulations is presented by population size and agent type for the different walking speeds. When all agents travelled at 1.34m/s (3mph), it showed that as the total population size increased, the overall evacuation time also increased (Figure 5-6). The difference in evacuation time was approximately 5.5 – 6.5 minutes between a population of 1000 compared to 10000. For the populations with varied walking speed by age only and for age and sex, a similar increase in evacuation time with increased total population size was observed. For varied walking speeds by age only, the difference in evacuation time was approximately 7 – 12 minutes (Figure 5-7) between a population of 1000 compared to 10000. For varied walking speeds by age and sex, the difference in evacuation time was approximately 5.5 – 10 minutes (Figure 5-8) between a population of 1000 compared to 10000.

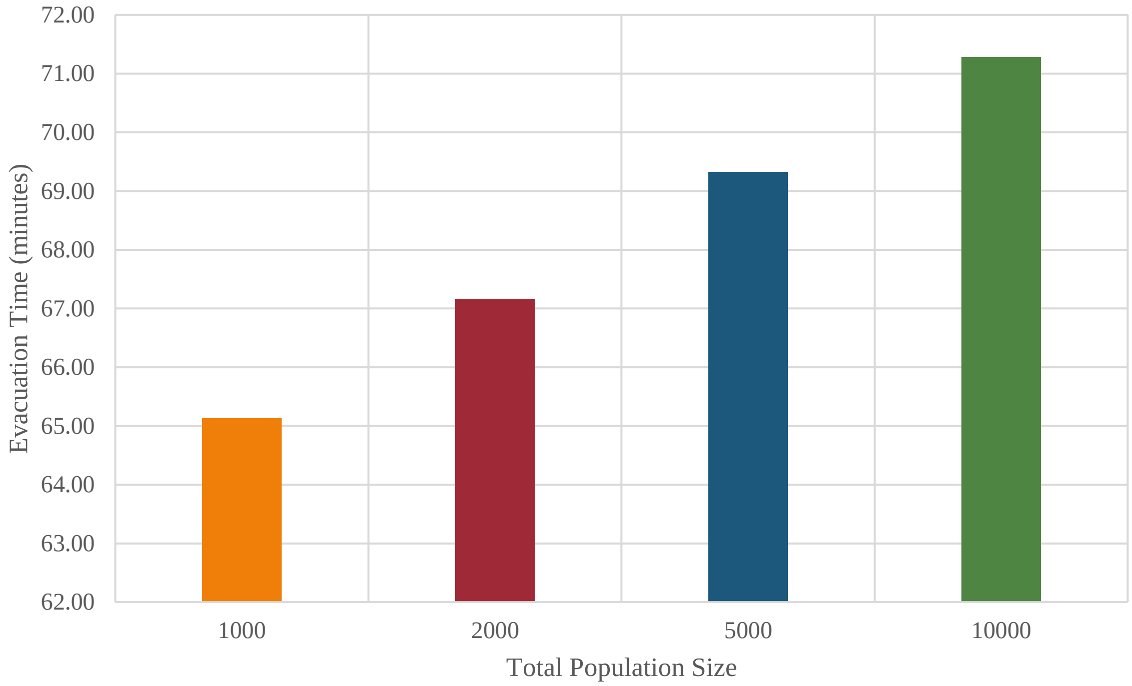


Figure 5-6 – Comparison of Total Population Size for all UK regional locations (e.g. Newcastle, East Devon etc.) with 1.34m/s (3mph) walking speed for all population types, approximate difference in evacuation times 5.5 – 6.5 minutes as total population size increases, mean of 68.22 minutes and standard deviation of 2.66 minutes

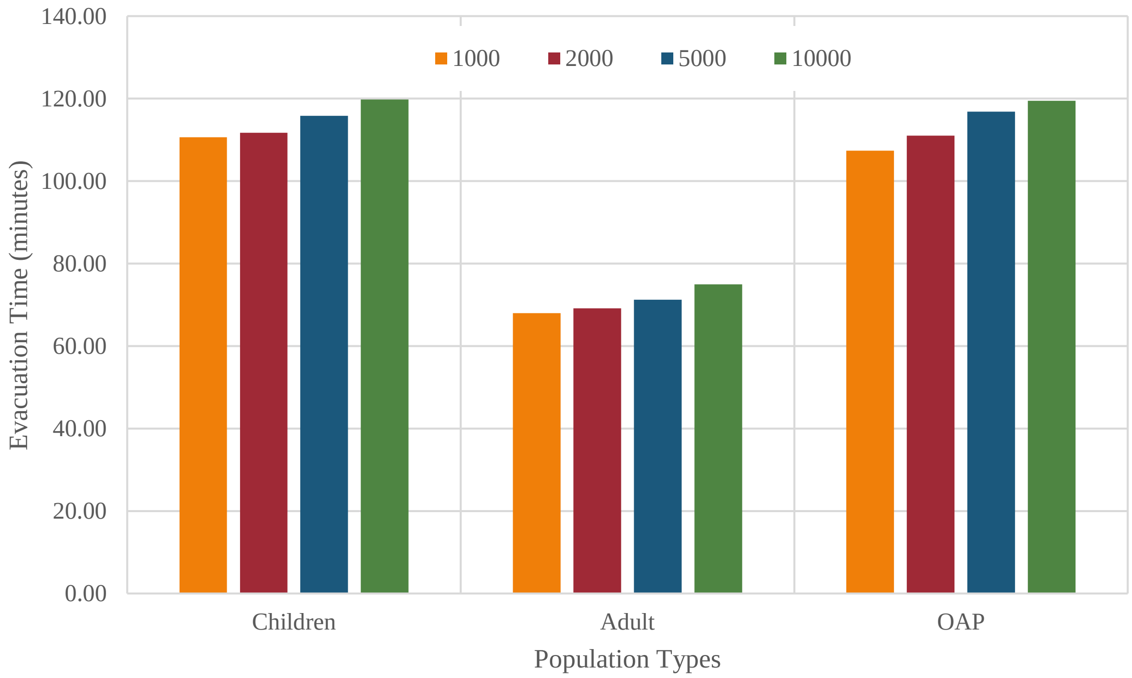


Figure 5-7 – Comparison of Population Size for all UK regional locations with varied walking speed for population types by age only, approximate difference in evacuation times 7 – 12 minutes as total population size increases, for each population type: mean (standard deviation), Children: 114.48 minutes (4.19 minutes), Adults: 70.82 minutes (3.08 minutes) and OAPs: 113.67 minutes (5.48 minutes)

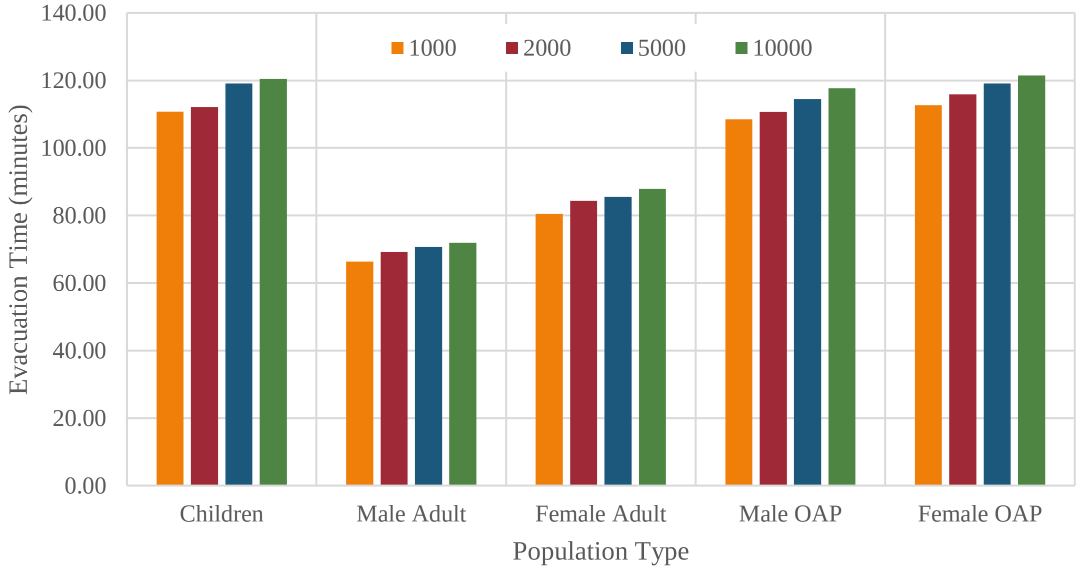


Figure 5-8 – Comparison of Population Size for all UK regional locations with varied walking speed for all different population types, approximate evacuation time difference 5.5 – 10 minutes as total population size increases, for each population type: mean (standard deviation), Children: 115.62 minutes (4.87 minutes), Male Adults: 69.57 minutes (2.40 minutes), Female Adults 84.57 minutes (3.12 minutes), Male OAPs 112.82 minutes (4.05 minutes) and Female OAPs 117.29 minutes (3.87 minutes)

The reason for the difference in evacuation time was the spatial variability of agents within the model. As the evacuation time is when the last person leaves the area, when the total population was larger, it was much more likely that there would be slow agents at the spatial extents of the model and therefore would need more time to evacuate (e.g. furthest from the point of safety) (Figure 5-9 and Figure 5-10). It should also be noted that when there were varied walking speeds applied, larger evacuation times were produced for the slowest agents in the model, which was expected despite there being a smaller percentage of these agent types in the model as their walking speed was greatly reduced (0.76m/s – 1.12m/s or 1.74mph – 2.5mph) compared to the standard 1.34m/s (3mph). It was also more likely with larger total populations that there was a slow agent at the model boundary so with a greater distance to travel and a reduced walking speed, the evacuation time would increase.

Figure 5-9 – Macroscale Model with Total Population Size = 1000 agents, agents are not densely covering the available starting locations with low total population size

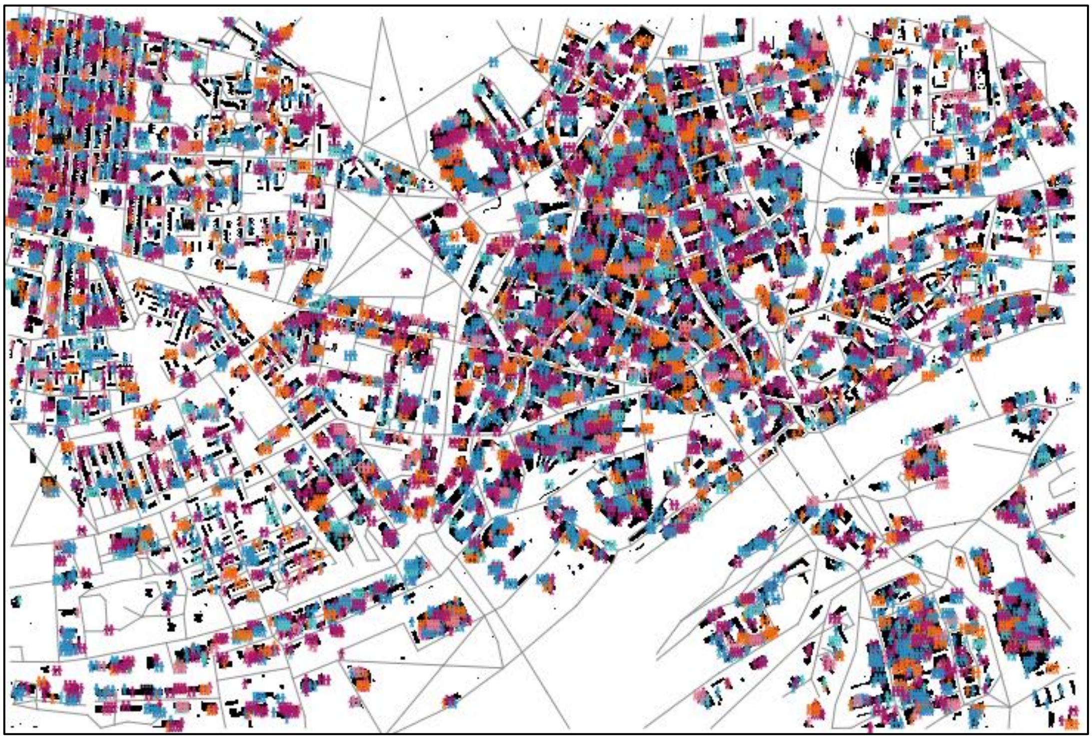


Figure 5-10 – Macroscale Model with Total Population Size = 10000 agent, agents are more comprehensively covering the available starting locations as total population size has increased

5.2.4 *Effect of Population Extremes*

Secondly, the effect of population extremes on overall evacuation time was examined, to understand if there was a need to include a larger number of slow agents in the model environment. This was conducted for populations at different UK locations which had population extremes (e.g. larger child, OAP, and adult populations). A comparison of the locations with varied walking speeds by age and sex showed that there was only a small difference in the evacuation times for each slower population type even when a population extreme was present (Figure 5-11). The largest difference was for the female OAPs, the time difference was 9.5 minutes between the slowest and fastest evacuation time, the largest evacuation time was seen where the OAP population was highest and vice versa for the smallest evacuation time. This indicated that a larger number of a slower population type will influence evacuation time. In comparison, for the children the evacuation time difference was 4.9 minutes and male OAPs was 8.6 minutes. Although the number of slow agents has had a small impact on evacuation time the key factor appeared to be the inclusion of population characteristics in the first instance as long as there were some slow agents captured, it did not need to be at the extreme.

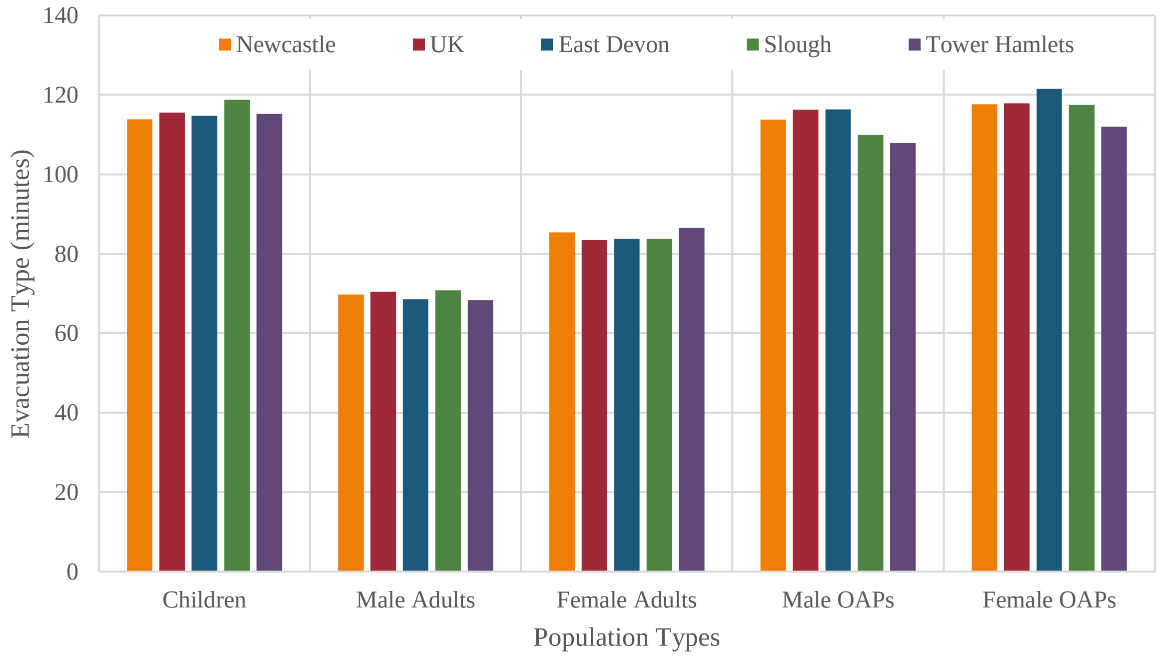


Figure 5-11 – Comparison of Different UK Locations and Average Evacuation Times in terms of Population Extremes (East Devon – large OAP population, Slough – large child population and Tower Hamlets – large adult population), with Varied Walking Speeds by age and sex, for each population type: mean (standard deviation), Children: 115.62 minutes (1.67 minutes), Male Adults: 69.57 minutes (1.00 minutes), Female Adults: 84.57 minutes (1.19 minutes), Male OAPs: 112.82 minutes (3.41 minutes) and Female OAPs: 117.29 minutes (3.03 minutes)

5.2.5 *Minimum & Maximum Times*

To further compare the evacuation times produced for the population extremes, the minimum and maximum times were plotted (Figure 5-12), this information was taken from all the available simulations. However, the maximum times were all found to be produced from simulations, which included a greater number of population characteristics whereas the minimum times were all produced from simulations with agents travelling at the same speed (1.34m/s or 3mph). The results show that there was little difference in the minimum and maximum times produced for each location, for the maximum times, the time difference was approximately 3.3 minutes and for the minimum times, the time difference was approximately 5.5 minutes. This again contributes to the idea that there is no need to simulate the model at a population extreme. A further plot was completed to identify the population type for each of the minimum and maximum evacuation times (Figure 5-13). This showed that all the maximum times were caused by slower agent population types but interestingly that the minimum was also attributed to the slower agent types. The maximum times generally tally with the largest percentage of slower agents as it more probable that one of the agents is at the model extents and therefore takes a longer time to exit the model. The converse of this is true when the model runs at 1.34m/s (3mph), in that there were far fewer of the additional agent types (children and OAPs) to exit the model and all agents were travelling at the same speed, which results in a faster evacuation time overall.

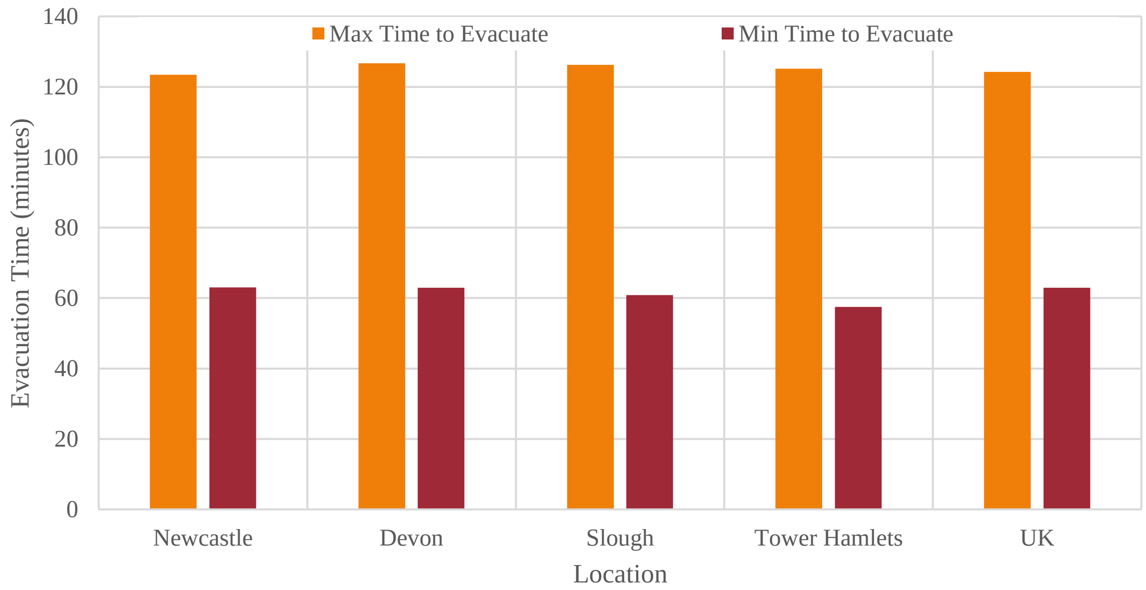


Figure 5-12 – Minimum and Maximum Evacuation Times (minutes) at UK Locations, time difference for maximum times approximately 3.3 minutes, time difference for minimum times approximately 5.5 minutes

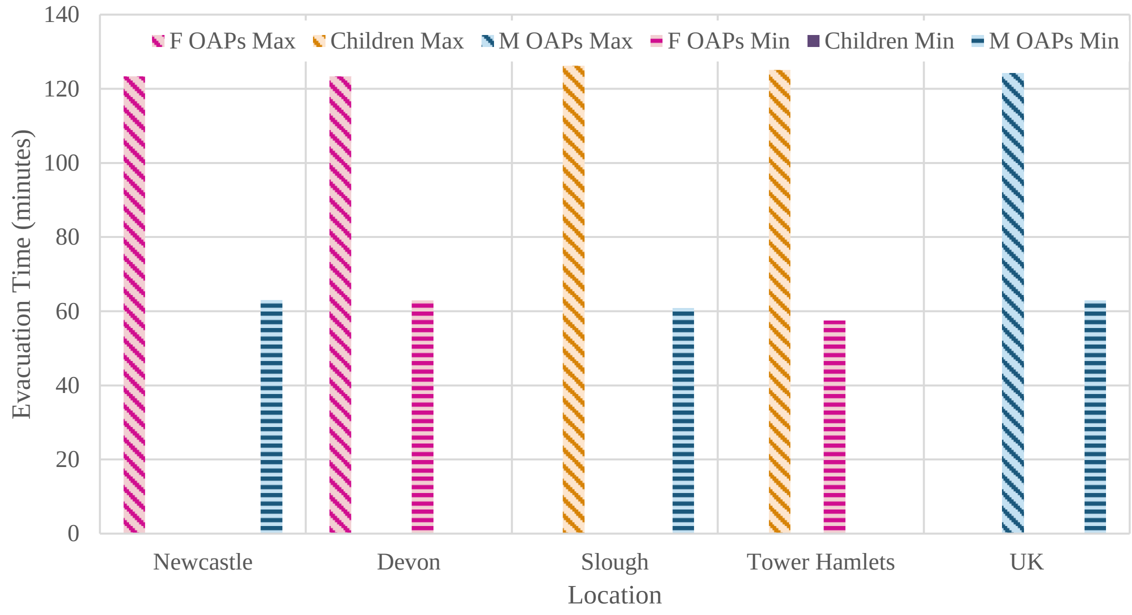


Figure 5-13 – Minimum and Maximum Evacuation Times (minutes), depicting the different population types at various UK Locations, Newcastle: maximum time by Female OAP, minimum time Male OAP, Devon: maximum and minimum time by Female OAP, Slough: maximum time by child and minimum time by Male OAP, Tower Hamlets: maximum time by child and minimum time by Female OAP and the UK: maximum and minimum time by Male OAP

5.2.6 Effect of Population Characteristics

Once it was ascertained that neither the total population size nor the inclusion of a population extreme was the primary cause for the differences in evacuation times calculated by the model the inclusion of the population characteristics was investigated. A comparison was made between the model considering only walking speeds of 1.34m/s (3mph) and the inclusion of varied walking speeds based on age or alternatively by age and sex (Table 5-5). This showed that there were some large time differences between the model simulations, an average of 30.6 minutes when walking speeds were added by age and sex and an average of 30.4 minutes when walking speeds were added by age only. This resulted in large percentage time differences and was particularly seen with the slower agent types. For varied walking speeds by age and sex in Newcastle, the children had 67%-time difference, male OAPs had 68%-time difference and female OAPs had 75% time difference when compared with a 1.34m/s (3mph) model (Figure 5-14). For varied walking speeds by age only in Newcastle, the children had 65% time difference and the OAPs had 70% time difference (Figure 5-15).

These large time differences demonstrate that the current evacuation models that include only agents walking at 1.34m/s (3mph) are producing misleading evacuation times by failing to consider a range of walking speeds. It also shows that there was little difference in the results produced by including age and sex versus age only, meaning where computational power is restricted it may be beneficial to consider reducing the number of population characteristics included, as additional variables appeared to make the simulations take longer to complete.

Table 5-5 – Comparison between UK Average Evacuation Times (minutes) and Simulations for different regions in the UK, showing (in the third column) the difference in average evacuation times between all agents walking at 1.34m/s and agents adopting walking speeds based on their age only and (in the fourth column) the difference in evacuation times between all agents walking at 1.34m/s and agents adopting walking speeds based on their age and sex

	Population Type	1.34m/s (3mph) Model vs. Varied Walking Speed by age only (minutes)	1.34 m/s (3mph) Model vs. Varied Walking Speed by age and sex (minutes)
Newcastle	Children	44.5	45.6
	M Adults	-1.0	-1.8
	F Adults		13.8
	M OAPs	47.2	46.2
	F OAPs		50.5
East Devon (Large OAP population)	Children	46.0	46.5
	M Adults	-0.8	-3.0
	F Adults		12.2
	M OAPs	49.3	48.8
	F OAPs		54.4
Slough (Large Child population)	Children	45.6	50.5
	M Adults	-0.7	-0.8
	F Adults		12.2
	M OAPs	45.5	42.4
	F OAPs		50.3
Tower Hamlets (Large Adult population)	Children	48.3	47.0
	M Adults	-0.8	-3.2
	F Adults		15.0
	M OAPs	41.8	40.3
	F OAPs		44.9
Average Time Difference		30.4	30.6
Average % Difference		44%	44%

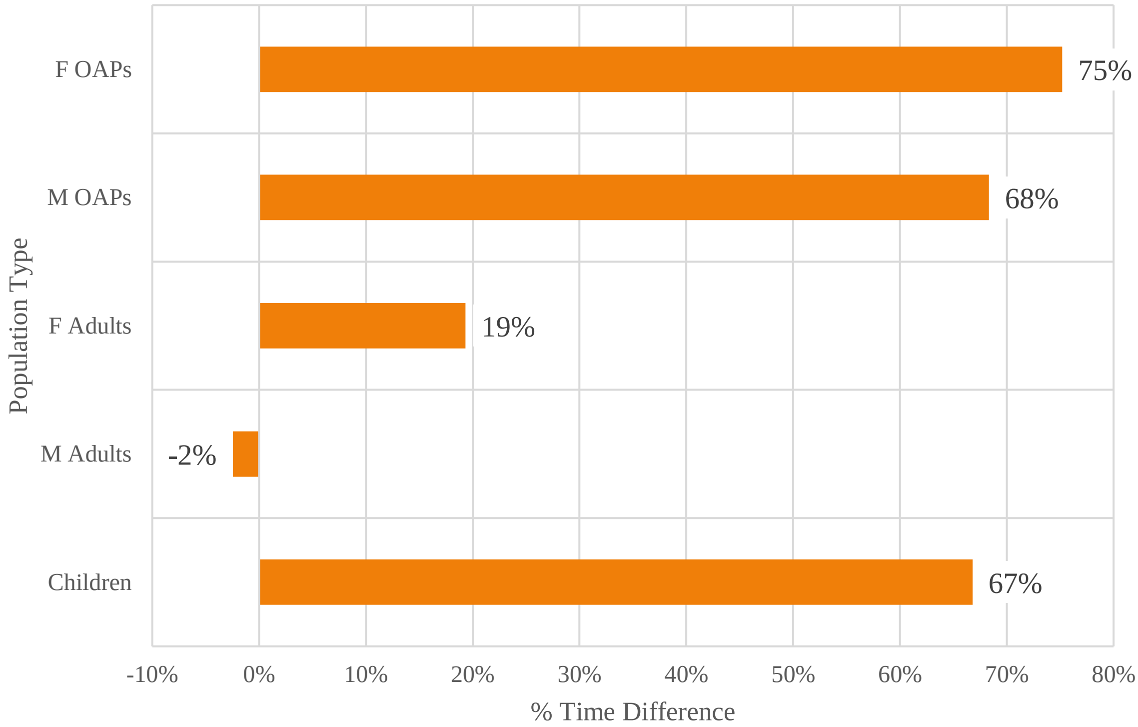


Figure 5-14 – Comparison of UK Average Population Data to Newcastle Population Data for 1.34m/s (3mph) Walking Speed vs. Varied Walking Speeds for All Population Types by Age and Sex, Mean Time Difference of 30.9 minutes and Standard Deviation of 23.4 minutes

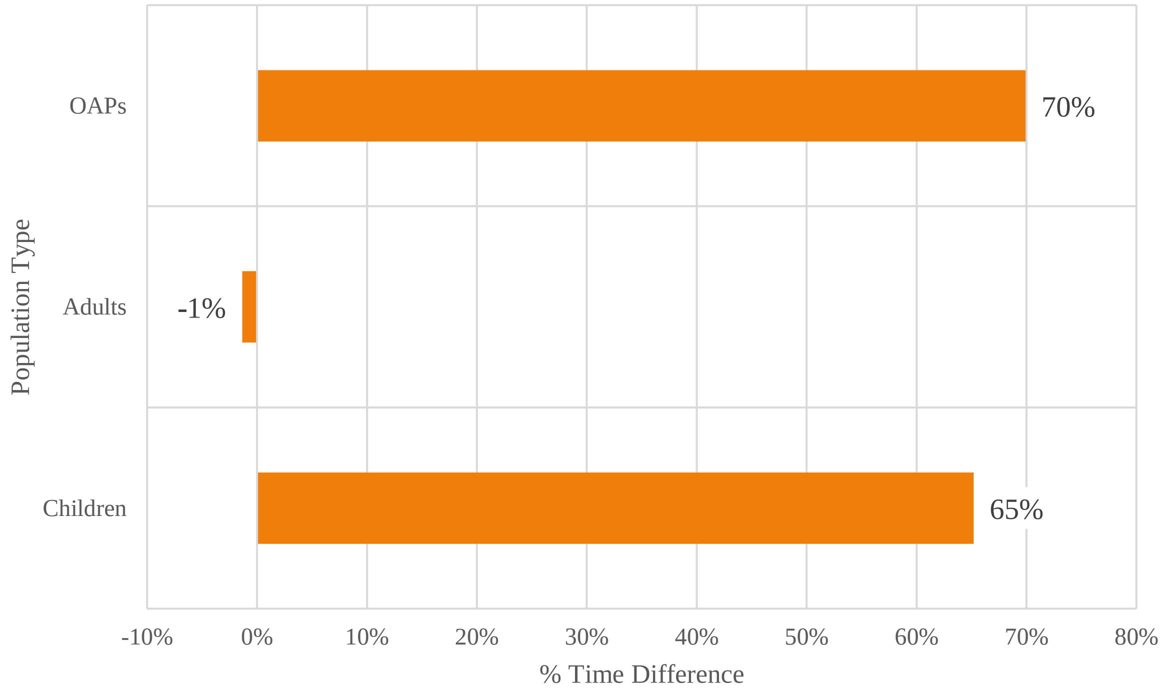


Figure 5-15 – Comparison of UK Average Population Data to Newcastle Population Data for 1.34m/s (3mph) Walking Speed vs. Varied Walking Speed for Population Types by Age Only, Mean Time Difference of 30.3 minutes and Standard Deviation of 27.1 minutes

5.3 Test 3 – Grouping of Agents & Walking Speed Ratio

5.3.1 Test Aim & Variables

The previous tests have shown that the introduction of population characteristics has had an impact on the evacuation times produced. The inclusion of varied walking speeds by age and sex was only a small number of the possible human behaviours that could be included within an agent-based evacuation model. Hence, it was deemed important to consider the impact of the addition of further behaviour traits on the evacuation times produced. This included the grouping of agents and a walking speed ratio, as it was previously demonstrated in the literature review in Chapter 3 that an increase in group size had the effect of decreasing walking speed (Bosina & Weidmann, 2017) (Rastogi, et al., 2011) (Moussaid, et al., 2010). This means that a robust agent-based evacuation model that includes groups should also consider the inclusion of a walking speed ratio.

The aim of this test was to ascertain whether using varied walking speeds, groups of agents and a walking speed ratio had any effect on the evacuation time of the case study area. Within the test, the model ran four scenarios to understand the effect on overall evacuation time: (1) all agents travelling at 1.34m/s (3mph) with groups of agents, (2) all agents travelling at 1.34m/s (3mph) with groups of agents and a walking speed ratio, (3) agents travelling at varied walking speeds by age and sex with groups of agents and (4) agents travelling at varied walking speeds by age and sex with groups of agents and a walking speed ratio . Each simulation was completed for one total population size of 1000 agents (Table 5-6) with the population make-up based on Newcastle, the test variations have been set out in Figure 5-18.

The group sizes were based on data from the Office for National Statistics (2016) on the UK household sizes from 2016, ranging from single person households to houses with four or more occupants. For ease within the model environment, the largest group size was capped at four agents. It was initially required to limit the group sizes to ensure that the variable had an impact on evacuation time, plus literature had shown that the groups larger than four did not significantly decrease their walking speed further. Hence, it was deemed acceptable to only include groups of up to four, but this may need to be reconsidered in the future with respects to capacity and congestion as larger groups will take additional space on the pathways and may affect evacuation times further. The model also assumed that the groups of agents took the speed of the slowest agent so if a child was present in a group, all agents would reduce their speed to that of the child, visually in the models the groups then changed to the colour of a child, to highlight to the user the slowest agent.

The walking speed ratio was adapted from previous studies on the impact of group size and walking speed by Bosina & Weidmann (2017), Rastogi et al (2011) and Moussaid et al (2010) (Figure 5-17). This meant that for single agents there would be no change to their walking speed but for agents in groups of four the walking speed would be reduced to 79% of their original speed (Figure 5-17). In total, each set of variables and walking speed scenarios will be tested 10 times; this will result in 40 sets of evacuation times for this test (Table 5-7).

Table 5-6 – Variables for Macroscale City Evacuation Model in Test 3

Variables	Setting
No of Evacuees	1000 evacuees
Population Makeup	Based on population make-up of Newcastle: Children = 17%, Male Adults = 34%, Female Adults = 35%, Male OAPs = 7%, Female OAPs = 7%
Walking Speed	Children = 0.8 m/s (1.79mph) Male Adults = 1.34 m/s (3mph) Female Adults = 1.12 m/s (2.5mph) Male OAPs = 0.78 m/s (1.74mph) Female OAPs = 0.76 m/s (1.70mph)
Grouping	See Figure 5-16
Walking Speed Ratio	See Figure 5-17

Table 5-7 – Total Number of Results Expected from Test 3

	All Walking Speeds the Same	Varied Walking Speed by Age and Sex	Total Tests
Newcastle, 1000 Agents, Grouping	10	10	20
Newcastle, 1000 Agents, Grouping & Walking Speed Ratio	10	10	20

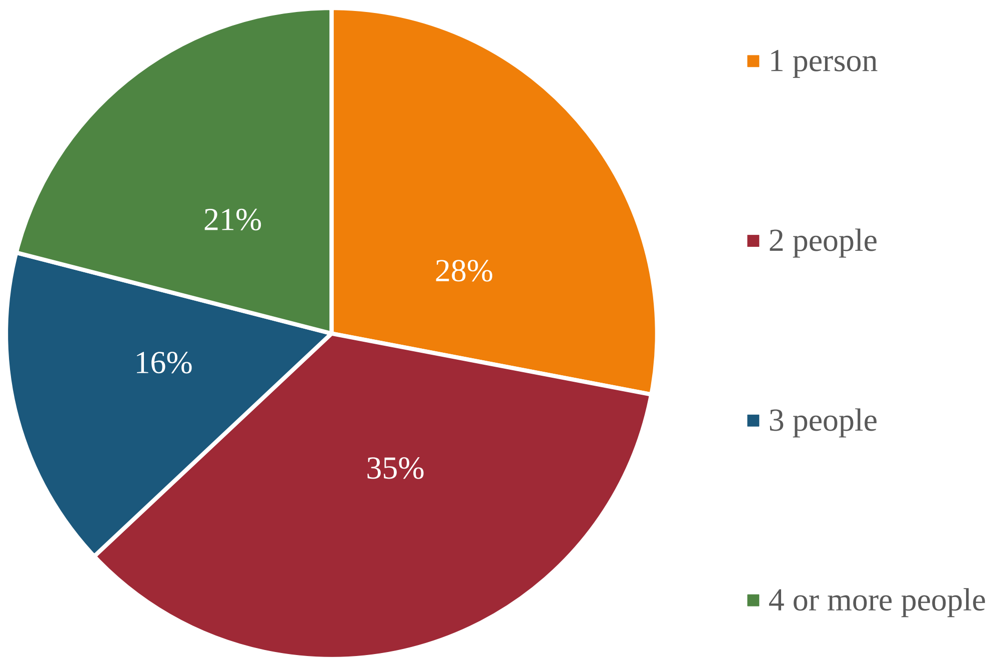


Figure 5-16 – Breakdown of UK Household Size (Office for National Statistics, 2016)

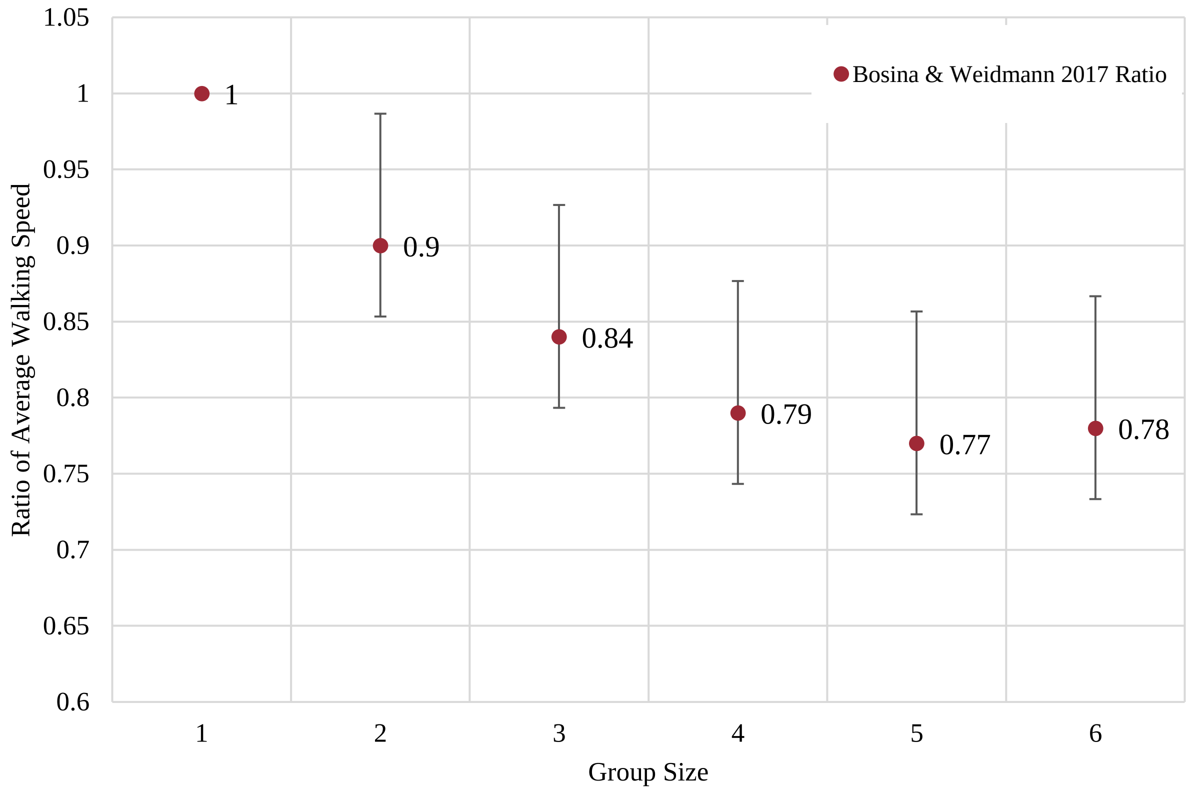


Figure 5-17 – Used Group Size Walking Ratio – Adapted from (Bosina & Weidmann, 2017), (Rastogi, et al., 2011), (Moussaid, et al., 2010)

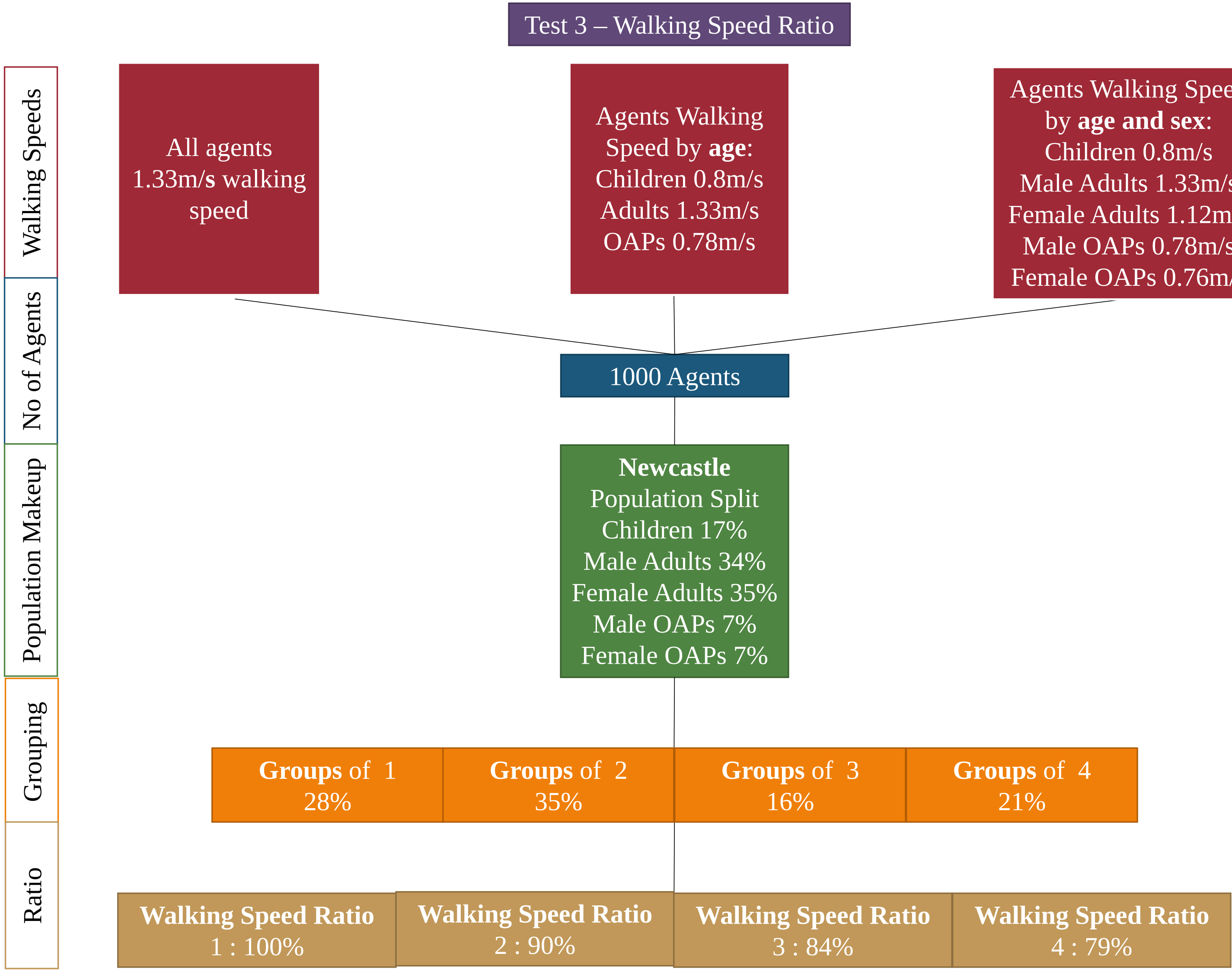


Figure 5-18 – Testing Regime for Test 3

5.3.2 Initial Evacuation Times

After completing the simulations for Newcastle with varied walking speeds, the groups of agents and the walking speed ratio, the averaged evacuation times for each population type were compiled (Table 5-8), due to the inclusion of groups, the number of population types increased. This showed that there were a range of evacuation times produced by altering the variables, demonstrating that there was an impact of including further population characteristics. There were some large time differences, particularly for the slower agent types compared to the 1.34m/s (3mph) model of between 25% and 127%. The male and female adults were also now more affected by time differences, ranging between 2% and 33%. The average time difference between the 1.34m/s (3mph) model and the model with varied walking speeds by age and sex plus groups was 57%. This was 7% greater than the average time difference without the ratio but varied walking speeds and groups included indicating that there was a need to also consider walking speed ratio within the model environment.

Table 5-8 – Comparison of Evacuation Time (minutes) with Varied Walking Speeds, Groups and Walking Speed Ratio Included for all Population Groups, showing (in the second column) the average evacuation times with all agents walking at 1.34m/s with grouping and walking speed ratio applied, (in the third column) the average evacuation times with agents adopting varied walking speeds with grouping and walking speed ratio applied, (in the fourth column) the difference in evacuation time and (in the fifth column) the percentage difference in evacuation time

Evacuation Population	1.34m/s (3mph) Walking Speed + Groups + Ratio (minutes)	Varied Walking Speeds by age and sex + Groups + Ratio (minutes)	Time Difference (minutes)	Time Difference (%)
Single Children	63.7	99.2	35.5	57%
Single Male Adults	64.5	65.5	1.0	2%
Single Female Adults	64.4	77.7	13.3	21%
Single Male OAPs	56.2	100.3	44.1	80%
Single Female OAPs	56.1	92.0	35.9	63%
Child Couples	68.1	119.0	50.9	88%
Male Adult Couples	67.0	71.6	4.6	7%
Female Adult Couples	68.0	84.4	16.3	25%
Male OAP Couples	57.0	108.5	51.5	104%
Female OAP Couples	56.5	104.5	48.0	90%
Child Triplets	68.5	94.3	25.9	54%
Male Adult Triplets	66.7	70.3	3.6	7%
Female Adult Triplets	69.3	75.5	6.2	11%
Male OAP Triplets	51.2	85.5	34.3	91%
Female OAP Triplets	40.7	85.0	44.3	115%

Child Quads	62.7	104.6	42.0	81%
Male Adult Quads	65.5	66.3	0.9	2%
Female Adult Quads	66.4	85.5	19.1	33%
Male OAP Quads	51.0	79.9	28.9	75%
Female OAP Quads	50.6	105.9	55.3	127%
AVERAGE	60.7	88.8	28.1	57%

The inclusion of groups created a greater number of population types, but a comparison needed to be made to the original five population types, to understand the impact on evacuation times. To compare the five main population types, the slowest evacuation time was taken from each of the 10 simulation runs and averaged to produce an evacuation time estimate. For the slower agent types, there were large time differences in evacuation time compared to the 1.34m/s (3mph) model of between 65% and 88% (Table 5-9) (Figure 5-19). The female adults were also affected by the addition of population characteristics, with an average time difference of 24%. The average time difference between the 1.34m/s (3mph) model and the varied walking speeds by age and sex with grouping was 35.5 minutes or 51%.

Table 5-9 – Comparison of Evacuation Time (minutes) with Varied Walking Speeds, Groups and Walking Speed Ratio Included for Main Population Groups (Children, Male Adults, Female Adults, Male OAPs and Female OAPs) (in the second column) the average evacuation times with all agents walking at 1.34m/s with grouping and walking speed ratio applied, (in the third column) the average evacuation times with agents adopting varied walking speeds with grouping and walking speed ratio applied, (in the fourth column) the difference in evacuation time and (in the fifth column) the percentage difference in evacuation time

Evacuation Population	1.34m/s (3mph) Walking Speed + Groups + Ratio (minutes)	Varied Walking Speeds by age and sex + Groups + Ratio (minutes)	Time Difference (minutes)	Time Difference (%)
Children	76.2	126.0	49.8	65%
Male Adults	75.9	75.7	-0.3	0%
Female Adults	74.3	92.4	18.1	24%
Male OAPs	66.7	118.9	52.3	78%
Female OAPs	65.6	123.3	57.7	88%
AVERAGE	71.7	107.3	35.5	51%

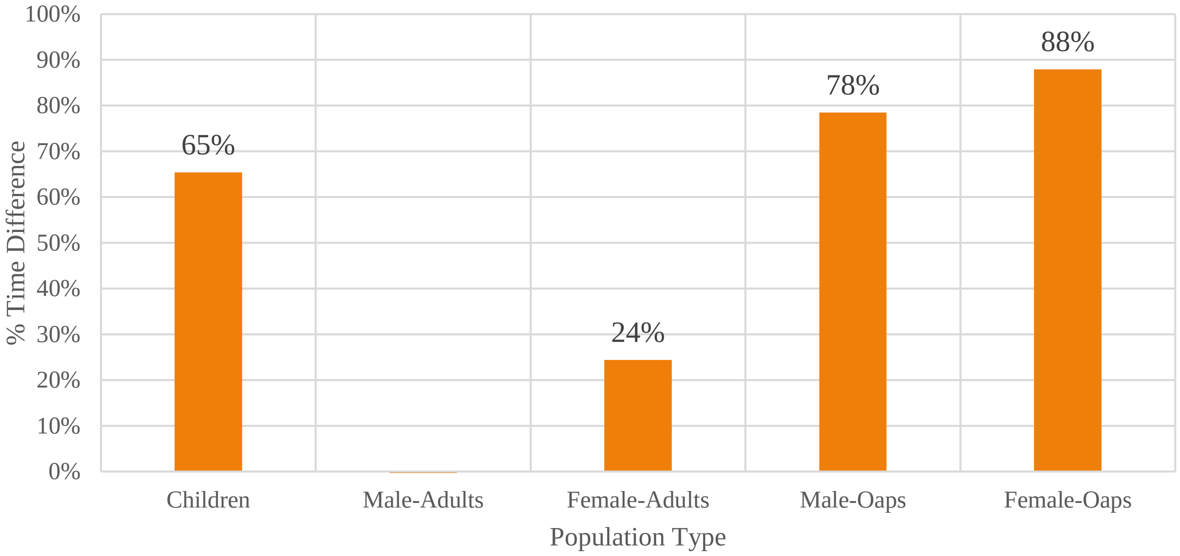


Figure 5-19 – Comparison of % Difference in Evacuation Times for Different Population Types with Applied Variables (Inclusion of Groups, Varied Walking Speed by age and sex and a Walking Speed Ratio), Mean Time Difference of 51%

5.3.3 Minimum, Average & Maximum Evacuation Times

To further compare the evacuation times produced, the minimum, average and maximum times were plotted (Figure 5-20). This again showed numerically and visually that the range in evacuation times produced for each overall population type had increased when compared to the previous tests. This meant that the groups and walking speed ratio were impacting evacuation time. Overall, it was found that the minimum evacuation times could be attributed to groups of three or four agents for each population type. It is believed that this was caused by the fact that there were far fewer groups of three or four, particularly when split across the population types, and therefore their place in the model was less likely to be at the extents so despite their walking speed being greatly reduced, the distance to travel was much lower resulting in a lower evacuation time. Interestingly, the maximum evacuation times were also attributed to groups of four agents, so when groups of agents were placed at the extent of the model, the distance to travel increased combined with a reduced walking speed meant the evacuation times were increased. The total population size did not significantly impact evacuation times, however in this instance as the population size was only 1000 agents, the spatial variability of the placement of agents and the number of different agent types has impacted the minimum and maximum evacuation times. The computational efficiency of the model was greatly reduced with the introduction of additional variables, which is the reason a smaller total population size was selected as well as the previous tests demonstrating that total population size did not significantly affect evacuation times. However, it does still highlight the need to include a range of walking speeds and population characteristics in order to produce accurate evacuation times. To reduce the spatial variability, the model user could run additional tests or increase the total population size if additional computational power were available.

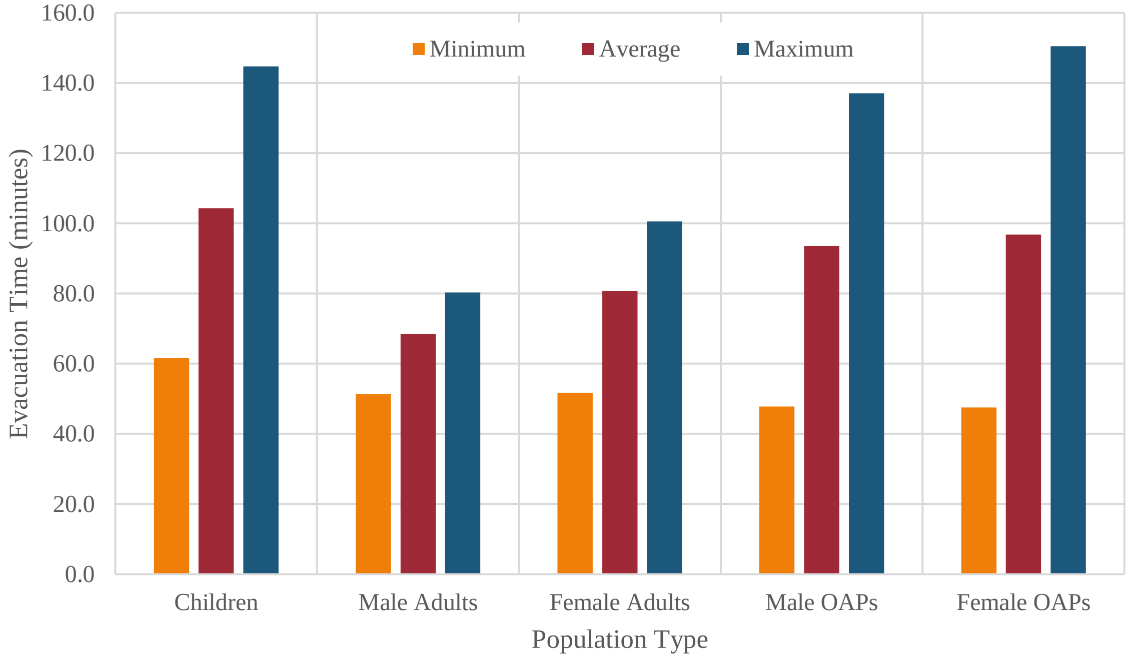


Figure 5-20 – Minimum, Average and Maximum Evacuation Times for Agents with Varied Walking Speeds by Age and Sex, Grouping Applied and a Walking Speed Ratio, for each population type: Mean (Standard Deviation), Children: 104.3 minutes (8.38 minutes), Male Adults: 68.4 minutes (4.09 minutes), Female Adults: 80.77 minutes (3.89 minutes), Male OAPs: 93.53 minutes (9.52 minutes) and Female OAPs: 96.85 minutes (12.78 minutes)

5.3.4 Comparison to 1.34m/s (3mph) Model

Finally, the various population characteristics have been compared to the 1.34m/s (3mph) model to understand their impact on evacuation time. This included the varied walking speeds by age and sex, the grouping of agents and walking speed ratio. The 1.34m/s (3mph) model also included the grouping of agents and walking speed ratio for comparison purposes. Three comparisons were completed (1) all agents walking at 1.34m/s (3mph) but with grouping applied vs. varied walking speeds by age and sex with grouping of agents, (2) all agents walking at 1.34m/s (3mph) with grouping applied vs. varied walking speeds by age and sex with grouping of agents and a walking speed ratio applied, and (3) all agents walking at 1.34m/s (3mph) with grouping and a walking speed ratio applied vs. varied walking speeds by age and sex with grouping of agents and a walking speed ratio applied.

For the first comparison, the time differences range between 0% – 106%, for the second 2% – 143% and the third from 1% - 109% (Table 5-10). The average time difference was greatest (71%) when comparing the 1.34m/s (3mph) model with groups with the varied walking speeds plus grouping and walking speed ratio (Table 5-10). This was to be expected as there were fewer factors applied to the 1.34m/s (3mph) model, which is a truer representation of existing agent-based evacuation models. However, it does demonstrate that there were still time differences present between the 1.34m/s (3mph) model with all factors applied when compared to the varied walking speed with all factors applied, meaning the evacuation times produced would still be misleading. Alternatively, this all indicates that there would be a benefit of emergency planners continuing to use a standardised (e.g. 1.34m/s (3mph)) speed provided additional characteristics were used, although this would still underestimate evacuation times it would be by a smaller factor.

Table 5-10 – Comparison of % Difference in Evacuation Time (minutes) with Varied Walking Speeds, Groups and Walking Speed Ratio applied compared with all agents walking at 1.34m/s showing (in second column) the difference between the 1.34m/s model with grouping added in and agents adopting varied walking speeds by age and sex with grouping, (in the third column) the difference between the 1.34m/s model with group added in and agents adopting varied walking speeds by age and sex with grouping and a walking speed ratio applied, (in the fourth column) the difference between the 1.34m/s model with group and walking speed ratio added in and agents adopting varied walking speeds by age and sex with grouping and a walking speed ratio applied

Evacuation Population	1.34m/s (3mph) Walking Speed + Groups vs. Varied Walking Speeds by age and sex + Groups	1.34m/s (3mph) Walking Speed + Groups vs. Varied Walking Speeds by age and sex + Groups + Ratio	1.34m/s (3mph) Walking Speed + Groups + Ratio vs. Varied Walking Speeds by age and sex + Groups + Ratio
Single Children	67%	60%	56%
Single Male Adults	0%	2%	2%
Single Female Adults	25%	22%	21%
Single Male OAPs	81%	83%	78%
Single Female OAPs	85%	61%	64%
Child Couples	76%	106%	75%
Male Adult Couples	2%	12%	7%
Female Adult Couples	20%	32%	24%
Male OAP Couples	81%	118%	90%
Female OAP Couples	74%	97%	85%
Child Triplets	62%	96%	38%
Male Adult Triplets	9%	32%	5%
Female Adult Triplets	19%	29%	9%
Male OAP Triplets	80%	126%	67%
Female OAP Triplets	97%	121%	109%
Child Quads	43%	102%	67%
Male Adult Quads	2%	20%	1%
Female Adult Quads	18%	48%	29%
Male OAP Quads	106%	107%	57%

Female OAP Quads	55%	143%	109%
AVERAGE	**50%**	**71%**	**50%**

To complete the comparison, the five main population types needed to be assessed, to understand the impact on evacuation times. This was again produced by taking the slowest evacuation time from each of the 10 simulation runs and averaging to produce an evacuation time estimate, before calculating the time difference. In comparison, the data showed that the greatest time differences were between the 1.34m/s (3mph) model with groups compared with the varied walking speed with grouping and walking speed ratio applied (Figure 5-21). Followed by the time differences between the 1.34m/s (3mph) model with all factors applied and the varied walking speeds with all factors applied. This clearly demonstrates the benefit of including additional population characteristics within an agent-based evacuation model if a user wants to produce accurate evacuation times.

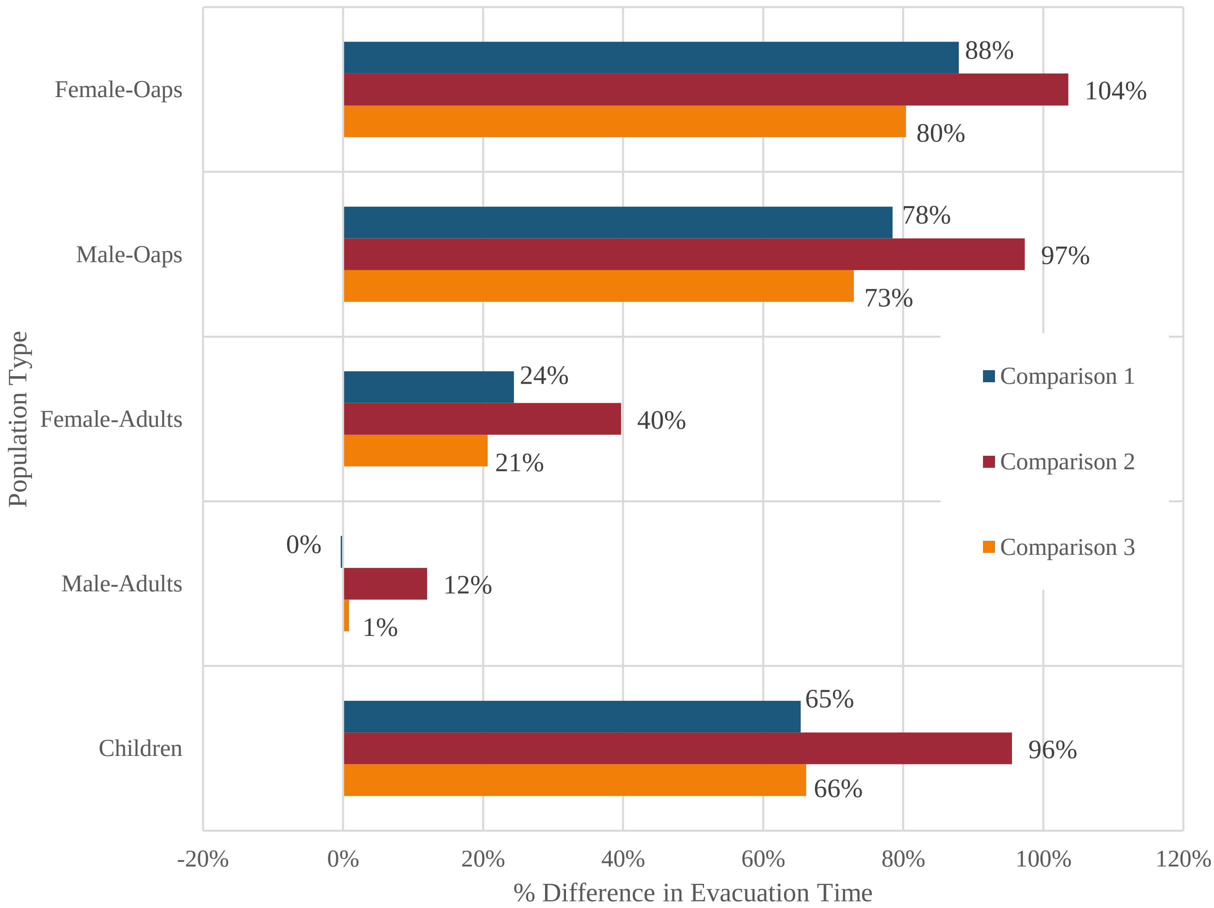


Figure 5-21 – Comparison of % Difference in Evacuation Time with Varied Walking Speeds, Groups and Walking Speed Ratio Included for Main Population Groups (Children, Male Adults, Female Adults, Male OAPs and Female OAPs. Comparison 1 = 1.34m/s (3mph) walking speed with grouping and walking ratio applied vs. Varied Walking Speeds by age and sex with grouping and walking speed ratio applied, Comparison 2 = 1.34m/s (3mph) walking speed with grouping applied vs. Varied Walking Speeds by age and sex with grouping and walking speed ratio applied, Comparison 3 = 1.34m/s (3mph) walking speed with grouping applied vs Varied Walking Speeds by age and sex with grouping applied.

5.4 Macroscale Model Testing Summary

The testing of the macroscale city evacuation model has demonstrated that including population characteristics (based on age and sex), varied walking speeds, grouping of agents and a walking speed ratio improves the robustness of the evacuation simulation when compared to existing evacuation models, which contain fewer or none of these variables. The addition of population characteristics based on age and varied walking speeds has shown an average evacuation time difference of 45% (Table 5-11). The further addition of population characteristics with sex considered has shown an average time difference of 46% (Table 5-11). This showed there was little difference between using population characteristics based on age or those based on age and sex, so where computational efficiency was an issue, the population characteristics could be reduced without impact. However, if additional variables were to be introduced such as grouping or the walking speed ratio, it is beneficial to split the population by age and sex.

The final addition of groups and a walking speed ratio has revealed an average time difference of 70% (Table 5-11). This clearly identifies the benefits of including supplementary variables in an agent-based evacuation model, these were the average time differences, which if broken down further show that the slower agent types (children and OAPs) were more significantly impacted by the introduction of these factors. With the addition of varied walking speeds by age or age and sex, the slowest population type's evacuation times were mis-calculated by between 67% - 83% (Table 5-12). The addition of the grouping and walking speed ratio saw the miscalculation jump higher still with differences of 92% and 109% (Table 5-12). Hence, if a user wishes to produce realistic and robust time estimates for an evacuation, it is necessary to consider a wider range of human behaviours and to effectively capture these within a model, else risk producing misleading results which could result in additional fatalities and injuries due to the inability to evacuate in time.

Table 5-11 – Comparison of the Average Results produced from Tests 1 – 3 with the Macroscale City Evacuation Model based on the addition of population characteristics, walking speeds, grouping and a walking speed ratio

Population Data	Population Types (Age)	Walking Speeds	Population Types (Sex)	Groups of Agents	Walking Speed Ratio	Compared to:
Newcastle	45%					1.34m/s (3mph) Model
East Devon	46%					
Slough	44%					
Tower Hamlets	44%					

Tokyo	48%	
Johannesburg	44%	
Seoul	45%	
Newcastle	45%	1.34m/s (3mph) Model
East Devon	47%	
Slough	46%	
Tower Hamlets	42%	
Tokyo	49%	
Johannesburg	44%	
Seoul	47%	
Newcastle	+70%	1.34m/s (3mph) Model with Groups
Newcastle	+50%	1.34m/s (3mph) Model with Groups and Walking Speed Ratio

Table 5-12 – Comparison of the Worst Case Results produced from Tests 1 – 3 on the Macroscale City Evacuation Model based on the addition of population characteristics, walking speeds, grouping and a walking speed ratio

Population Data	Population Types (Age)	Walking Speeds	Population Types (Sex)	Groups of Agents	Walking Speed Ratio	Comp
Newcastle	70% - OAPs					1.34m/s (3mph) Model
East Devon	73% - OAPs					
Slough	67% - OAPs & Children					
Tower Hamlets	71% - Children					
Tokyo	76% -OAPs					
Johannesburg	70% -Children					
Seoul	73% - OAPs					
Newcastle	75% - Female OAPs					1.34m/s (3mph) Model
East Devon	81% - Female OAPs					
Slough	75% - Female OAPs					

Tower Hamlets	69% - Children		
Tokyo	83% - Female OAPs		
Johannesburg	71% - Female OAPs		
Seoul	76% - Female OAPs		
Newcastle	109% - Male OAPs		1.34m/s (3mph) Model with Groups
Newcastle	92% - Female OAPs		1.34m/s (3mph) Model with Groups and Walking Speed Ratio

The macroscale evacuation model has successfully produced a series of evacuation time estimates for a range of population characteristics, walking speeds, groups of agents and applied a walking speed ratio. This has resulted in estimates that are more robust for times to evacuate an area of a city. However, to further improve the model's time estimates the spatial variability needs to be improved, capacity and congestion needs to be factored into the model and the model environment needs to be streamlined where possible. On top of this further validation needs to be carried out against real-world data or experiments to understand how realistic the time estimates produced are.

On top of this, despite the successes of the macroscale evacuation model, intricate human behaviours have not been fully captured such as passing on a pavement or a more complex interactions at a junction. To further increase the robustness of the model, these behaviours need to be captured within the model environment, to understand their impact on evacuation timings and the impact on capacity and congestion within an evacuation scenario.

Chapter 6. Microscale Model Setup

The previous chapters have demonstrated the need to robustly capture human behaviour within agent-based evacuation models. A macroscale agent-based model was created based on the city of Newcastle, to explore the inclusion of additional behaviour traits and their effect on evacuation timings. The model showed that the inclusion of population characteristics, varied walking speeds, groups of agents and reduction in walking speed for these groups produced more accurate evacuation timings for a city. It also demonstrated that current evacuation models may generate misleading evacuation times. However, the macroscale model could not capture the small intricate behaviours regarding congestion and capacity, which may have a further impact on evacuation timings.

This chapter will explore the creation of two microscale agent-based models (one consisting of a straight length of pavement and the other a crossroads) to understand the impacts of including capacity of corridors and multi-directional agent movement within the model environment. The models will again be created using Netlogo, for the reasons previously identified. The modelling outputs have been tested to ensure the rulesets used produce robust behaviours. The proposed testing regime has been set out alongside the anticipated outcomes of each test. Validation, calibration, and verification of the model has also been considered to ensure the validity of the model proposed.

6.1 Microscale Model (Pavement Model)

The first microscale agent-based model will investigate the interactions of humans when walking along a straight segment of pavement, specifically all agents moving in one direction with the ability to overtake slower agents. The model is again created using Netlogo software, as this is a grid-based system rather than continuous space, the pavement model is defined as a series of "lanes" (which agents walk along) rather than identifying one area for the agents to move freely within. The number of lanes, forming the pavement, can be varied to alter the overall width of the pavement (e.g. modelling a small lane to a large walkway). The aim of this model is to understand how people move along a pavement, in particular how agents overtake each other and how this is influenced by factors such as: the width of the pavement, the walking speeds of individuals and the population density.

The model is not based on any specific segment of pavement and is instead a generic representation, the maximum dimensions of which are 10 lanes wide by 1km long. The model can be used to calculate a travel time over the 1km length. In smaller cities such as Newcastle, the main shopping street is approximately 500m long, whereas larger cities like London, Manchester & Edinburgh they are 1km or longer. The 1km length is chosen as a mid-point between shorter and longer shopping streets in the UK (Table 6-1), and also provides sufficient length to display the agent behaviours, for example the model will attempt to capture overtaking behaviours which includes a varied patience level (i.e. how long would a faster walker wait behind a slower agent before attempting to overtake).

A standard pavement width in the UK is defined as 2m wide and the minimum road width is 4.8m, it is assumed that pedestrians primarily use a pavement when available; however, in stress situations such as evacuations, pedestrians are likely to move into using the road width to evacuate an area as quickly as possible (Table 6-2). As previously discussed in Chapter 3, section 3.4.2, all humans have a preferred interpersonal distance, which is the distance between themselves and another person, this can be varied depending on the situation, and how well the people know each other and whether the country is a contact or non-contact country. To understand the number of lanes required to form the width of a pavement in the model environment, the interpersonal distance as defined by Hall (1966) is used to find out the approximate number of lanes that would fit within a standard pavement and minimum road width (Table 6-2). The lower estimate for each of the distance categories (intimate, social and public) has been taken from Hall’s (1966) interpersonal distances and does not consider the person’s location. Using Hall’s (1966) distances, the number of lanes can range from one to ten lanes, as shown in Table 6-2; hence, it was decided to make this the upper and lower bounds for the number of lanes variable in this model. However, this model will only investigate three to five lanes as this would accommodate the grouping previously included in the city scale evacuation model. However, it is worth noting that this model does not include grouping in the same manner as the macroscale model, as the aim of this model is to capture the movement of individuals and understand the influence of the pavement width, walking speeds and patience for example.

Table 6-1 – Approximate Lengths of UK Shopping Streets (Google Maps, 2020)

Street	Location	Length (m)
Northumberland Street	Newcastle	480
Oxford Street	London	960
Deansgate	Manchester	1127

Royal Mile	Edinburgh	1810

Table 6-2 – Number of People on Pavements & Roads (rounded to the nearest whole number) based on Interpersonal Distance as defined by (Hall, 1966), (Baldassare & Feller, 1975) & (Sorokowska, et al., 2017), Road and Pavement Dimensions interpreted from Manual for Streets and Highway Design Guide (Department for Transport , 2007)

Interpersonal Distance		Number of People on:	
Hall, 1966	**Distance (m)**	**Standard Width Pavement (2m)**	**Minimum Width Road (4.8m)**
Intimate	0.46	4	10
Personal	1.22	2	4
Social	2.10	1	2

6.1.1 Model Description

The aim of this model is to explore the impact on travel time of: (1) agents overtaking each other on a pavement, (2) varying population density, (3) introducing a patience level for agents, (4) the variation of pavement width, and (5) including varied walking speed by age and sex. To achieve this, the model will include several variables, which are a mixture of previously defined variables taken from the macroscale model and new parameters introduced to simulate intricate human behaviours.

Table 6-3 – Microscale Pavement Model Variables

Variable	Defined in:
Population Types & Distribution	Chapter 4 (Table 4-1) & 5 (Table 5-2 and Figure 5-2)
Walking Speeds	Chapter 4 (Table 4-1) & 5 (Table 5-2)
Patience	New Variable
No of Lanes	New Variable

The previously defined variables, such as the population distribution and walking speeds are set out fully in Chapter 4 and 5, which allows the user to simulate a mixture of populations and walking speeds. A series of typical variables are suggested to the user, based on UK data and literature (Table 6-4).

To complement the previous variables, several new variables are included, specifically the population density, the number of lanes within the model environment and patience level of each agent. These variables are specifically included to help simulate the movement of agents, particularly when overtaking slower agents. The number of lanes variable is created to simulate a range of pavement widths (allowing for comparison) and will be varied between three to five lanes of agents (Table 6-2). The population density is introduced to remove the inconsistency of initial agent placement caused when using a total population size, as was the case with the macroscale model.

In this model, the aim is to capture a population moving along a pavement, to do this accurately, there is a need to allow the agents to overtake. From observations of a typical pavement, it is easy to see that it is not always possible to pass another person immediately and there may be time waiting to find a suitable gap to pass. In some instances, a person will slow to the speed of the slower individual, whilst others will seek the first possible opportunity to overtake and continue at their preferred speed. This can be interpreted as a level of patience, the person willing to wait will have a high level of patience whereas the individual looking for the first opportunity to overtake will have a low level of patience. In stress situations, such as an evacuation it can be assumed that the levels of patience would be decreased to zero.

In Chapter 3, multiple human behaviours were set out, which included crowd behaviour and the aggression that may be present. One study suggested the inclusion of a panic parameter, to capture the panic involved in an evacuation scenario (Helbing, et al., 2000), the inclusion of which may provide more robust evacuation simulations. Using the principle of the panic parameter i.e. a random numerical value assigned as a level of panic, the patience level is created within this model. There is no literature to guide the patience level values and this would be outside the scope of this study, instead the variable is being used to assess the impact on overall behaviour and travel times along the pavement. The patience level of the agents demonstrates the frustration an individual or at times a crowd may experience, which is often heightened during stress situations. The patience level included in this model is effectively equivalent to the number of time steps an agent will wait behind a slower agent before attempting to move around another agent to an empty lane. A low patience level means an agent will seek to change lanes more often than an agent with a high patience level. To model this, each agent starts with a level of patience (assigned as a numerical value), which reduces to zero when they are behind a slower agent (losing one point each time step). When the patience level reaches zero, the agent will look either side for a gap to move into. If there is no space available the agent will not move and will continue behind the slower agent at their speed, whilst continually looking for an available gap. If there is a space available, the agent will change lanes, accelerate back to their original chosen speed and reset their patience value

(Figure 6-1). It should be noted that the model has not attempted to capture the pushing and shoving that may occur during panicked scenarios. This is primarily due to the constraint of Netlogo's gridded cell system which does not all true free movement of the agents in the model. Without the free movement, it is difficult to allow the pushing and shoving to occur as agents need to base their movement decision on the space ability in their surrounding cells. The user has the ability to alter the aggression within the crowd by setting low patience levels which encourages agents to make more movement decisions and to overtake more frequently, which is as close as this model can get to producing pushing and shoving that may occur. This approach allows the user to find balance between "normal" scenarios i.e. no hazard event and scenarios where hazards are present.

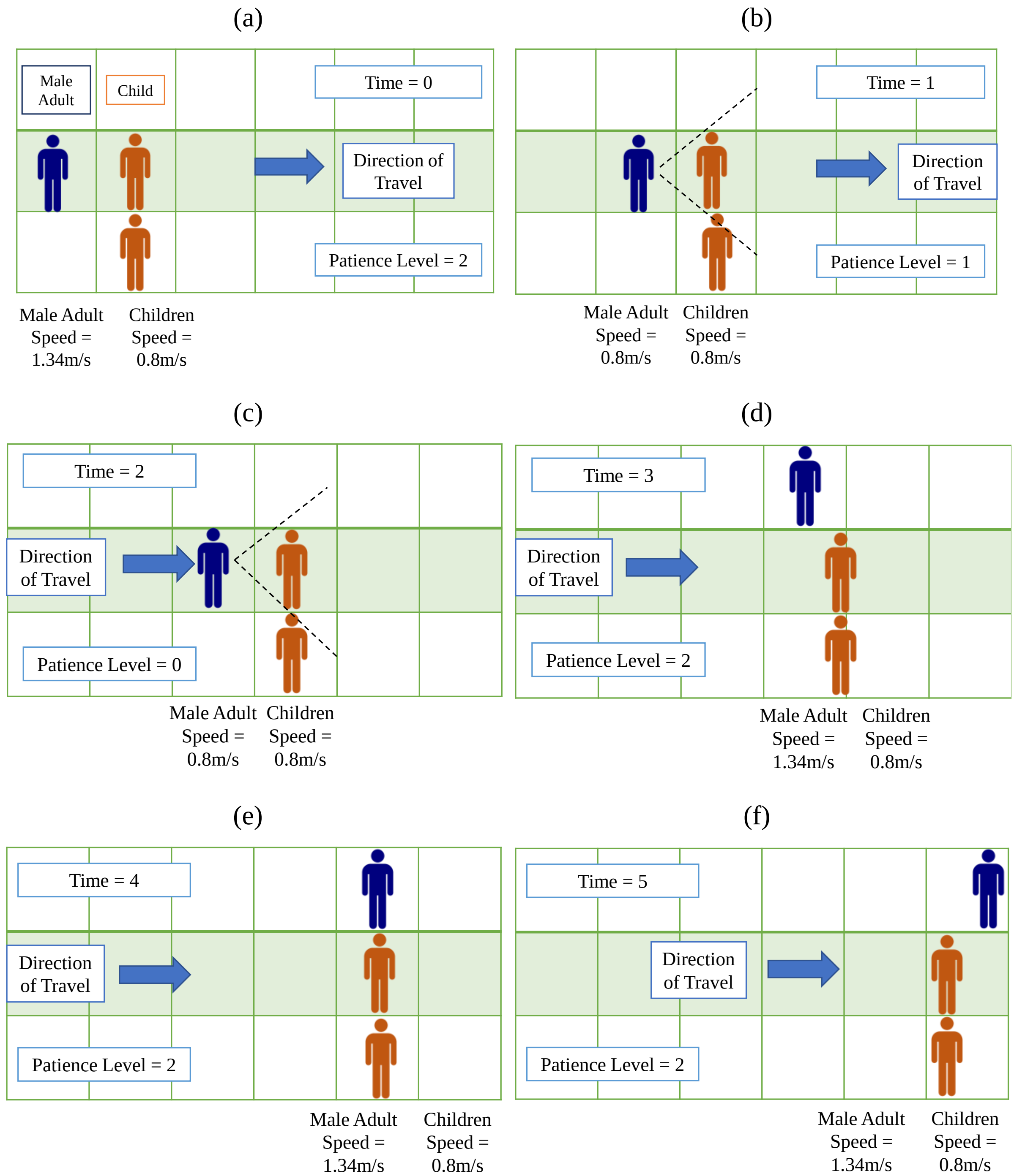


Figure 6-1 – Number of Lanes Agent Movement Diagrams – An example of three agents interacting to demonstrate the use of the new variables, this shows two slower agents (children) blocking the path of a faster male adult agent (Figure 6-1(a)). Initially, the male adult has to identify that his path has been blocked, this is done by looking one patch (i.e. step) ahead along the direction of travel, if an agent is present then the male adult needs to slow down, so decelerates to the speed the children are travelling at (Figure 6-1(b)). This then begins the patience level countdown; the patience level is only set at two, meaning the agent will attempt to move after only two time steps of having a blocked path (Figure 6-1(c)). Once the patience level has reached zero, the agent looks to identify which of the adjacent lanes are empty, in this example there is only one lane empty (Figure 6-1(d)). If both lanes were empty, the agent chooses at random the direction of movement, as the distance to travel is equidistant. On identifying the available lane, the male adult must accelerate back to their top speed and into the new lane, whilst resetting his patience level (Figure 6-1I (e) and (f)).

In the previous macroscale model, the agents were randomly assigned a starting location, meaning it was difficult to compare the travel times produced, as the agents may not always be placed at the model extents. This is particularly an issue when the population density is low as each agent may not be placed at the positions furthest from the exit location, which can produce unrealistic differences in travel time. To alleviate this, a series of agents (Bob (male adult), Betty (female adult), Ben (child), Barry (male OAP) and Barbara (female OAP)) are created on home squares so their starting location are constant in the pavement, this allows travel times over the entire 1km length to be compared more effectively.

The model interface features the variables described, which can be set by the user, and the representation of the pavement, shown by patches of grass and grey patches marked with lines to delineate the pavement surface and different lanes (Figure 6-2 and Figure 6-3), which was interpreted from existing Netlogo models available in the model library on traffic intersections (Wilensky, 1997) (Wilensky & Payette, 1998). An exit (safety) is marked by a line of red patches at the end of the 1km stretch, this can then be used to calculate the travel time of the different agent types placed on home squares. There are also several counters displaying population types and speeds, alongside a graphical output of the speeds, population levels and number of people using each lane (Figure 6-2). Once the setup of the model is complete, the user uses the "go" button to simulate the pavement. A diagrammatic flowchart of the running procedure for the user to set the variables (Figure 6-4) and an agent thought process (Figure 6-5) in the model environment have been detailed.

Table 6-4 – Microscale Pavement Model Typical Values for User Variables

Typical Variable Values		
Variable	**Typical Value**	**Data Source**
Population Density	0.5	N/A
Population Types	Children = 18% Male Adults = 32% Female Adults = 33% Male OAPs = 8% Female OAPs = 9%	UK Average Population splits (Office for National Statistics, 2014)
Walking Speeds	Children = 0.8m/s (1.8mph) Male Adults = 1.34m/s (3mph) Female Adults = 1.12m/s (2.5mph)	Values combined from literature (Bosina & Weidmann, 2017) (Rastogi,

	Male OAPs = 0.78m/s (1.74mph) Female OAPs = 0.76m/s (1.7mph)	et al., 2011) (Schimpl, et al., 2011) (Silva, et al., 2014)
Patience	2	N/A
No of Lanes	>3	N/A

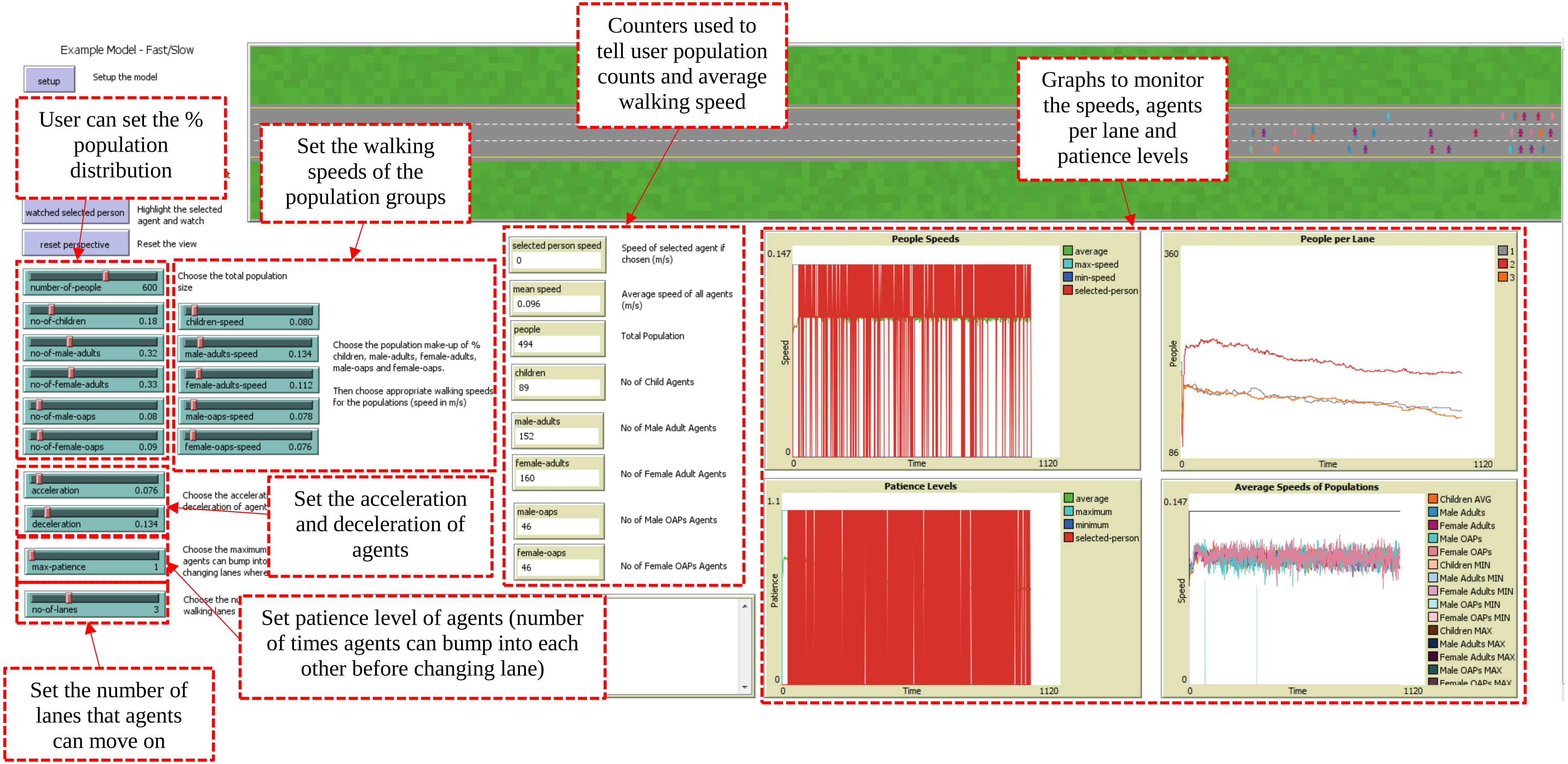


Figure 6-2 – Pavement Example Congestion Model User Interface

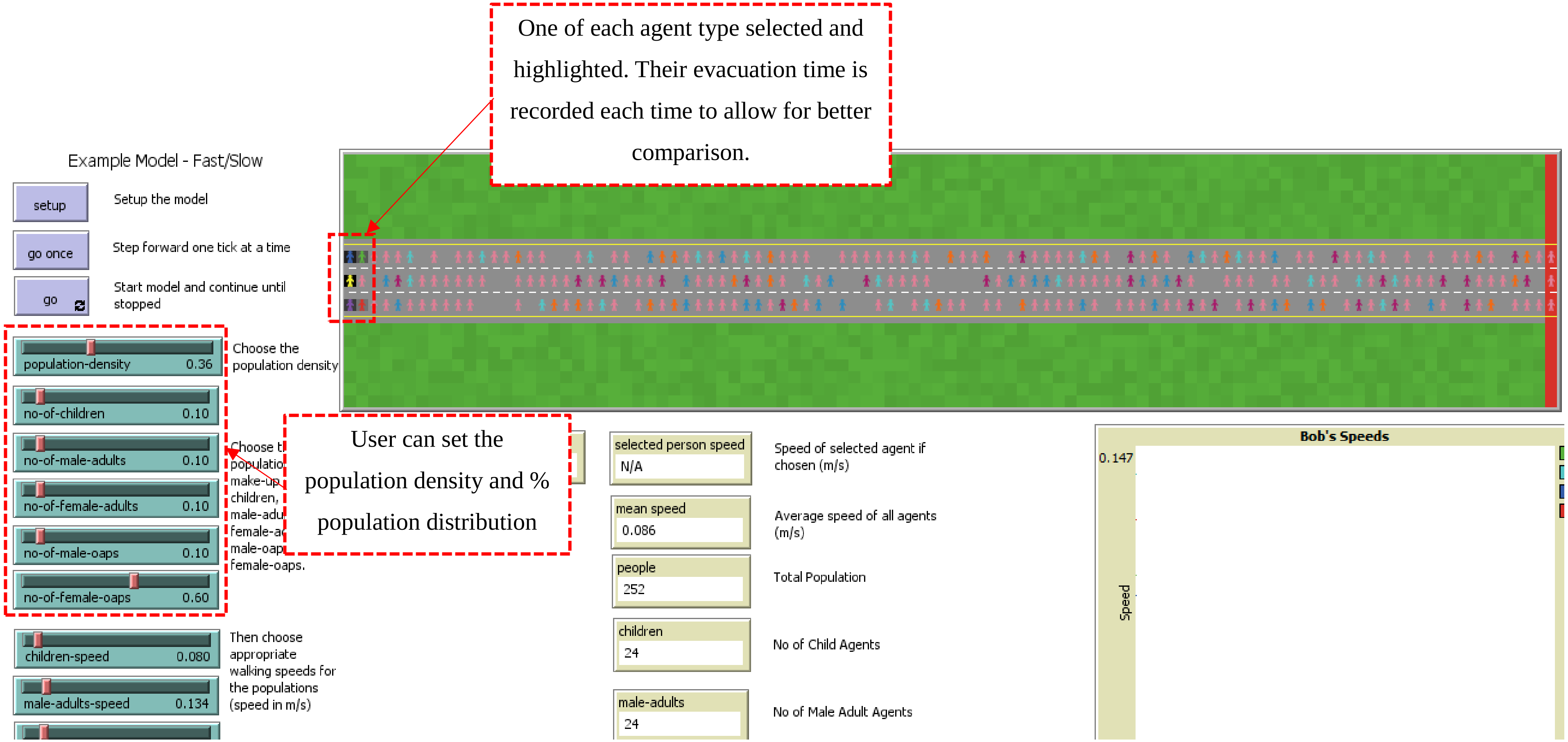


Figure 6-3 – Pavement Example Congestion Model Improved User Interface

Set Model Variables	
Population Density (population-density)	Value: 0 – 0.95 (Represents the number of patches occupied in the model)
Evacuation Population Split (no-of-children, no-of-male-adults, no-of-female-adults, no-of-male-oaps, no-of-female-oaps)	Value: 0 - 1 (Represents percentage e.g. 0.01 = 1%, the 5 parameters must sum to 1)
Walking Speed of Evacuation Population (children-speed, male-adults-speed, female-adults-speed, male-oaps-speed, female-oaps-speed)	Value: 0 - 1 (Represents speed in m/s, allows for running as well as walking speeds, can all be the same value or different)
Patience Level (max-patience)	Value: 1 - 100 (Represents the number of times steps an agent will wait behind another agent before attempting to switch lanes)
Number of Lanes (no-of-lanes)	Value: 0 - 10 (Represents the number of lanes created)

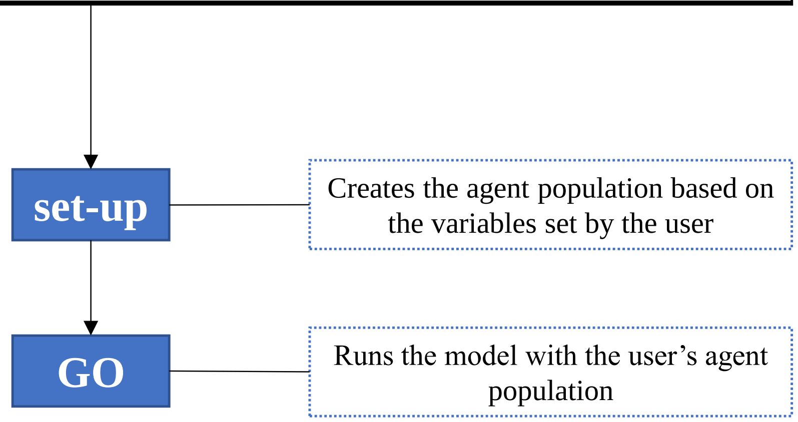


Figure 6-4 – Lanes Model User Variables

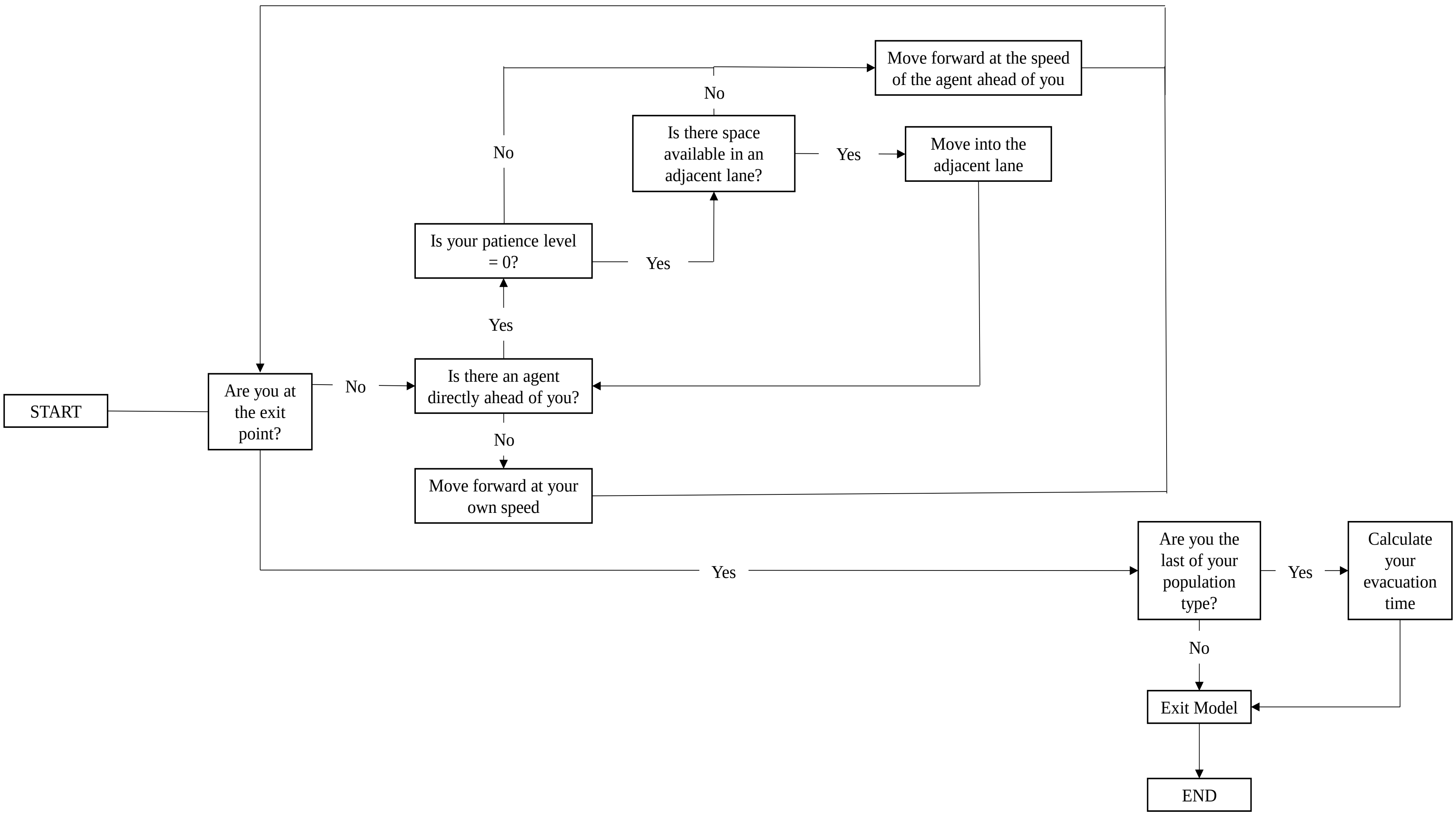


Figure 6-5 – Agent Thought Process for Microscale Pavement Model

6.2 Pavement Model Initial Check

It is important to ensure that the microscale pavement model not only produces robust travel time estimates but also observes the behaviour of agents, to ensure this is replicating the desired human behaviours. Several observations can be carried out to verify the anticipated behaviours, such as, (1) are agents travelling within their lanes, (2) are agents capable of switching to alternate lanes, and (3) once an agent has switched lane are, they correctly placed in a lane. Following these observations, the minimum travel times can be calculated to carry out a further validation check.

The aim of this validation check is to ensure that the microscale pavement model is producing robust travel time estimates which are not less than the minimum possible exit time of the model. The pavement is not based on a specific pavement; hence it is not possible to validate the model using real-life data. Instead the minimum possible distance for each of the population types from their home squares have been calculated and an evacuation time calculated from the distance (e.g. speed = distance/time) (Table 6-5).

Table 6-5 – Minimum Calculated Evacuation Times from Microscale Pavement Model

Population Type	Distance (m)	Speed (m/s)	Time (minutes)
Child (Ben)	990	0.80	20.8
Male Adult (Bob)	980	1.34	12.4
Female Adult (Betty)	980	1.12	14.9
Male OAP (Barry)	990	0.78	21.4
Female OAP (Barbara)	990	0.76	21.9

The calculated minimum travel time and the model travel times can be plotted on a scatter graph (Figure 6-6). This shows that all the travel times achieve either the minimum calculated travel time or greater; all the travel times are above the green line (Figure 6-6). The difference between the calculated minimum travel time and the model travel time can be calculated and averaged for all the runs completed. This can be plotted and shows that the slower population types (children and OAPs) do not have much variation from the minimum calculated travel times, whereas the faster agents (male and female adults) have greater variations. This will be investigated with further modelling testing in Chapter 7 but demonstrates that the model is producing congestion and considering the capacity of the pavement.

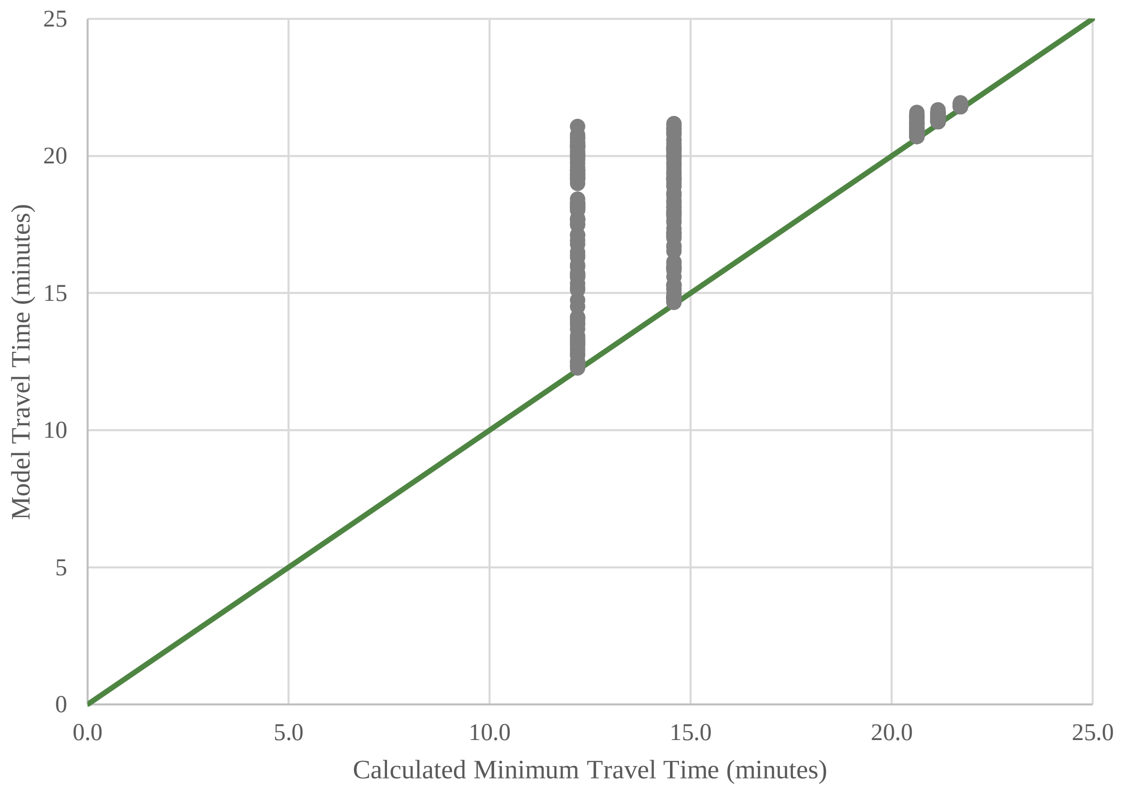


Figure 6-6 – Microscale Pavement Model Calibration Check – Scatter graph of calculated minimum travel times (minutes) vs. model travel times (minutes)

6.3 Proposed Pavement Model Testing

As previously discussed in Chapter 4, Section 4.2, calibration, verification and validation are key components of a robust agent-based model. The proposed structural validation is one approach to ensuring that a model produces the anticipated behaviours and to ensuring it is accurate. Before any testing of the models can occur, calibration checks should be undertaken to check the model's validity. Then a series of tests will be undertaken to understand which variables primarily affect the evacuation times.

6.3.1 Microscale Pavement Model Proposed Testing

An initial calibration check will be completed to ensure that the evacuation times produced are realistic estimates. The pavement is not based on any specific pavement, so it is not possible to compare the travel times with real-life data or utilise route planners as done previously. However, the distance travelled by the agent can be used to work out a minimum possible evacuation time at 1.34m/s (3mph) and other speeds if required. Comparison to these figures will then ensure that the agents are not exiting the model quicker than expected. A visual check will also be undertaken to confirm that agents are passing each other as anticipated. The testing schedule for the microscale pavement model will explore the effect of altering variables such as the number of lanes, population distribution, patience levels and population density (Table 6-6).

Table 6-6 – Proposed Testing Schedule for Microscale Pavement Model

Test No.	Variable(s)	Research Questions
1A	No of Lanes Patience Level Population Density	- How the variables (number of lanes, population density and patience level) can be used to create congestion and capacity within an agent-based pavement model - If the width of the pavement (number of lanes) influences the travel time of agents - If the population density influences the travel time of a pavement - If a varied patience level can influence the overtaking occurring and effect overall travel time
1B	Comparison to the 3mph Model	- Understand if there are any travel time differences between current agent-based models of human behaviour and the pavements model caused by the introduction of additional variables

6.4 Microscale Model (Crossroads Model)

The second microscale agent-based model is to investigate the interactions of humans when using a crossroads, specifically agents walking in two directions. The aim of this model is to understand how people move along a pavement and interact at a crossroads, in particular how agents overtake each other or give way to each other and how this is influenced by factors such as: the width of the pavement, the walking speeds of individuals and the population density.

The model is not based on any specific crossroads and is instead a generic representation, aiming to reproduce the complex interactions that occur when two or more people meet at a junction. The maximum dimensions of which are 100m wide (10m per lane) by 500m long. The model can be used to calculate a travel time over the 1km length. The maximum number of lanes is 10 in each direction, which is the same as the pavement model, this model is effectively two pavement models crossing at 90° to each other. The number of lanes can again be varied to create different crossroad dimensions, this model will only test lane configurations between three and five lanes. As with the pavement model, this model does not include any grouping which was considered in the macroscale model, as the aim of this model is to capture the movement of individuals at a junction.

6.4.1 Model Description

The aim of this model is to explore the effect on travel time of: (1) agents giving way to each other at the junction and of agents overtaking each other on a pavement, (2) varied population density, (3) the introduction of patience, (4) the variation of pavement width, and (5) the inclusion of varied walking speed by age and sex. To achieve this, the model needs to include several variables, which are a mixture of previously defined variables taken from the macroscale model and pavement microscale model plus new parameters introduced to simulate intricate human behaviours at a junction.

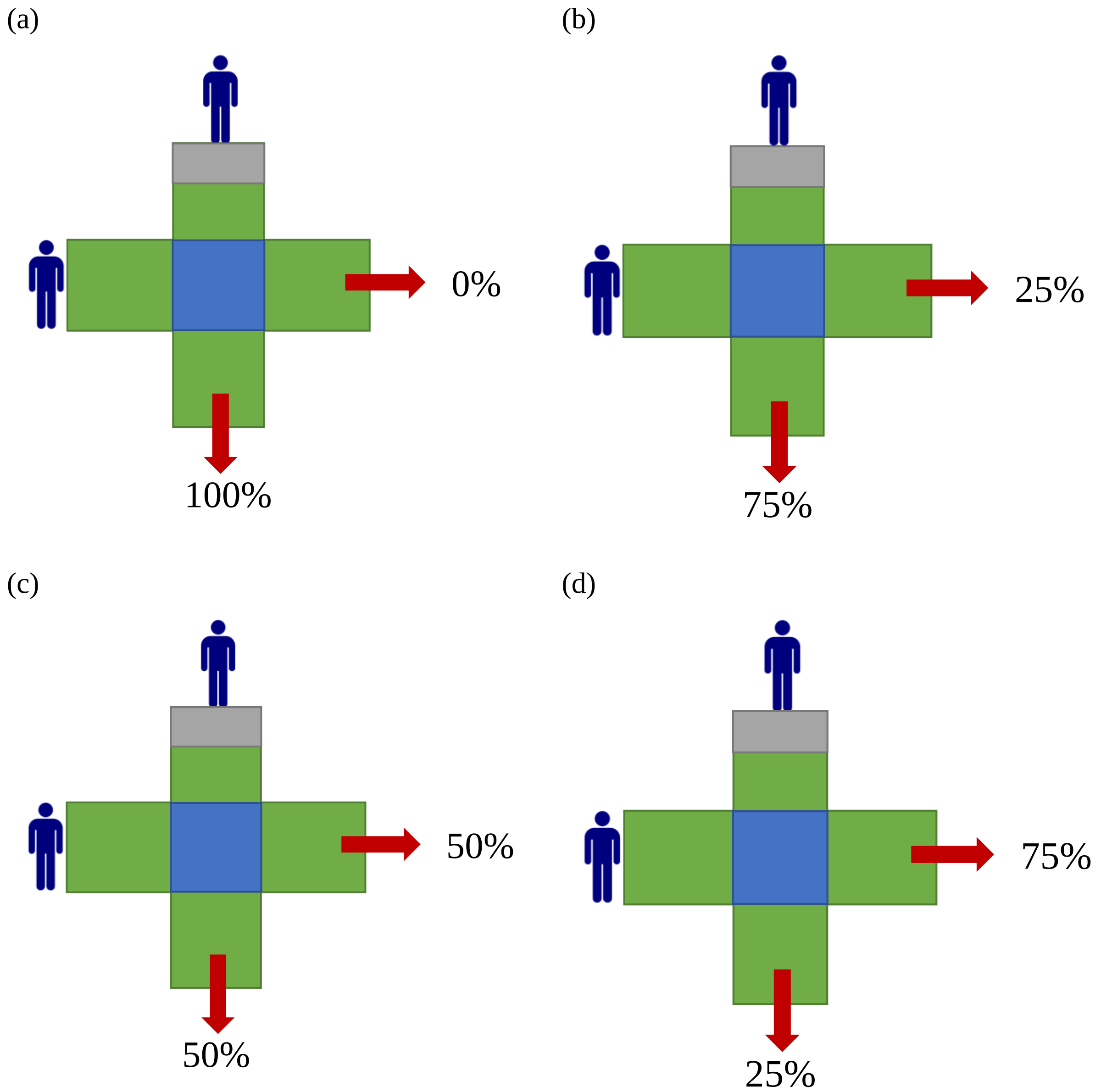
Table 6-7 – Microscale Pavement Model Variables

Variable	Defined in:
Population Types & Distribution	Chapter 4 (Table 4-1) & 5 (Table 5-2 and Figure 5-2)
Walking Speeds	Chapter 4 (Table 4-1) & 5 (Table 5-2)
Population Density	New Variable – Pavement Model
Patience	New Variable – Pavement Model
No of Lanes	New Variable – Pavement Model
South Exit Percentage	New Variable

The previously defined variables, such as the population distribution and walking speeds are set out fully in Chapter 4 and 5, which allows the user to simulate a mixture of populations and walking speeds. A series of typical variables are suggested to the user, based on UK data and literature (Table 6-8). The variables from the pavements model, population density, number of lanes and patience level, are set out fully in Section 6.1.

To complement the previous variables, one new variable is included, south exit percentage. This variable is specifically included to help simulate the movement of agents at the crossroads in terms of their exit direction. The number of lanes and patience level variables, previously created in the pavement model, are used to simulate a range of pavement widths (allowing for comparison) and varied levels of frustration for individuals.

In this model, the aim is to capture a population interacting at a crossroads, to do this accurately, there is a need to allow the agents to overtake and to give way to each other. The south exit percentage is used to vary the number of agents exiting in each direction, to understand the implications of all agents travelling in the same direction alongside agents travelling in two directions, hence increasing the need to give way. The variable can be altered between 0% and 100% exiting in the south direction. The chosen percentage is then used to allocate agent's directions when they reach the centre of the crossroads (marked as blue). The agent's will be assigned a random number on entry into the centre area, if this number is lower than the south exit percentage then the agent will exit to the south and if higher, to the east. This also ensures that the number of agents is equivalent to the percentage exit split, e.g. if there were 100 agents with a south exit percentage of 25%, 25 agents would exit south and 75 would exit east. For this model, five different exit splits will be tested to understand the implications of exit direction on overall travel time (Figure 6-7).



(e)

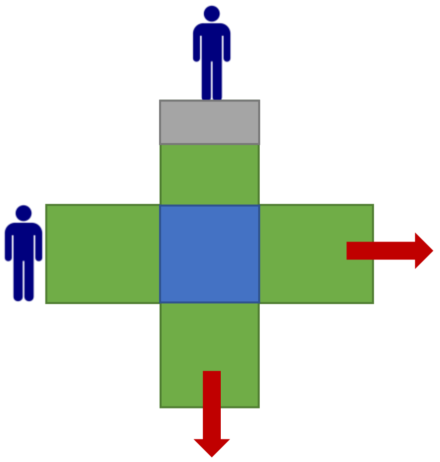
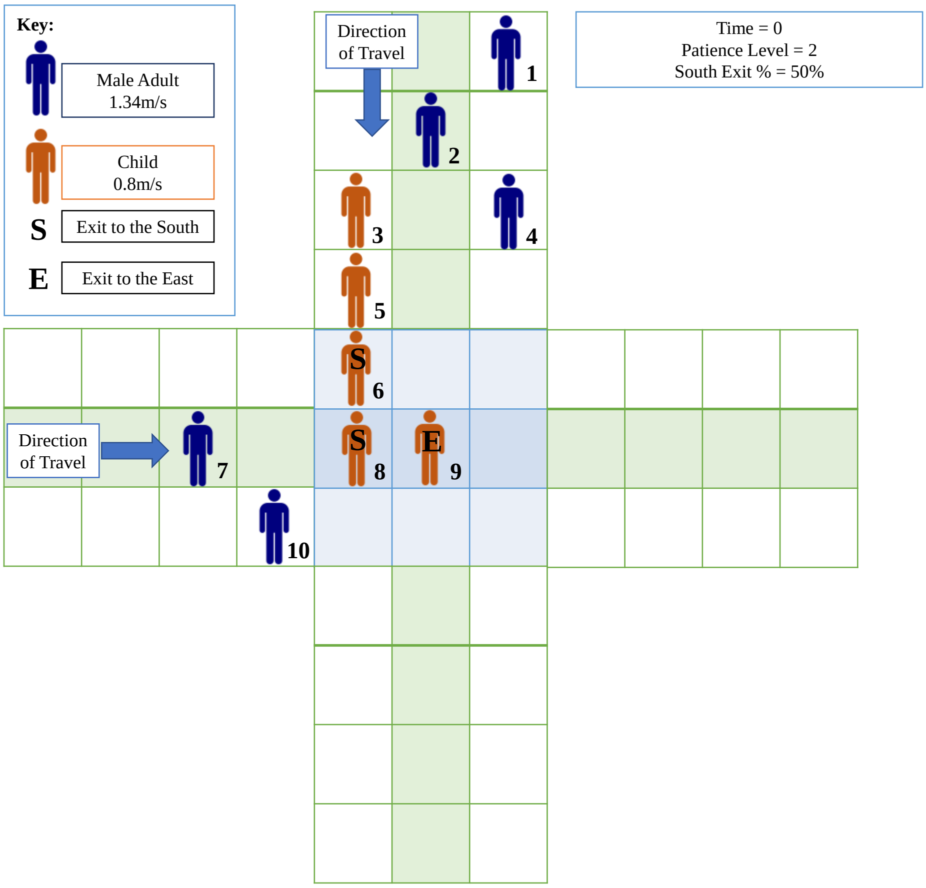


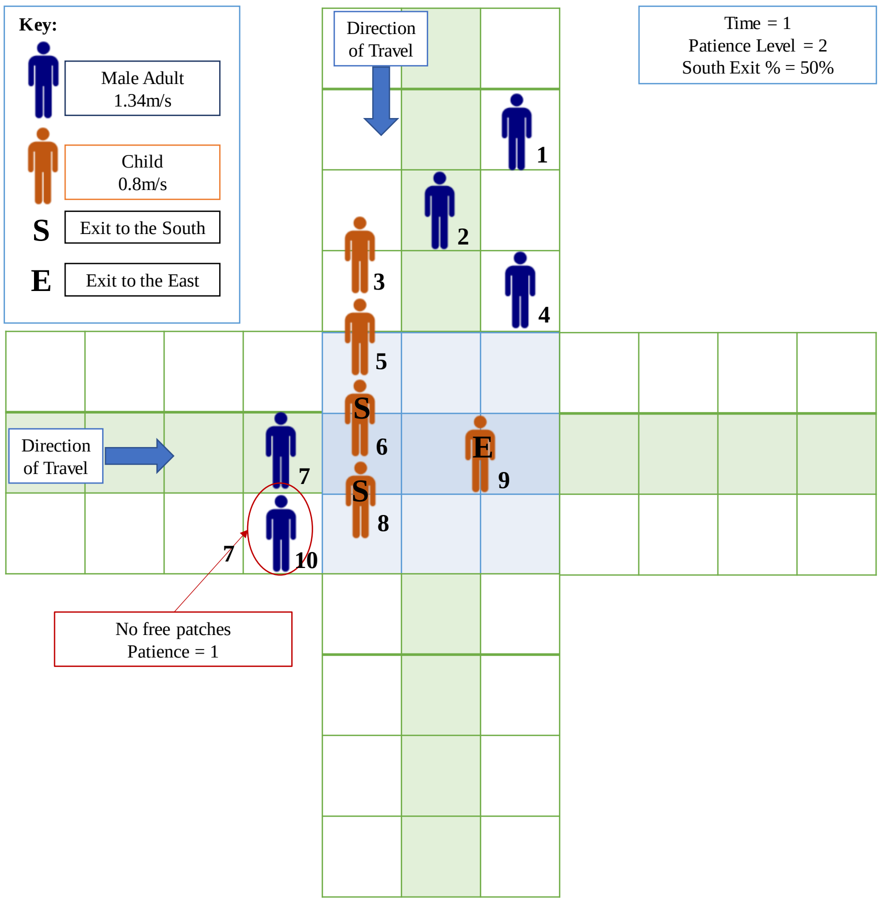
Figure 6-7 – Possible Exit Splits for Crossroads Microscale Model (a) all agents exiting to south, (b) 25% agents to east and 75% south, (c) 50% east and 50% south, (d) 75% agents to east and (e)25% south and I all agents exiting east

An example of ten agents on a crossroads has been set out in Figure 6-8 to demonstrate the use of the new variables, this shows five slower agents (children) interacting with five faster male adult agents, all agents have been assigned a number to make it easier to follow their paths. When agents reach the centre of the crossroads (marked as blue), their exit direction is assigned at random. Initially, all agents can move forward in their desired directions and speeds apart from agent 10, who has a blocked path, as described previously this begins the patience level countdown for this agent (Figure 6-8(b)). In the next time step, the path of agent 7 is also blocked, agent 10's patience reaches zero, however, there is no available space to move to so the agent must give way (Figure 6-8(c)). When additional agents reach the centre of the crossroads, it creates additional congestion and the agents must give way to each other (Figure 6-8(d)). The agents continue along their desired paths, giving way to each other in the crossroads and overtaking when necessary to avoid slower agents (Figure 6-8I-(k)) until reaching the exit location.

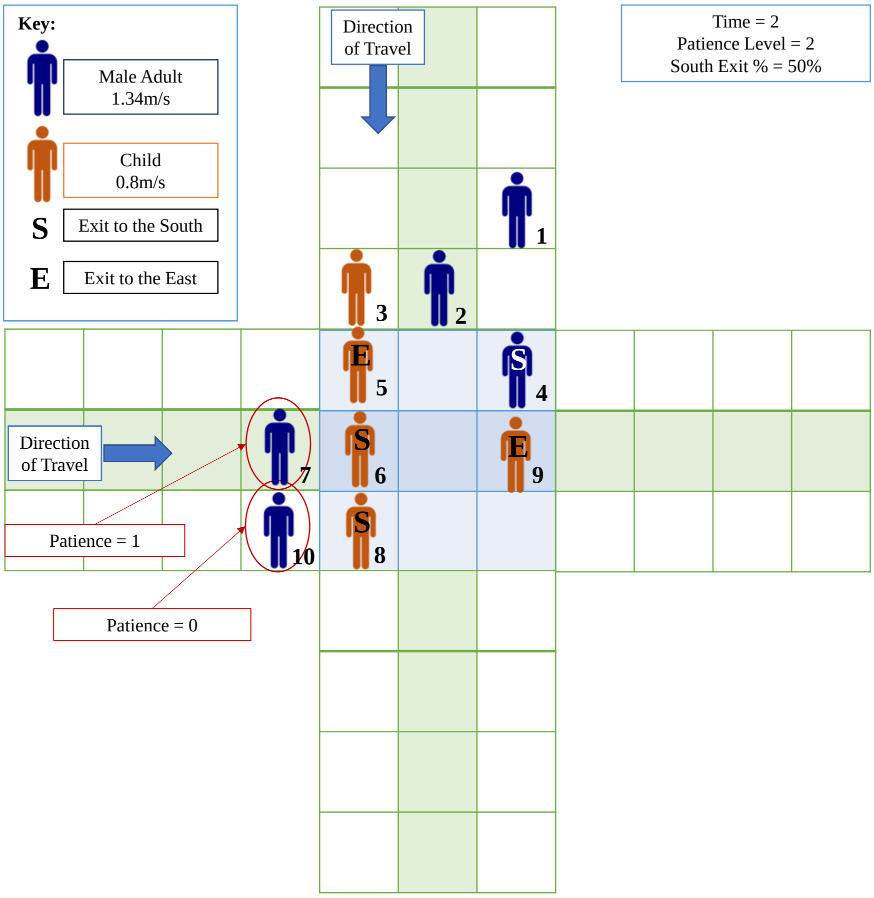
(a)


Key:
Male Adult
1.34m/s
Child
0.8m/s
S
Exit to the South
E
Exit to the East
Direction
of Travel
Time = 0
Patience Level = 2
South Exit % = 50%
1
2
3
4
5
S
6
Direction
of Travel
7
S
8
E
9
10

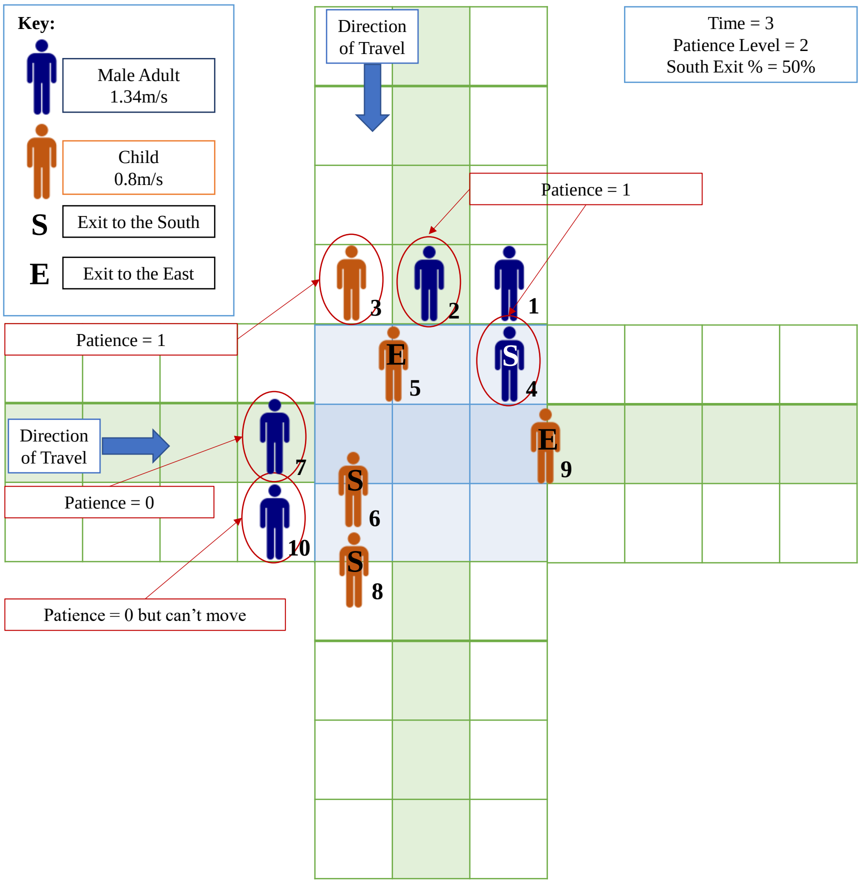
(b)


Key:
Male Adult
1.34m/s
Child
0.8m/s
S
Exit to the South
E
Exit to the East
Direction
of Travel
Time = 1
Patience Level = 2
South Exit % = 50%
1
2
3
4
5
S
6
Direction
of Travel
7
E
9
S
8
7
10
No free patches
Patience = 1

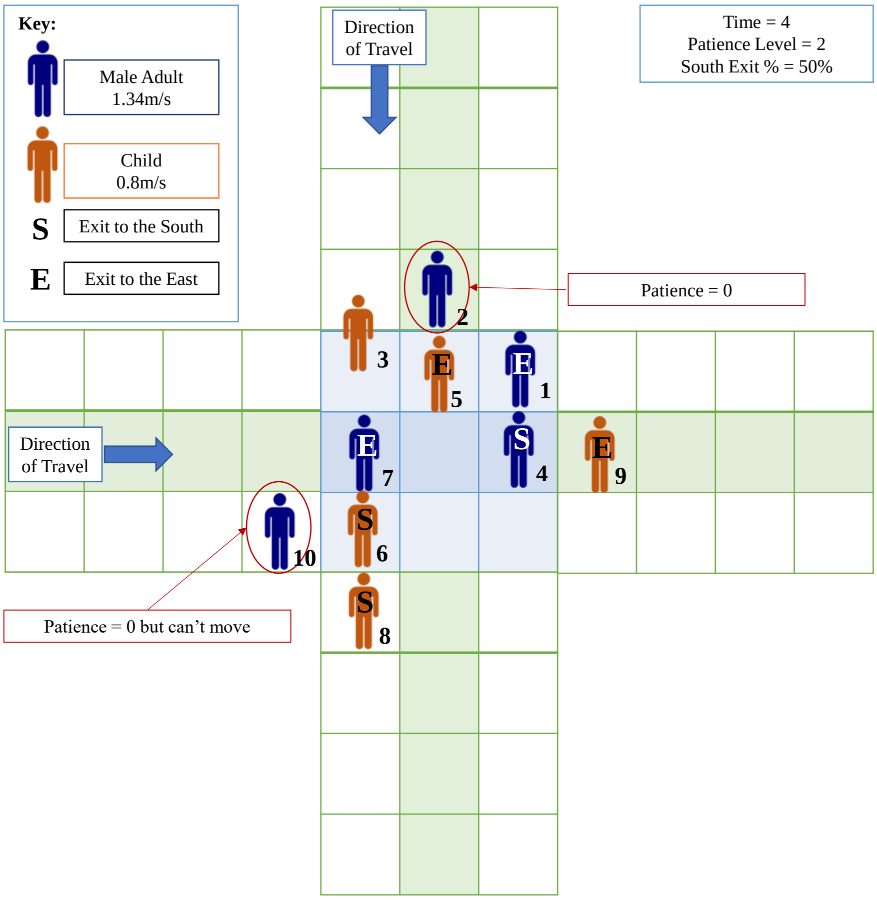
(c)


Key:
Male Adult
1.34m/s
Child
0.8m/s
S
Exit to the South
E
Exit to the East
Direction
of Travel
Time = 2
Patience Level = 2
South Exit % = 50%
Direction
of Travel
Patience = 1
Patience = 0
1
2
3
4
5
6
7
8
9
10

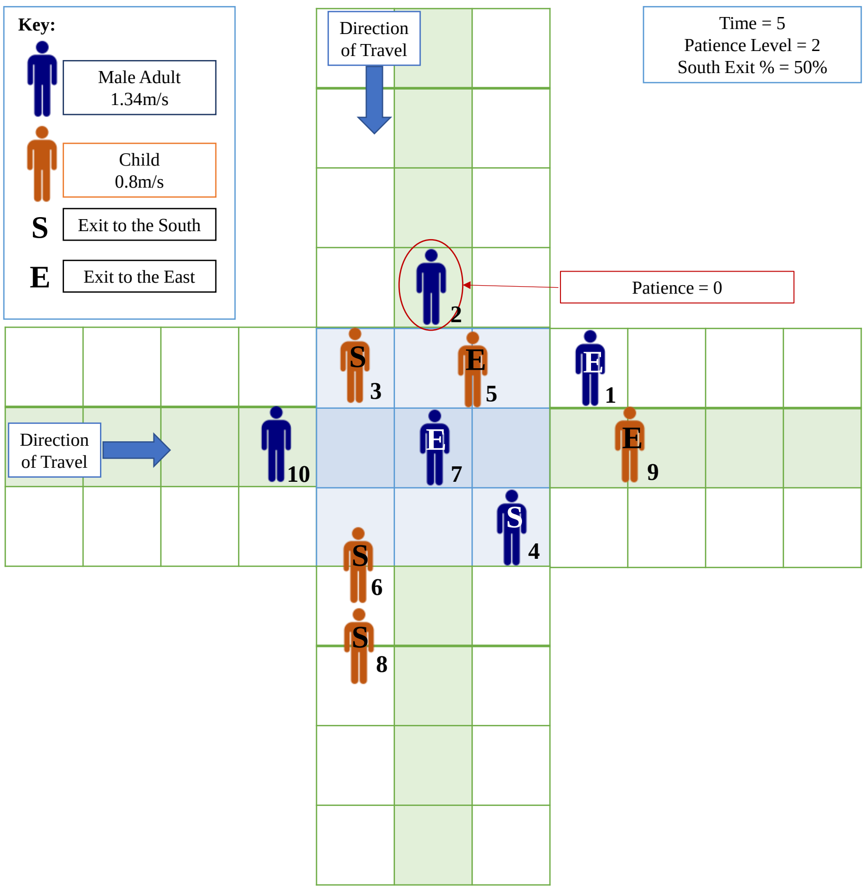
(d)


Key:
Male Adult
1.34m/s
Child
0.8m/s
S
Exit to the South
E
Exit to the East
Direction
of Travel
Time = 3
Patience Level = 2
South Exit % = 50%
Patience = 1
Patience = 1
Direction
of Travel
Patience = 0
Patience = 0 but can't move
1
2
3
4
5
6
7
8
9
10

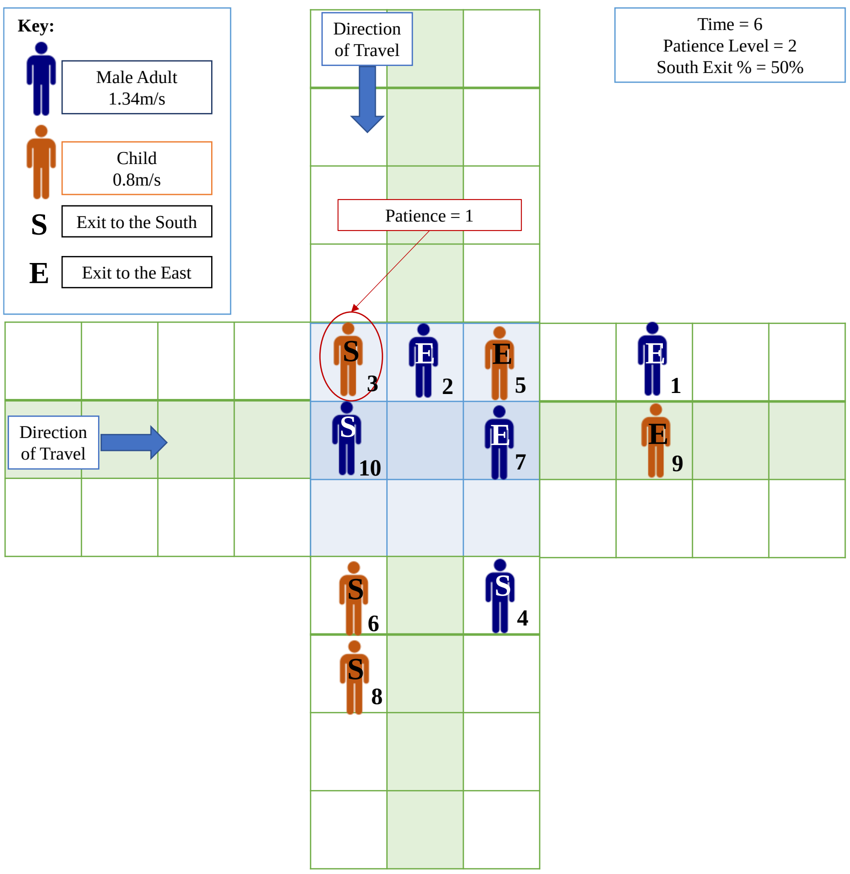
(e)


Key:
Male Adult 1.34m/s
Child 0.8m/s
S Exit to the South
E Exit to the East
Direction of Travel
Time = 4
Patience Level = 2
South Exit % = 50%
Patience = 0
Patience = 0 but can't move
Direction of Travel

(f)

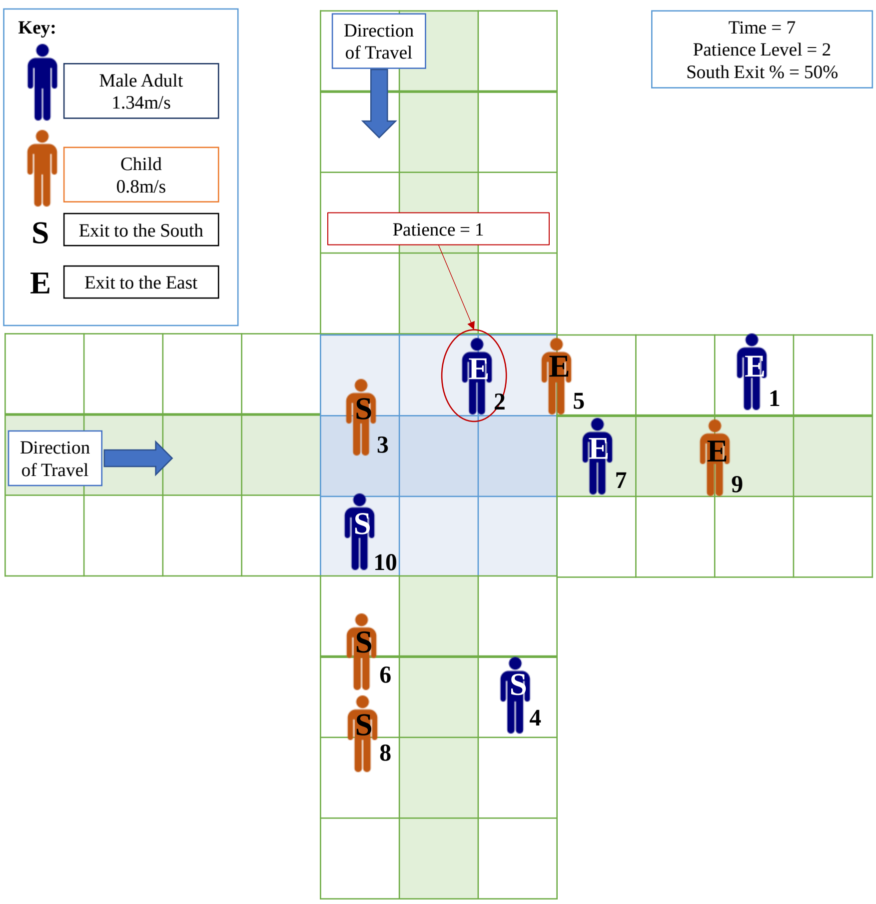

Key:
Male Adult 1.34m/s
Child 0.8m/s
S Exit to the South
E Exit to the East
Direction of Travel
Time = 5
Patience Level = 2
South Exit % = 50%
Patience = 0
Direction of Travel

(g)



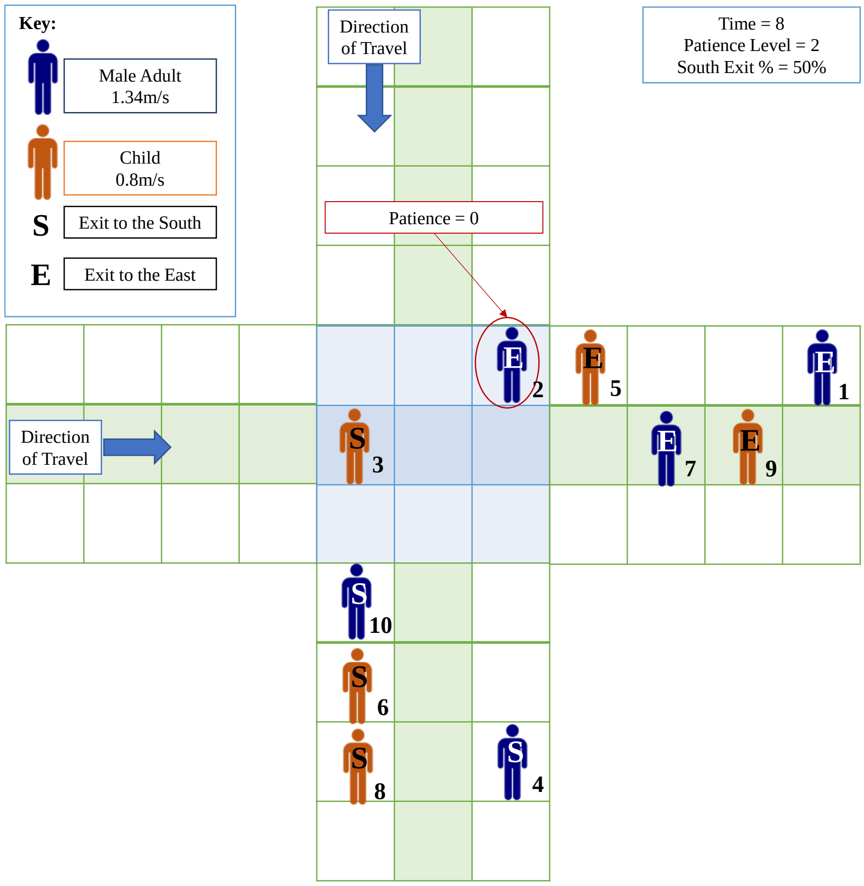
Key:
Male Adult
1.34m/s
Child
0.8m/s
S Exit to the South
E Exit to the East
Direction of Travel
Time = 6
Patience Level = 2
South Exit % = 50%
Patience = 1
S 3
E 2
E 5
E 1
S 10
E 7
E 9
Direction of Travel
S 6
S 4
S 8

(h)



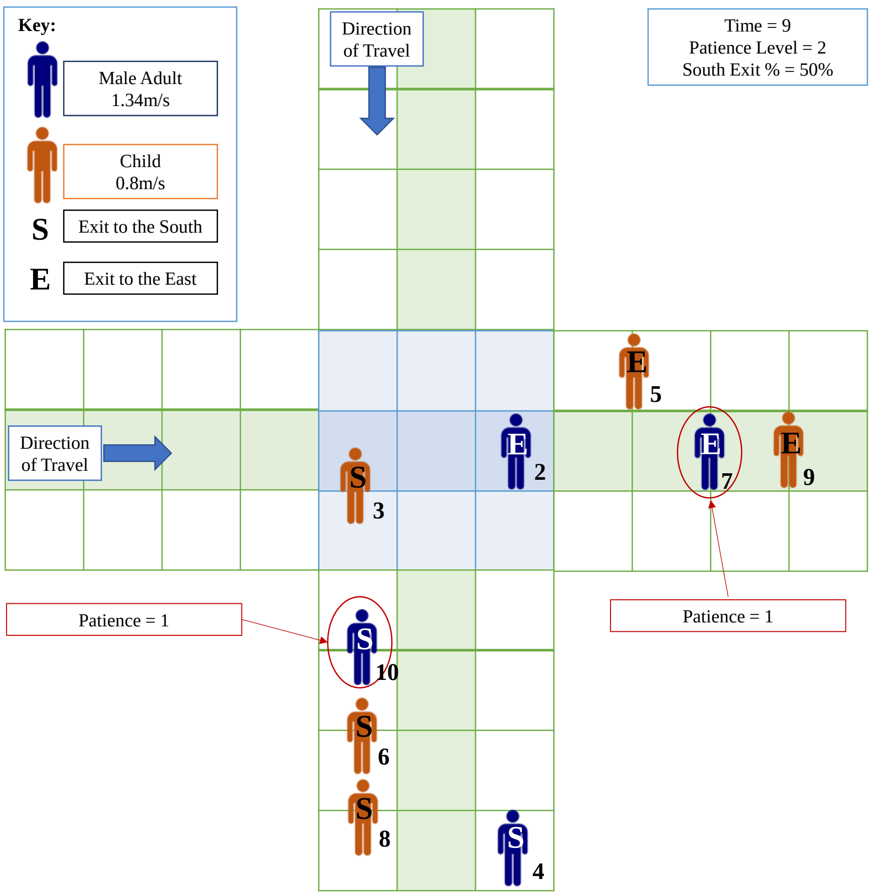
Key:
Male Adult
1.34m/s
Child
0.8m/s
S Exit to the South
E Exit to the East
Direction of Travel
Time = 7
Patience Level = 2
South Exit % = 50%
Patience = 1
E 2
E 5
E 1
S 3
E 7
E 9
Direction of Travel
S 10
S 6
S 4
S 8

(i)



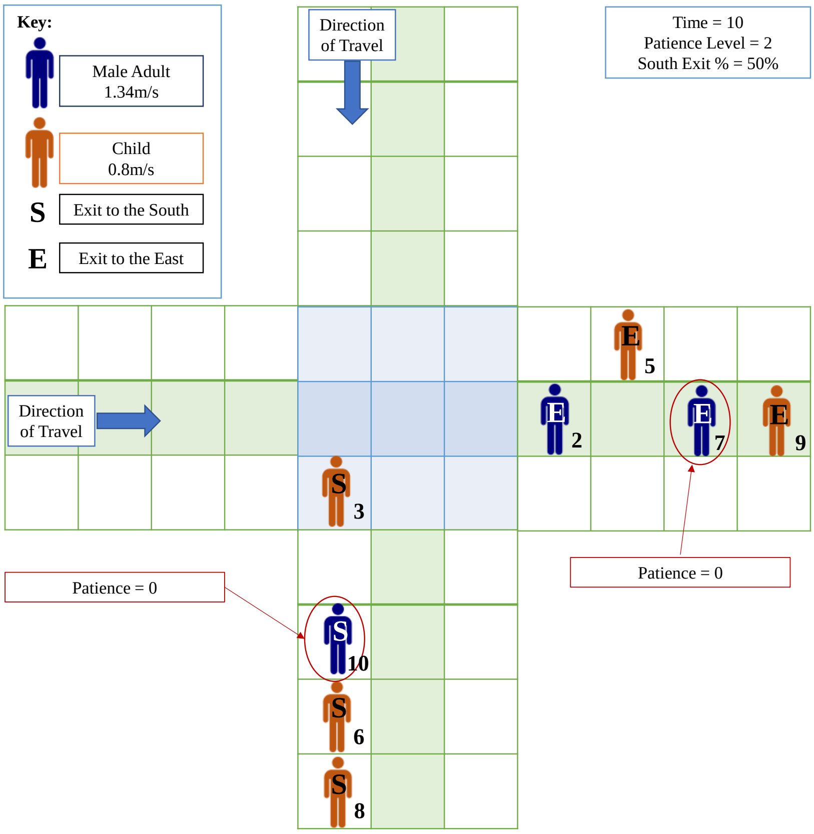
Key:
Male Adult 1.34m/s
Child 0.8m/s
S Exit to the South
E Exit to the East
Direction of Travel
Time = 8
Patience Level = 2
South Exit % = 50%
Patience = 0
Direction of Travel

(j)



Key:
Male Adult 1.34m/s
Child 0.8m/s
S Exit to the South
E Exit to the East
Direction of Travel
Time = 9
Patience Level = 2
South Exit % = 50%
Direction of Travel
Patience = 1
Patience = 1

(k)



(l)

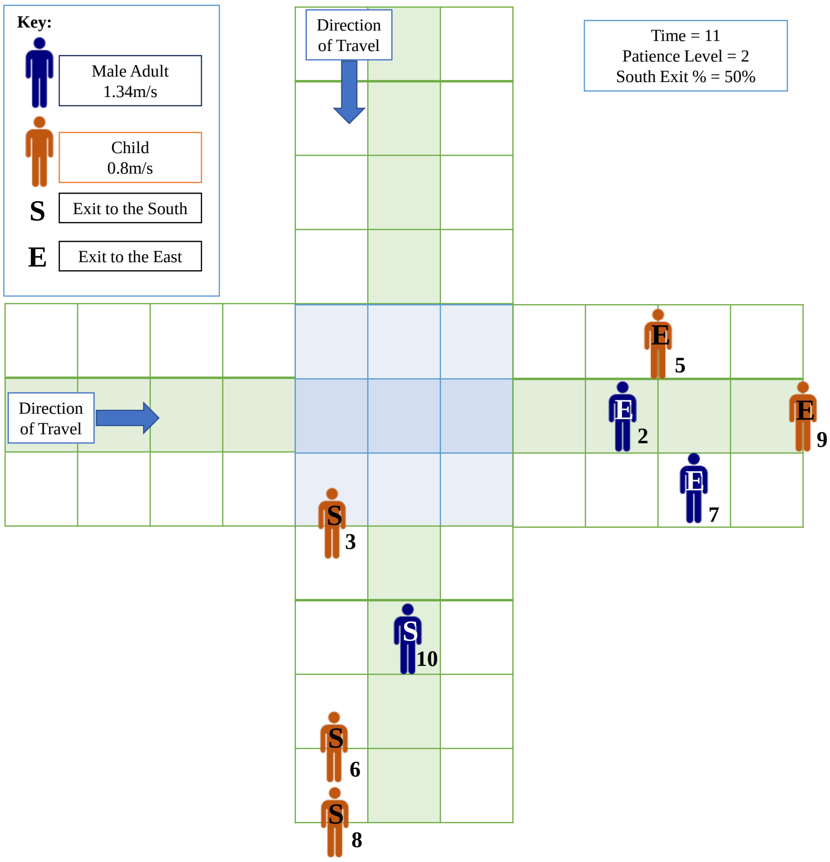


Figure 6-8 – Crossroads Agent Movement Diagrams (a) – (k) depicts time 0 -11

In the previous macroscale model and microscale pavement model, the five population types are all assigned a static home square, this will be recreated in this model too, with the home squares placed on the northern arm. The model interface is also identical to the microscale pavement model, other than that there are effectively two pavements at 90° to each other, with a central blue crossroads area (Figure 6-9). The centre of the crossroads is shown as a blue area as this allows agents to be assigned an exit direction, as previously outlined. In the same manner as the macroscale model, a series of typical variables are provided to the user, they are based on UK data and literature (Table 6-8). The model outputs the travel time recorded for each population type and those placed on a home square initially. Once the setup of the model is complete, the user uses the "go" button to simulate the pavement. A diagrammatic flowchart of the running procedure for the user to set the variables (Figure 6-10) and an agent thought process (Figure 6-11) in the model environment are detailed.

Table 6-8 – Crossroads Model Typical Values for User Variables

Typical Variable Values		
Variable	**Typical Value**	**Data Source**
Population Density	0.5	N/A – gives good spatial variability in the model
Population Types	Children = 18% Male Adults = 32% Female Adults = 33% Male OAPs = 8% Female OAPs = 9%	UK Average Population splits (Office for National Statistics, 2014)
Walking Speeds	Children = 0.8m/s (1.8mph) Male Adults = 1.34m/s (3mph) Female Adults = 1.12m/s (2.5mph) Male OAPs = 0.78m/s (1.74mph) Female OAPs = 0.76m/s (1.7mph)	Values combined from literature (Bosina & Weidmann, 2017) (Rastogi, et al., 2011) (Schimpl, et al., 2011) (Silva, et al., 2014)
Patience	2	N/A – encourages a good level of movement
No of Lanes	>3 in both directions	N/A – allows for passing in 2 lanes in both directions
South Exit Percentage	50%	Creates an even split leaving in each direction but does not test the model extremes.

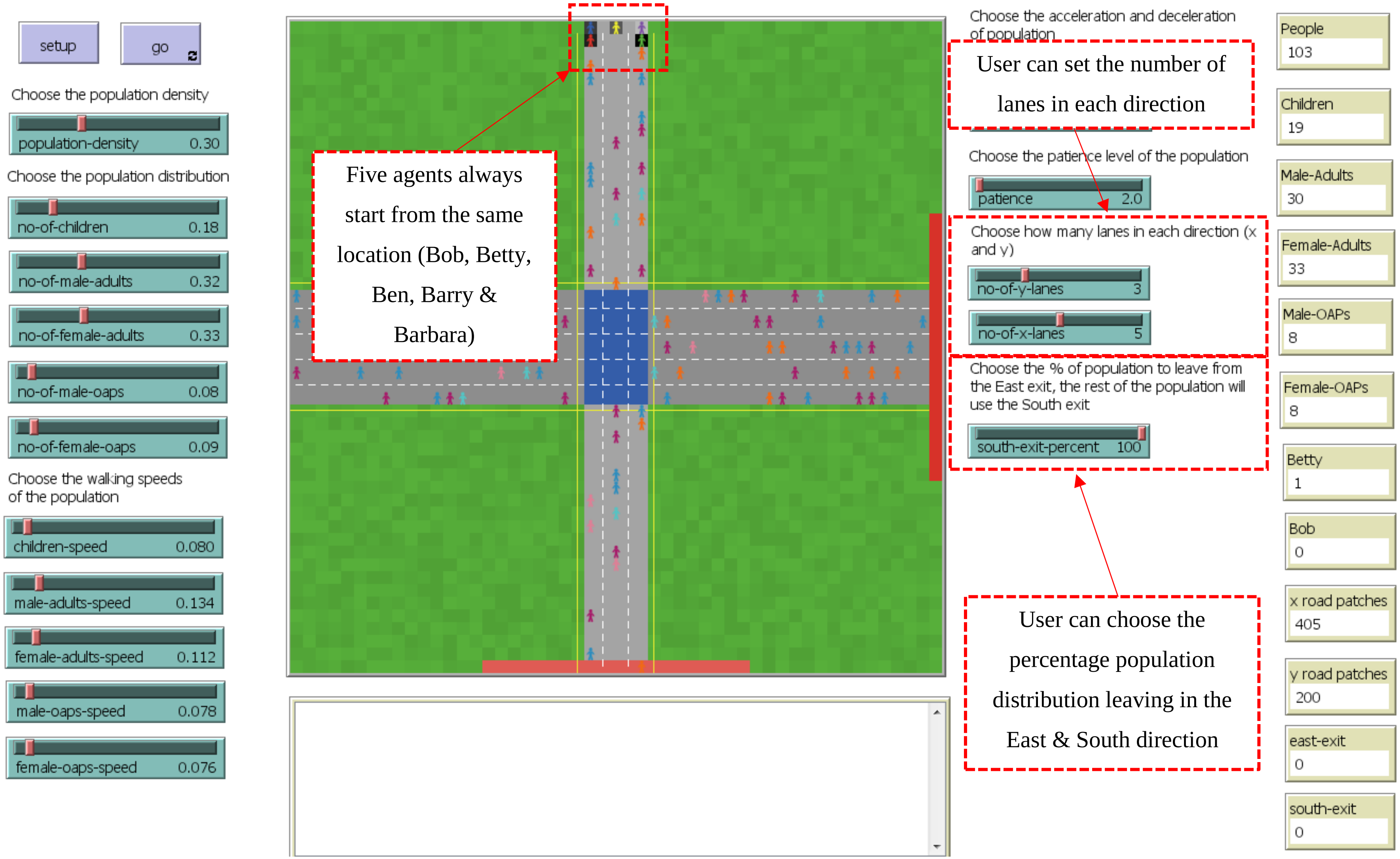


Figure 6-9 – Microscale Crossroads Model Screenshot

Set Agent Variables	
Population Density (population-density)	Value: 0 – 0.95 (Represents the number of patches occupied in the model)
Evacuation Population Split (no-of-children, no-of-male-adults, no-of-female-adults, no-of-male-oaps, no-of-female-oaps)	Value: 0 - 1 (Represents percentage e.g. 0.01 = 1%, the 5 parameters must sum to 1)
Walking Speed of Evacuation Population (children-speed, male-adults-speed, female-adults-speed, male-oaps-speed, female-oaps-speed)	Value: 0 - 1 (Represents speed in m/s, allows for running as well as walking speeds, can all be the same value or different)
Patience Level (max-patience)	Value: 1 - 100 (Represents the number of times steps an agent will wait behind another agent before attempting to switch lanes)
Number of Lanes (no-of-x-lanes, no-of-y-lanes)	Value: 0 - 10 (Represents the number of lanes created in the x and y direction)
% Leaving South Exit (south-exit-percent)	Value 0 - 100 (Represents the percentage of agents will choose the south exit of the model)

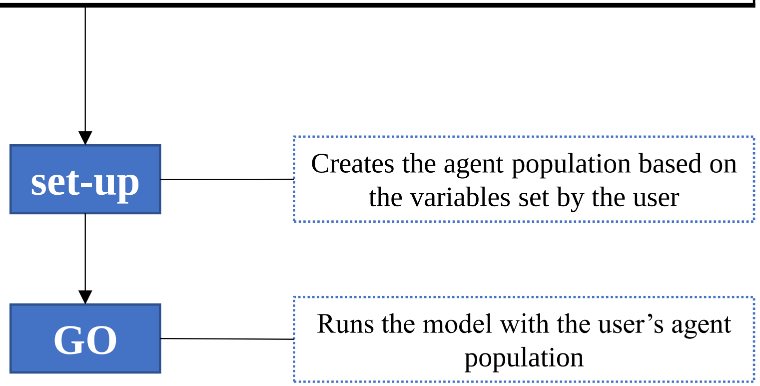


Figure 6-10 – Microscale Crossroads Model User Variables

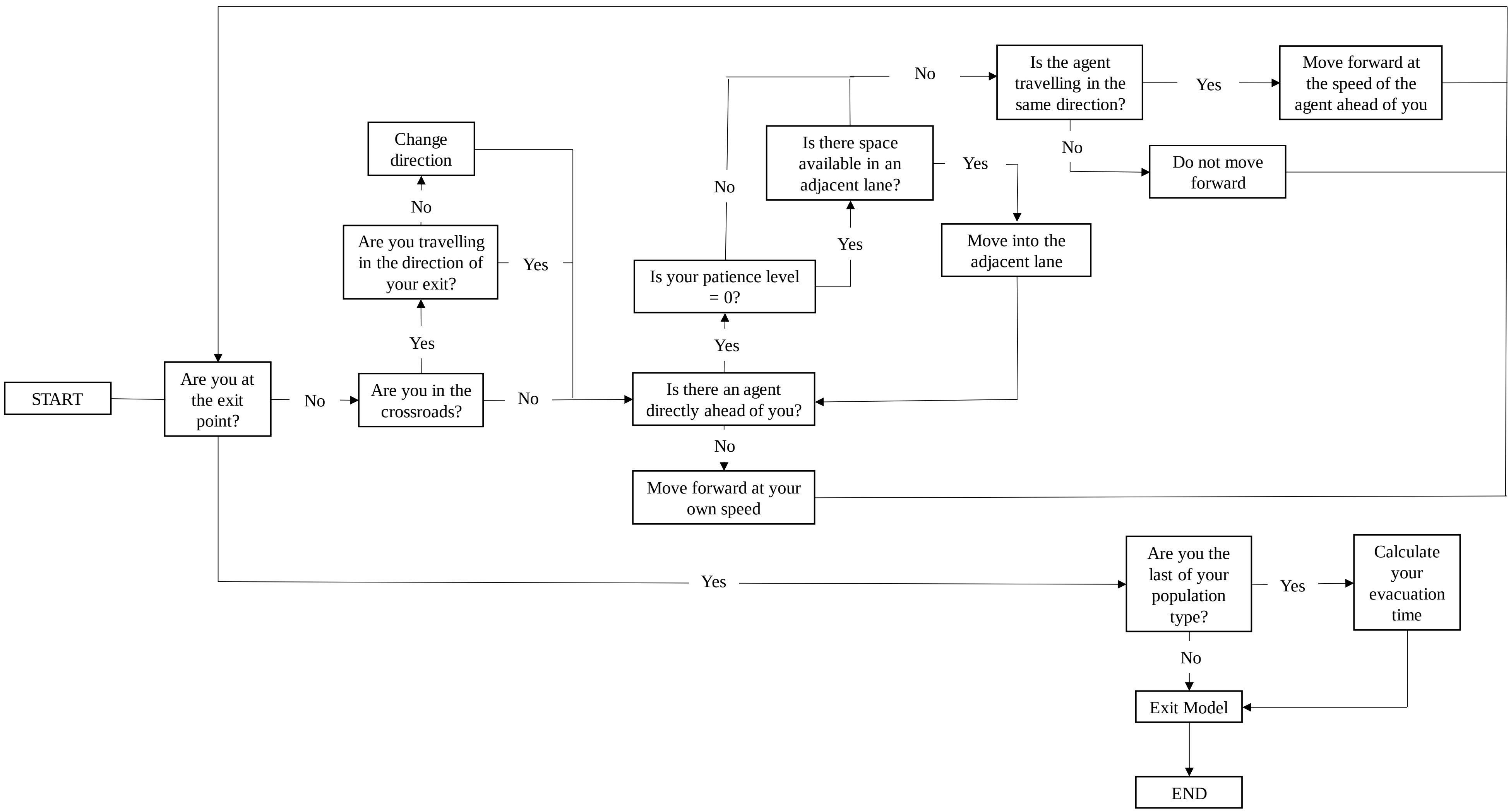


Figure 6-11 – Agent Thought Process for Microscale Crossroads Model

6.5 Crossroads Model Initial Check

It is important to ensure that the microscale crossroads model not only produces robust travel time estimates but also observes the behaviour of agents to ensure this is replicating the desired human behaviours. Several observations can be carried out to verify behaviour traits, although this is not checked against real-life data as the crossroad are just a generic representation of a junction, some of which are similar to the previous pavement model, including: (1) are agents travelling within their lanes left to right, (2) are agents capable of switching to alternate lanes, and (3) once an agent has switched lane are, they correctly placed in a lane. Observations can also be carried out to examine alternative behaviours only seen at the crossroads, (1) are agents able to give way to each other at the junction, (2) does congestion occur around the crossroads when agent numbers increase, (3) are agents capable of choosing alternative lanes to avoid congestion. Following these observations, the minimum travel times can be calculated to carry out a further validation check.

The aim of this validation check is to ensure that the microscale crossroads model is producing robust travel time estimates which are not less than the minimum possible exit time of the model. The crossroads is not based on a specific crossroads; hence it is not possible to validate and verify the model using real-life data. Instead the minimum possible distance for each population type (Ben, Bob, Betty, Barry, and Barbara) for the varied lane configurations is calculated and a travel time calculated from the distance. The pathways for each agent are calculated from their home square at the northern extents of the model to the safety zone in the East and South. The journey's distance is split into three parts: north (distance travelled on the northern arm), the middle (the blue central crossroads area) and the south/east (distance travelled on the eastern or southern arm) (Table 6-9). The distances needed to be calculated for each possible lane configuration and each of the population types, as there will be differences in the pathways and starting/end locations (Table 6-10). From the distances a travel time can be calculated for each agent (e.g. speed = distance/time).

Table 6-9 – Example of Calculating the Minimum Pathways for each Population Type to Exit the Microscale Crossroads Model

Lanes	**3 x 3 – South Exit**				**3 x 3 – East Exit**			
	North	**Middle**	**South**	**Total**	**North**	**Middle**	**East**	**Total**
Ben	220	50	220	490	220	30	220	470
Bob	210	50	220	480	210	10	220	440
Betty	210	50	220	480	210	50	220	480

Barry	220	50	220	490	220	50	220	490
Barbara	220	50	220	490	220	10	220	450

Table 6-10 – Crossroads Calibration Check Minimum Distance Travelled for each Population Type to Exit Microscale Crossroads Model

Lanes	**3 x 3**		**3 x 4**		**3 x 5**	
Exit Direction	**South (m)**	**East (m)**	**South (m)**	**East (m)**	**South (m)**	**East (m)**
Ben	490	470	490	460	490	450
Bob	480	440	480	430	480	420
Betty	480	480	480	470	480	460
Barry	490	490	490	480	490	470
Barbara	490	450	490	440	490	430
Lanes	**4 x 3**		**4 x 4**		**4 x 5**	
Exit Direction	**South (m)**	**East (m)**	**South (m)**	**East (m)**	**South (m)**	**East (m)**
Ben	490	480	490	470	490	460
Bob	480	450	480	440	480	430
Betty	480	470	480	460	480	450
Barry	490	500	490	490	490	480
Barbara	490	440	490	430	490	420
Lanes	**5 x 3**		**5 x 4**		**5 x 5**	
Exit Direction	**South (m)**	**East (m)**	**South (m)**	**East (m)**	**South (m)**	**East (m)**
Ben	490	470	490	460	490	450
Bob	480	440	480	430	480	420
Betty	480	480	480	470	480	460
Barry	490	490	490	480	490	470
Barbara	490	450	490	440	490	430

The calculated minimum travel time and the model travel times can be plotted on a scatter graph (Figure 6-12). This shows that all the travel times achieve either the minimum calculated travel time or greater; all the travel times are above the yellow line (Figure 6-12). The difference between the calculated minimum travel time and the model travel time can be calculated and averaged for all the runs completed. This can be plotted and shows that the slower population types (children and OAPs) do not have much variation from the minimum calculated travel times, whereas the faster agents (male and female adults) have greater variations (Figure 6-13 and Figure 6-14.

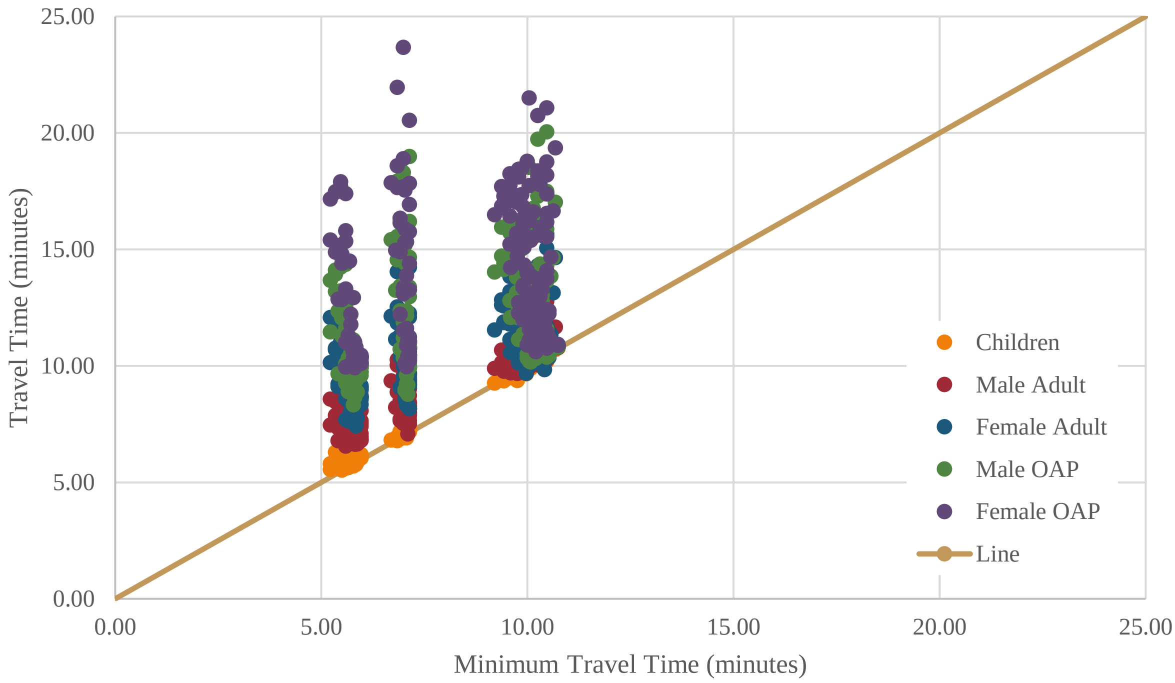


Figure 6-12 – Microscale Crossroads Model Calibration Check – Scatter graph of calculated minimum travel times (minutes) vs. model travel times (minutes)

The comparison of the calculated and computed times shows that when population density is low, regardless of the other variables the difference is small, this is likely to be a result of the low number of agents in the model and therefore lack of congestion. As population density increases, the difference between the computed and calculated times also increases, this is greater when the exit split percentage is lower i.e. agents need to change direction from north to east rather than travelling north to south (Figure 6-14). The time differences are higher for the male and female adults in the model regardless of the lane configuration, this is likely to be caused by the congestion in the model, which affects the fastest agents the most. This suggests that the model is capturing congestion and the passing of agents. This is backed up when population density increases the time difference is greatest for male and female adults too (Figure 6-13), which demonstrates that congestion is occurring, and capacity of the crossroads is being captured. It will now be important to test the model further to better understand the impact of the variables on influencing travel times. The calibration check has shown that the variables can influence the travel time that the travel times produced are not below the calculated minimum exit times and that capacity and congestion has been captured in the model environment.

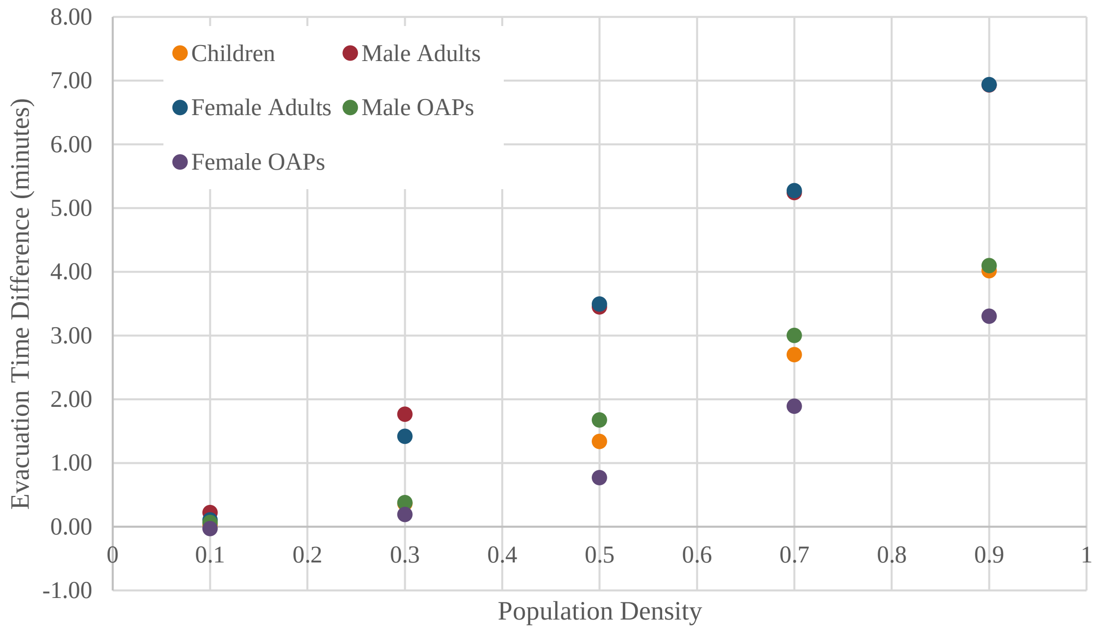


Figure 6-13 – Average Travel Time Difference between Calculated Minimum Model Times and Computed Model Times by Population Density

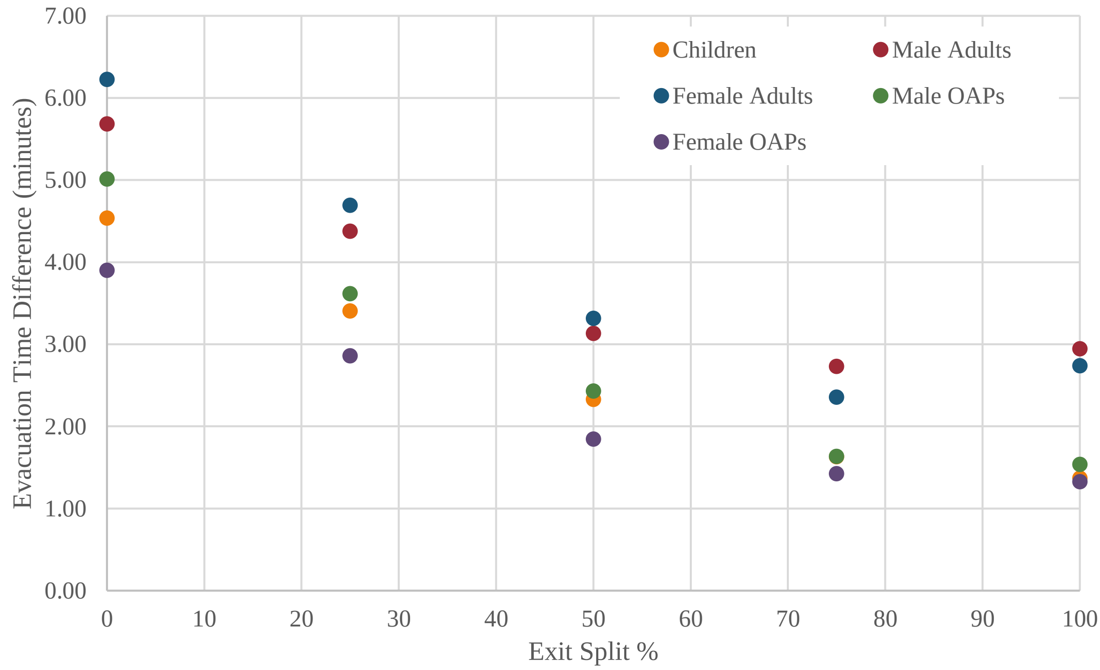


Figure 6-14 – Average Travel Time Difference between Calculated Minimum Model Times and Computed Model Times by Exit Split Percentage

6.6 Proposed Testing and Calibration, Verification & Validation

6.6.1 Microscale Crossroads Model Proposed Testing

It is important to carry out an initial calibration check to ensure the travel times produced by the model are realistic. The crossroads created was not based on a specific road junction so real-life times to travel the crossroads cannot be used to calibrate the model. Instead the minimum possible time to exit the crossroads will be calculated for each available pathway for each of the five agents (Bob, Betty, Ben, Barry, and Barbara). This will be done by calculating the distance travelled and then dividing it by the agent's speed, to produce a travel time estimate. This will provide a check to ensure that agents are not exiting the model quicker than the minimum possible travel time and to ensure that the agents are moving in the model as anticipated. An observational check will also be carried out to ensure that the model is performing as expected, e.g. are agents moving to their assigned exits, are agents moving in their correct lanes and able to overtake, is the patience function still working.

After completing the calibration check, further tests will be run with the model to understand the effect of altering the variables such as population density, lane configuration and population distribution (Table 6-11). The model will also be compared to existing agent-based models, which feature only 1.34m/s (3mph) walking speeds and no other variables.

Table 6-11 – Proposed Testing Schedule for Microscale Crossroads Model

Test No.	Variable(s)	Research Question
1A	No of Lanes Population Density Exit Split	- How the variables (crossroad configuration, population density and exit lane split) can be used to create congestion and capacity within an agent-based crossroads model - If the width of the crossroads (number of lanes) influences the travel time of agents - If the population density influences the travel time of a crossroads - If a varied exit split can influence the number of agent interactions and effect overall travel time
1B	Comparison to the 1.34m/s (3mph) Model	- Understand if there are any travel time differences between current agent-based models of human behaviour and the crossroads model caused by the introduction of additional variables

6.7 Microscale Model Summary

Two microscale models one of a straight length of a pavement and one of an intersecting crossroads are created, which are not based on any specific streets but instead generic representations. The models feature several variables which are the same as the macroscale model such as population types and walking speeds as well as several new variables which are: population density, number of lanes, patience and exit split percentage (crossroads model only). The aim of these models is to consider capacity and congestion within an agent-based model, with better representation of more intricate human behaviour traits such as overtaking and giving way. Calibration, validation, and verification is important to ensure the model is robust. The two microscale models have both been successfully developed to calculate minimum exit times, which could then be compared with the model simulations. A visual inspection of the simulations was conducted to validate that the agents moved as expected in the model environment, for example exhibiting overtaking and giving way to other agents. The proposed testing regime for the microscale models has been set out and must test the different pavement characteristics i.e. varying the number of lanes, population density and patience level and for the crossroads the additional characteristic of exit split percentage. In the next chapter, these tests will be completed, and comparisons will be made to existing agent-based models to understand the impact of including additional variables on exit timings and the inclusion of capacity and congestion within the model environment. The test results will be explored comprehensively in Chapter 7.

Chapter 7. Microscale Model Testing

In Chapter 6, the microscale model of the pavement and crossroads were created and combined with rulesets capturing robust human behaviour and capacity, including checks to ensure the behaviours had been validated. In this chapter, these microscale models will be tested to check the human behaviour parameters are appropriate representations of the anticipated human behaviours and to understand whether it is possible to include capacity within an agent-based model. The testing will focus on population data as a UK average as the macroscale model demonstrated that the population distribution was not a primary contributor to increases in evacuation time (see Chapter 5, section 5.3.7). The microscale models will not include the addition of groups of agents or a walking speed ratio, as these models are focused on the behaviour of individuals and how they react to others. Finally, conclusions will be drawn as to the benefits of incorporating additional robust behaviours in the microscale models.

7.1 Testing Schedule

Both the pavement and crossroads model have been validated using an observational check of behaviours and through the comparison of travel times with the minimum possible model exit times calculated using the distance of the agent's shortest exit paths (Section 6.2 and 6.5). On completion of this it was then necessary to test the models to understand the effect of including robust human behaviour rulesets. These tests were focused on the addition of reactive human behaviours to capture the capacity and congestion of a pavement and crossroads. The population distribution data used in both models was based on the UK average (Figure 5-2(b)). Alongside this, the varied walking speeds by age and sex identified in the macroscale model were replicated in both the pavement and crossroads model (Table 4-1). In this Chapter, we will run a series of tests to assess the introduction of the variables being used to create reactive human behaviours (Table 7-1).

Table 7-1 – Proposed Testing Schedule for Microscale Pavement & Crossroads Models

Pavement		
No.	**Variable(s)**	**Research Questions**
1	No of Lanes	- If the width of the pavement (number of lanes) influenced the travel time of agents.
2	Population Density	- If the population density influenced the travel time of a pavement.
3	Patience Level	- If a varied patience level influenced the overtaking occurring and effected overall travel time.

4	Comparison to the 1.34 m/s (3mph) Model	- Understand if there were any travel time differences between current agent-based models of human behaviour and this pavement model caused by the introduction of additional variables.
Crossroads		
No.	**Variable(s)**	**Research Questions**
1	No of Lanes	- If the width of the crossroads (number of lanes) influences the travel time of agents.
2	Population Density	- If the population density influences the travel time of a crossroads.
3	Exit Split	- If a varied exit split can influence the number of agent interactions and effect overall travel time.
4	Comparison to the 1.34m/s (3mph) Model	- Understand if there are any travel time differences between current agent-based models of human behaviour and the crossroads model caused by the introduction of additional variables.

7.2 Pavement Testing

7.2.1 Test Aim & Variables

The initial testing of the pavement was based on the number of lanes in the pavement, the population density and the utilisation of patience level. The aim of this test was to ascertain whether the: (1) number of lanes in the pavement, (2) population density, and (3) application of a patience level had any effect on the travel time of agents over a given pavement length of 1km. Within the test, two different scenarios were conducted to assess the overall impact on travel time: (1) all agents walk at the same speed (1.34m/s or 3mph) and (2) varied walking speeds by age and sex. These scenarios were run with several numbers of lanes to alter the pavement width (3, 4 and 5) referred to as Test 1, a range of population densities (0.1, 0.3, 0.5, 0.7 and 0.9) referred to as Test 2 and different patience levels (1, 5, 10, 25, 50 and 100) referred to as Test 3 (Table 7-2), the test variations have been set out in Figure 7-1. The comparison between the 1.34m/s (3mph) model and varied walking speeds is discussed in Test 4. To understand the variability in the results, each set of variables and the varied walking speed scenario will have 10 realisations, this results in 900 sets of travel times for this test (Table 7-3), which can then be averaged for comparison purposes. The comparison to the 1.34m/s (3mph) model will be completed using calculated simulations using the distances travelled by agents rather than run as simulations.

Table 7-2 – Microscale Pavement Model Variables for Test 1 (For the walking speeds: C = Children, MA = Male Adults, FA = Female Adults, MO = Male OAPs and FO = Female OAPs)

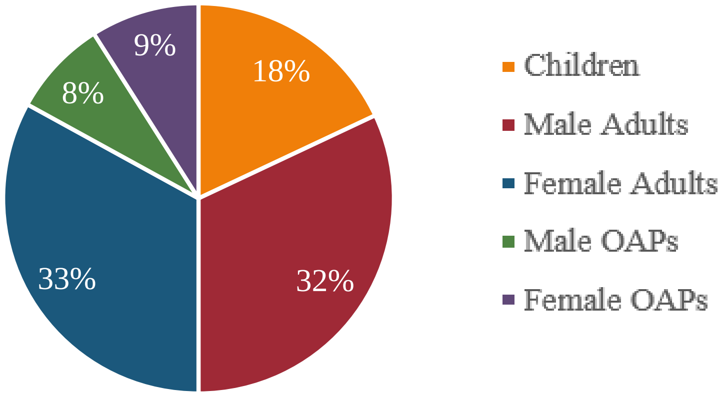
Variables	1.34m/s (3mph) Walking Speed	Varied Walking Speed by age and sex
Population Makeup	C = 18%, MA = 32%, FA = 33%, MO = 8% and FO = 9% 	
Population Density	0.1, 0.3, 0.5, 0.7, 0.9	
Walking Speed (Bosina & Weidmann, 2017)	All = 1.34 m/s (3mph)	C = 0.8 m/s (1.79mph) MA = 1.34 m/s (3mph) FA = 1.12 m/s (2.5mph) MO = 0.78 m/s (1.74mph) FO = 0.76 m/s (1.70mph)
Number of Lanes	3, 4, 5	
Patience Level	1, 5, 10, 25, 50, 100	

Table 7-3 – Total Number of Results Expected from Test 1

No. of Lanes		**3 Lanes**					**4 Lanes**					**5 Lanes**					**Total**
Population Density		**0.1**	**0.3**	**0.5**	**0.7**	**0.9**	**0.1**	**0.3**	**0.5**	**0.7**	**0.9**	**0.1**	**0.3**	**0.5**	**0.7**	**0.9**	
Patience Level	**1**	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	150
	5	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	150
	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	150
	25	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	150
	50	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	150
	100	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	150
Total Number of Simulation Runs = 900																	

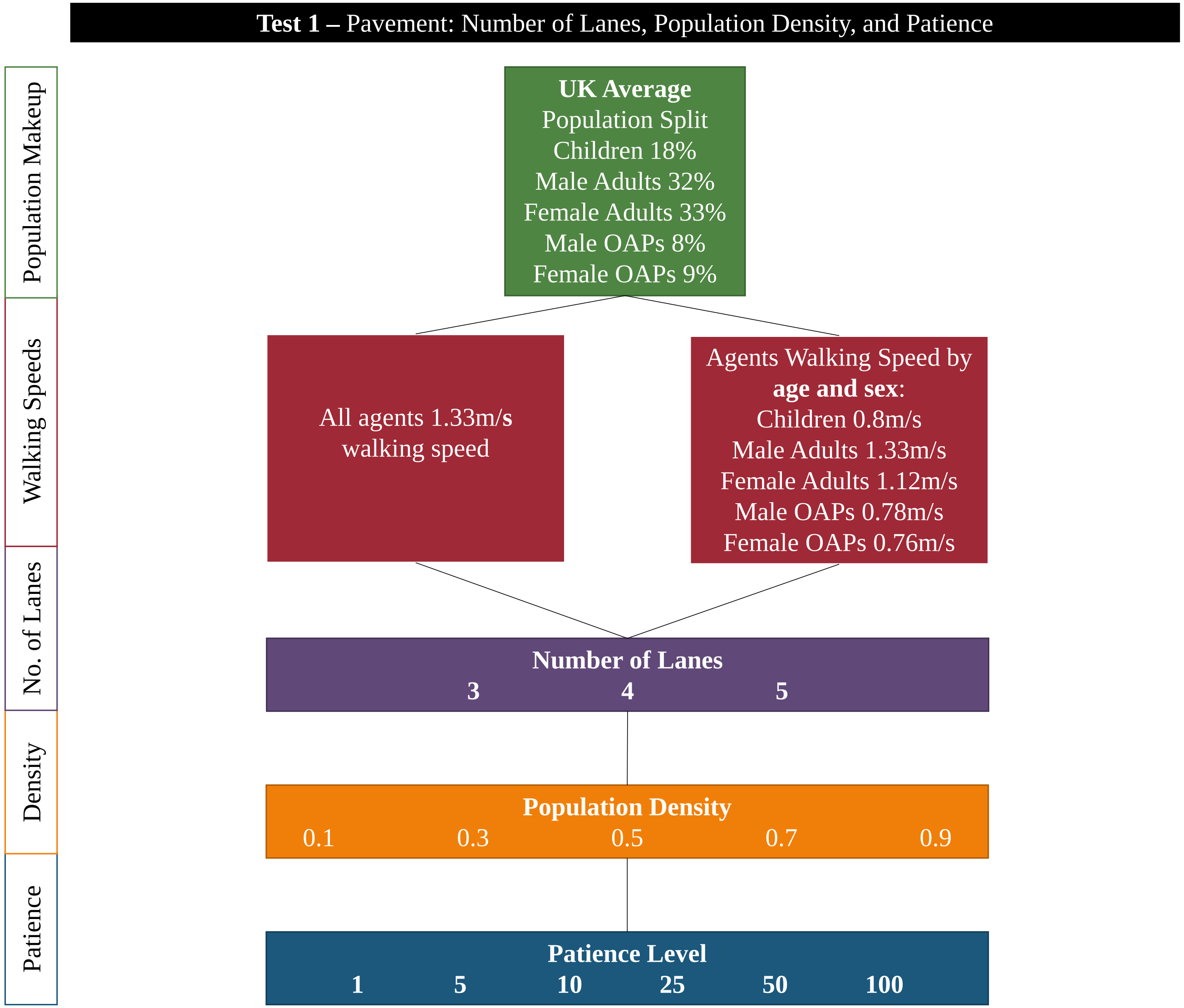


Figure 7-1 – Testing Regime for Test 1

7.2.2 Average Travel Times

After completing the simulations for the varied walking speeds by age and sex with the defined variables (number of lanes, population density and patience level), the averaged evacuation times for each population type were compiled (Table 7-4). These results show that there were a range of travel times produced when the variables were considered, demonstrating that the model may be successfully reproducing congestion and reactive agent behaviours. However, it was important to understand if this was an impact of population density, patience level, and the width of the pavement or a combination of these factors. When walking speeds are all the same, there was little variation seen in the averaged travel times, standard deviation is 0.07 minutes. Unlike the varied walking speeds, which showed there was large variations for the male and female adults, (approximately 30-40% difference between the minimum and maximum times recorded for these population types), suggesting that the model has been impacted by the variables (Table 7-4). It is important to ascertain from this whether there is a primary variable influencing travel times or a combination required to produce congestion within the microscale pavement model.

Table 7-4 – Average, Minimum, Maximum and Standard Deviations for each population type for all 900 simulation runs with varied walking speeds compared to the Average, Minimum, Maximum and Standard Deviations for the calculated simulations with all walking speeds the same 1.34m/s (3mph)

Varied Walking Speeds by Age and Sex				
Population Type	**Minimum (minutes)**	**Average (minutes)**	**Maximum (minutes)**	**Standard Deviation (minutes)**
Children	20.72	20.92	21.60	0.24
Male Adults	12.28	17.06	21.09	2.75
Female Adults	14.67	17.92	21.19	2.08
Male OAPs	21.25	21.33	21.69	0.11
Female OAPs	21.80	21.83	21.95	0.03
All Walking Speeds the Same				
Population Type	**Minimum (minutes)**	**Average (minutes)**	**Maximum (minutes)**	**Standard Deviation (minutes)**
All	12.19	12.26	12.31	0.07

A plot of all simulation travel times (900 in total) was also compiled to show the variation (Figure 7-2). This shows the fluctuation in the times produced for male and female adults, the standard deviation for male adults is 2.75 minutes and female adults is 2.08 minutes, but the relatively static travel times for the slower agents (children, male and female OAPs), with standard deviations around 0.03 – 0.24 minutes. This suggests the children and OAPs are successfully slowing the adult agent types and causing congestion in the model (Figure 7-2) but there is a need to understand if there is a particular variable that influences the travel times or a combination required to cause congestion.

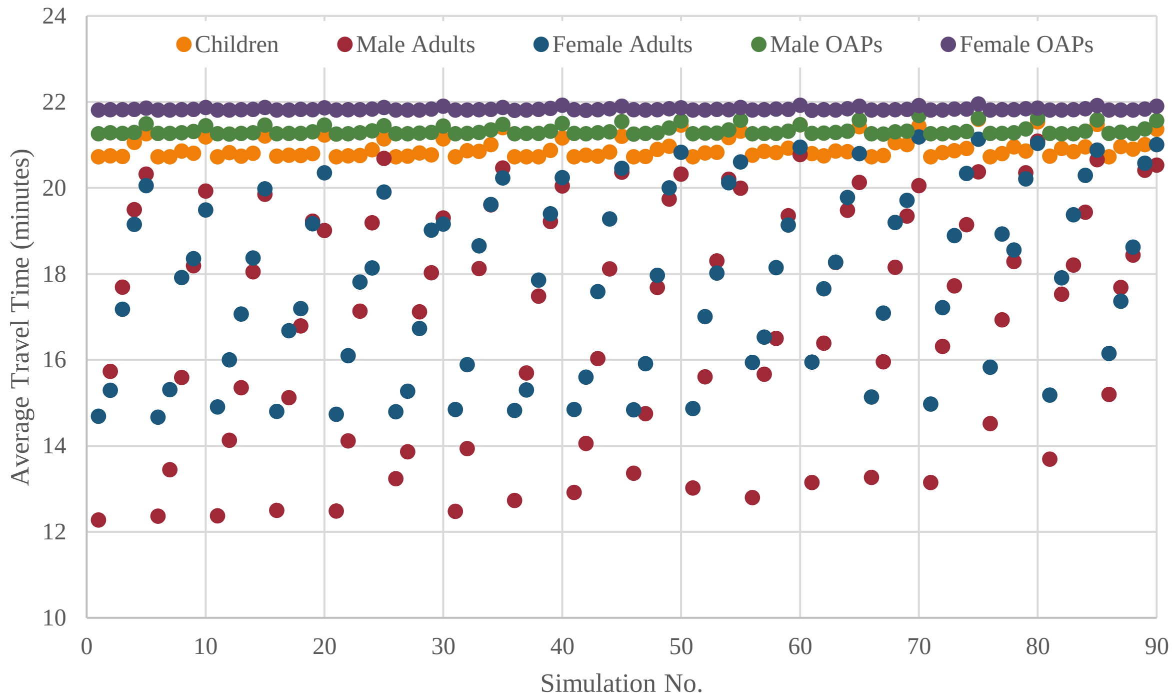


Figure 7-2 – Average Travel Time (minutes) for all Pavement Simulations, Simulation No. is arbitrary (for each of the simulation numbers, there are 10 simulation runs averaged to produce a single value, equating to 900 simulations in total), for each population type: mean (standard deviation), Children: 20.92 minutes (0.24 minutes), Male Adults: 17.06 minutes (2.75 minutes), Female Adults: 17.92 minutes (2.08 minutes), Male OAPs: 21.33 minutes (0.11 minutes) and Female OAPs: 21.83 minutes (0.03 minutes)

7.2.3 Test 1 – Effect of Pavement Width

In this section, the effect of the pavement width is explored, it has been demonstrated in Chapter 6, that a range of pavement widths can be anticipated in any city and depending on the scenario any pavement can be split into a number of lanes. In this test, only pavements of three to five lanes were considered, but it is anticipated that pavements may form as many as ten lanes during stress situations such as evacuations. In Figure 7-3, the average travel times for the 900 simulations with varied walking speeds is presented by population type and the number of lanes, this means there is a range of population densities considered. This shows that there is variation between the population types, which was expected based on the results of Chapter 5, as it was shown that the introduction of varied walking speeds results in different travel times for the population types. However, there is little variation between the number of lanes within each population type, for example, Children have a standard deviation of only 0.01 minutes and Male Adults have the most variation at 0.17 minutes. It is anticipated that the male adults have a larger variation as a result of the male adults passing other agents as their walking speed is the highest in the model. It can be argued that the width of the pavement has no significant impact on overall travel time and therefore the introduction of congestion into a microscale pavement model, other than its ability to create space to allow overtaking and interactions to occur in.

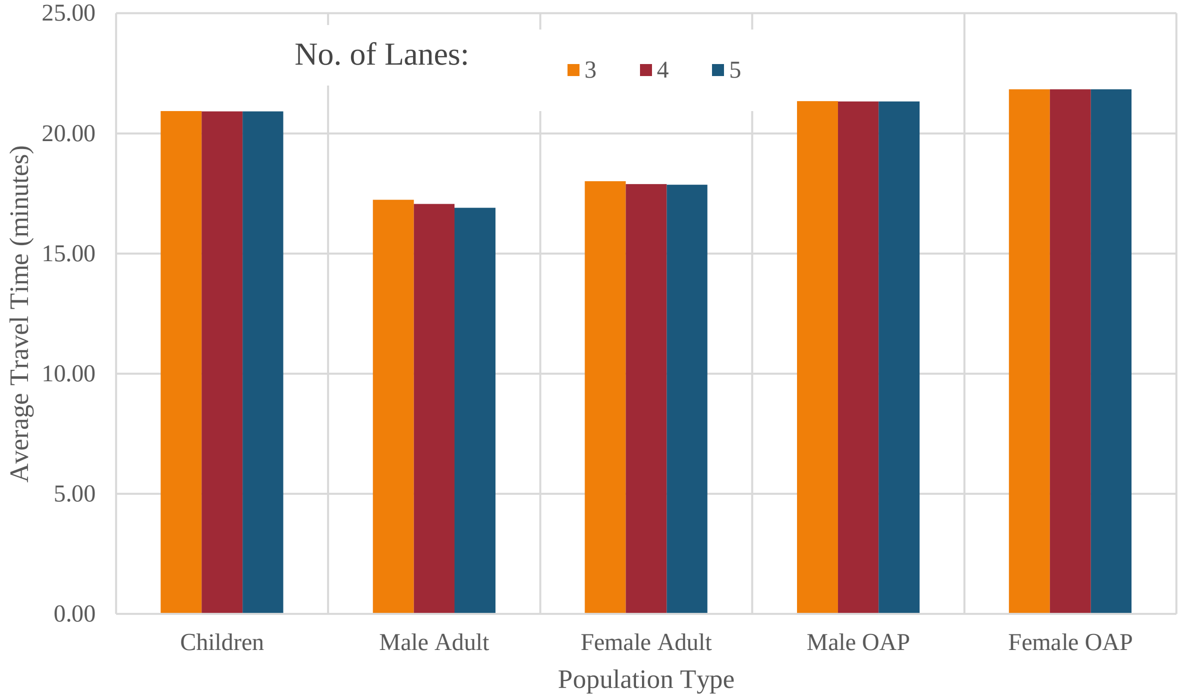


Figure 7-3 – Average Travel Times for each population type when considering the width of the pavement between three and five lanes, for each population type: mean (standard deviation), Children:20.92 minutes (0.01 minutes), Male Adults: 17.06 minutes (0.17 minutes), Female Adults: 17.92 minutes (0.08 minutes), Male OAPs: 21.33 minutes (0.01 minutes) and Female OAPs: 21.83 minutes (0.00 minutes)

To explore the number of lanes further, the average travel times from the simulations were plotted in terms of population density and the applied patience level (Figure 7-4 and Figure 7-5). In terms of population density, again the number of lanes produced little variation, as expected, but there were larger variations caused by population density, which could be a contributing factor to the introduction of congestion. When examining the patience level, the number of lanes again had produced little variation, but larger variations appeared to have been caused by applying a patience level, which could be aiding the introduction of congestion. The population density and patience level will be explored further in subsequent sections to understand their impacts on travel time and capturing congestion in a microscale model.

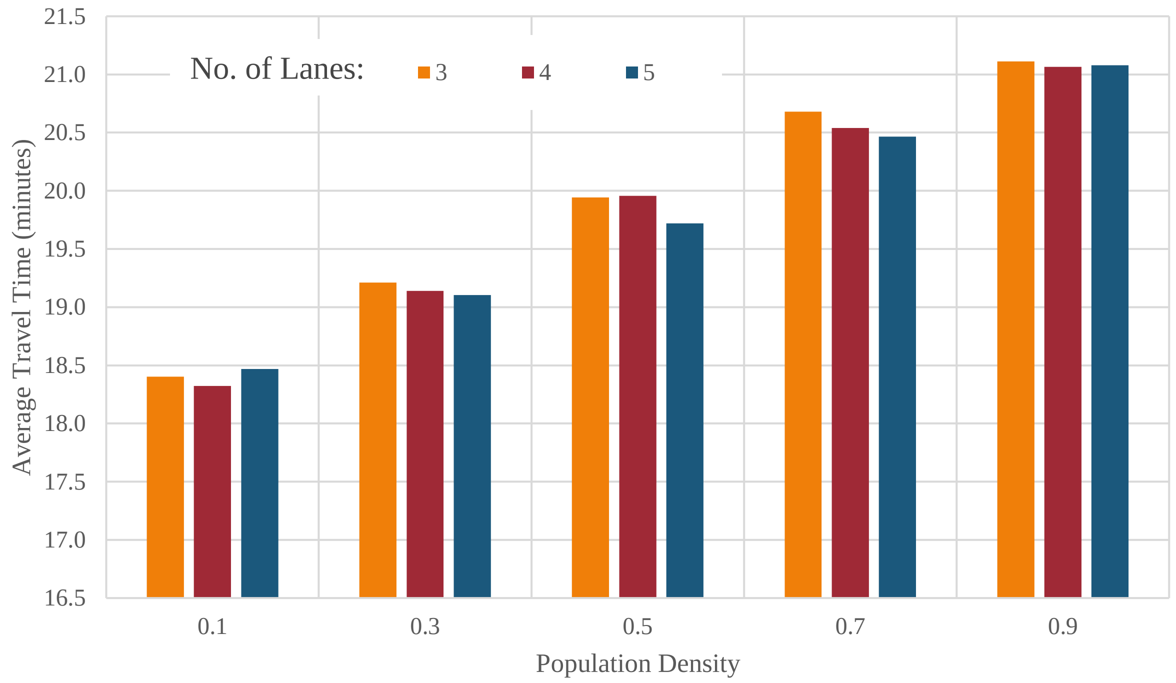


Figure 7-4 – Average Travel Time for each Population Density when considering the width of the pavement between three and five lanes, for each population density: mean (standard deviation), 0.1: 18.40 minutes (0.07 minutes), 0.3: 19.15 minutes (0.06 minutes), 0.5: 19.87 minutes (0.13 minutes), 0.7: 20.56 minutes (0.11 minutes) and 0.9: 21.09 minutes (0.02 minutes)

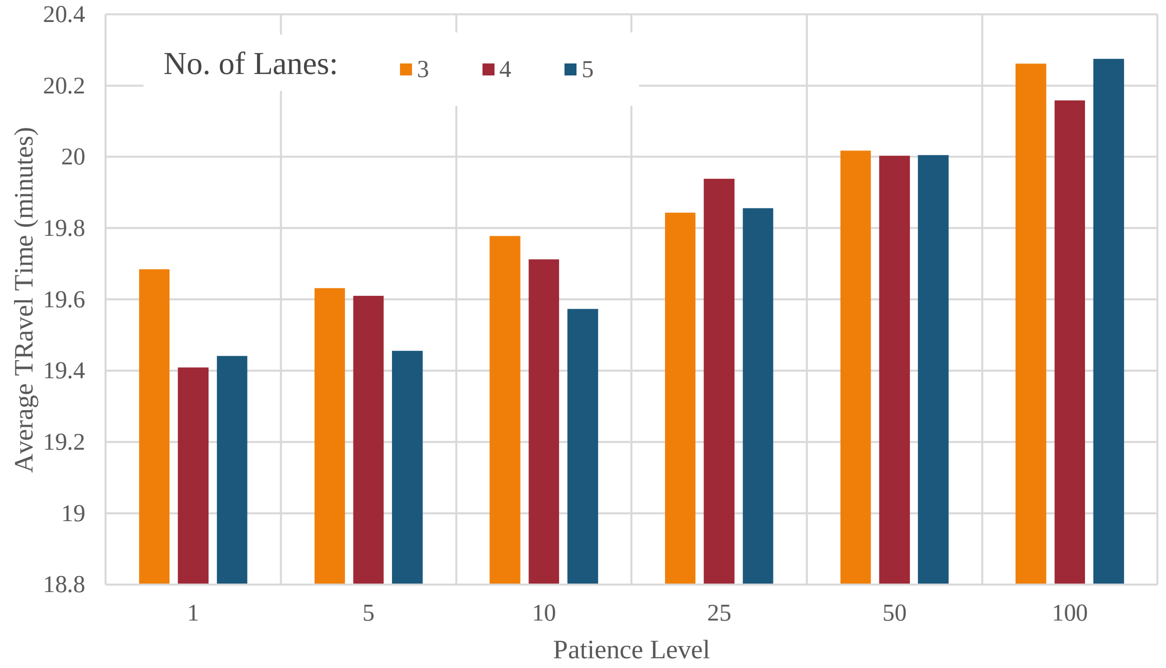


Figure 7-5 – Average Travel Time for each Patience Level when considering pavement width between three and five lanes, with 1 being considered as low patience and 100 being high patience, for each Patience Level: mean (standard deviation), 1: 19.51 minutes (0.15 minutes), 5: 19.57 minutes (0.10 minutes), 10: 19.69 minutes (0.10 minutes), 25: 19.88 minutes (0.05 minutes), 50: 20.01 minutes (0.01 minutes) and 100: 20.23 minutes (0.06 minutes)

7.2.4 Test 2 – Effect of Population Density

A further plot has been compiled to show population density by population type from the 900 simulations of varied walking speeds and altered variables (Figure 7-6). This shows that in general as population density increases the average travel time also increases, from an average of 18.40 minutes (population density of 0.1) to 21.09 minutes (with a population density of 0.9). Another trend is that the travel times for population types are less varied as the population density increases, i.e. the travel times converge, as reflected by the standard deviation of 4.01 minutes (at 0.1 population density), which lowers to 0.72 minutes (at 0.9 population density). It can also be seen that the travel times for the slow agents (children and OAPs) only make small changes (standard deviation ranges from 0.04 – 0.27 minutes) with population density compared with the faster adults (standard deviation ranges from 1.21 – 1.44 minutes), demonstrating that the adult population is more greatly affected by the introduction of congestion than the slower agent types. It was anticipated that travel times would increase with population density as the agents experience more congestion as density increases. It would also be expected that the travel times would increase by population type with times reducing in variance as population density increases as the faster agents (adults) are impeded by the slower population types. It can therefore be argued that the inclusion of population density is a requirement if a microscale pavement model is to successfully replicate congestion.

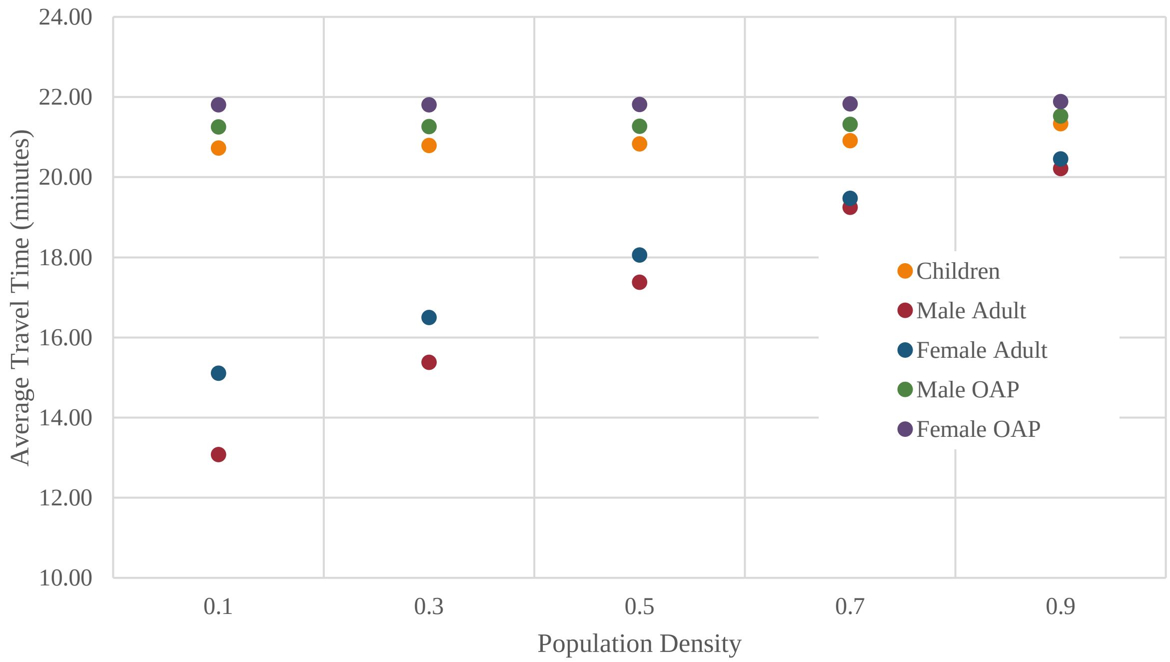


Figure 7-6 – Average Travel Times for each population type when considering population density between 0.1 and 0.9, for each population type: mean (standard deviation), Children:21.03 minutes (0.27 minutes), Male Adults: 18.95 minutes (1.44 minutes), Female Adults:19.33 minutes (1.21 minutes), Male OAPs: 21.38 minutes (0.13 minutes) and Female OAPs: 21.85 minutes (0.04 minutes)

7.2.5 Test 3 – Effect of Patience Level

An additional plot has been completed to show the patience level by population type for the 900 simulations of varied walking speed and different variables (Figure 7-7). This shows that the patience level has had little impact on the slower agent types (children and OAPs), the standard deviation ranges from 0.00 – 0.06 minutes. However, for the male and female adults there has been an increase in travel time with increased patience level, for the male adults from 16.32 minutes to 18.20 minutes and for the female adults from 17.23 minutes to 18.79 minutes. This suggests that the higher patience level is causing a reduced amount of overtaking in the model and hence the faster agent types are remaining behind slower agents for longer, resulting in the increased travel times. It therefore seems necessary to include patience level within a microscale pavement model if a robust representation of congestion is required.

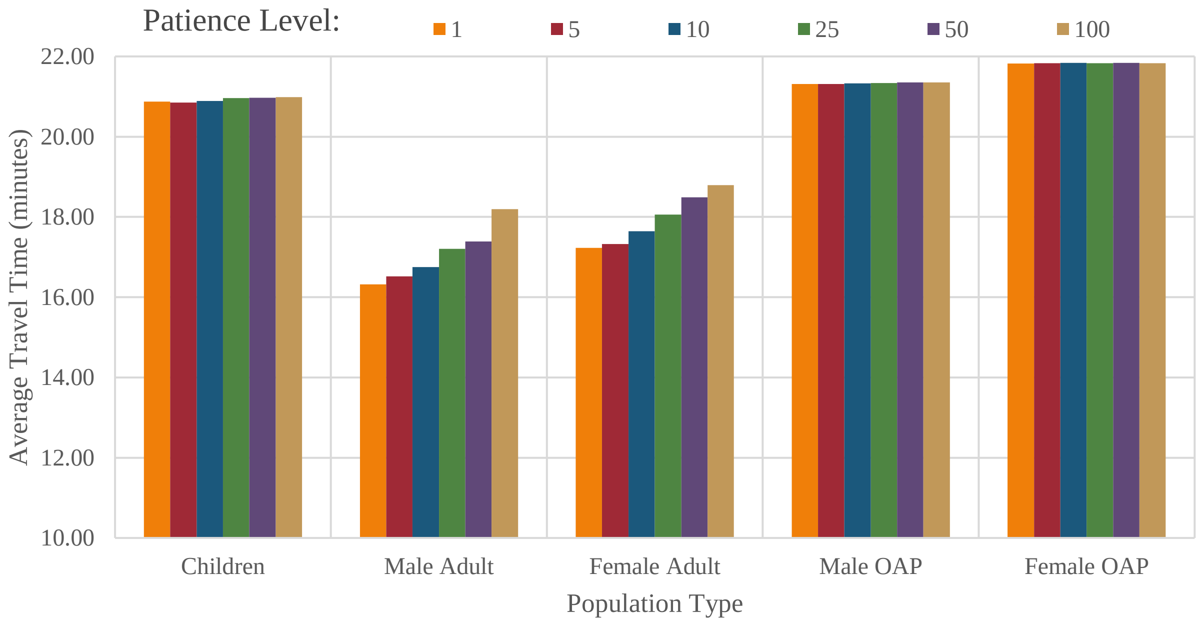


Figure 7-7 – Average Travel Times for each population type when considering patience level between 1 and 100, for each population type: mean (standard deviation), Children: 20.93 minutes (0.06 minutes), Male Adults: 17.21 minutes (0.65 minutes), Female Adults: 18.06 minutes (0.6 minutes), Male OAPs: 21.34 minutes (0.02 minutes) and Female OAPs: 21.83 minutes (0.00 minutes)

A further plot was compiled to consider the patience level and population density within the microscale pavement model (Figure 7-8). This shows that as population density increases, travel time increases and that the largest travel time is attributed to the highest patience level each time. As before when population density increases, the travel time variance decreases, and the values converge to a similar value. This indicates that both patience level and population density are having an impact on the model and should therefore both be considered for inclusion when a model needs to factor in congestion and capacity.

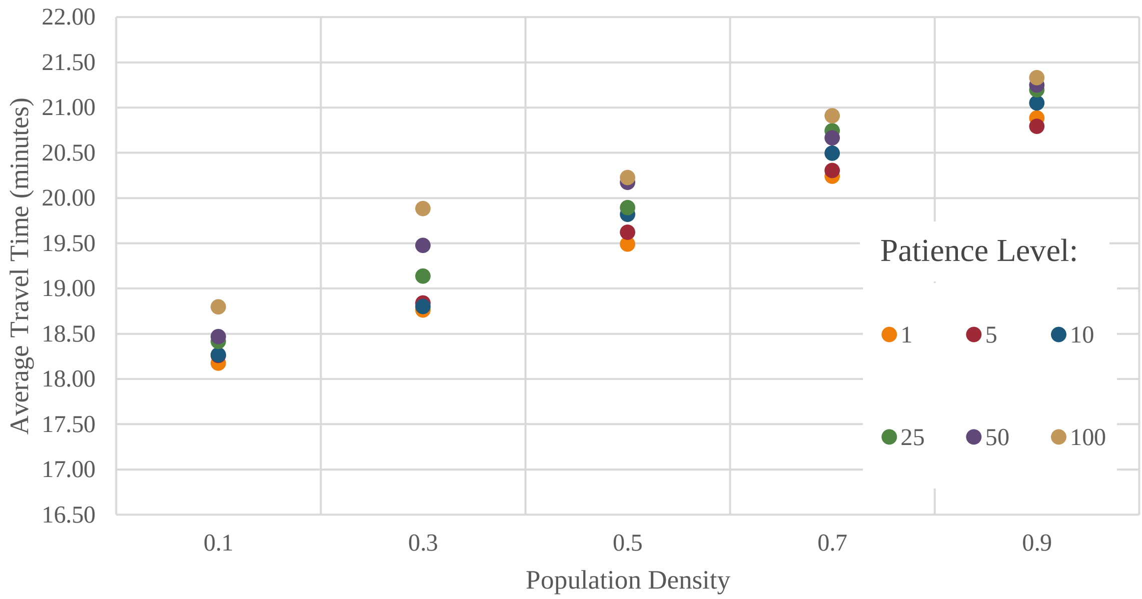


Figure 7-8 – Average Travel Times based on Population Density between 0.1 and 0.9 and Patience Level between 1 and 100, for each patience level: mean (standard deviation),1: 20.21 minutes (0.70 minutes), 5: 20.24 minutes (0.59 minutes), 10: 20.46 minutes (0.62 minutes), 25: 20.61 minutes (0.66 minutes), 50: 20.70 minutes (0.54 minutes) and 100: 20.82 minutes (0.56 minutes)

7.2.6 Test 4 – Comparison to 1.34m/s (3mph) Model

There is a need to understand if this microscale model of a pavement differs from a calculated model with walking speeds of only 1.34m/s (3mph) with no additional variables included. The calculated travel times for the 1.34m/s (3mph) model were an average of 12.26 minutes. These calculated travel times were compared with the travel times produced through the 900 simulations for varied walking speeds, this allowed a time difference to be estimated. It has been shown that for all population types, there is a travel time difference between the 1.34m/s (3mph) model and the simulated values. The percentage time differences are greatest for the slower agent types when considering the application of varied walking speeds only, which was anticipated as their speeds had been reduced significantly compared to the 1.34m/s (3mph) value (Figure 7-9).

However, when population density and patience level are also considered, the male and female adults are severely impacted in terms of travel time, although the slower population types (children and OAPs) are not. The slower population types are not significantly impacted by the population density and patience level as they form the slowest agents therefore have less need to overtake but serve the important purpose of causing congestion for the adult population. Initially, if population density is kept low (0.1) but patience level is high (100), the male adults travel time increases by 19% and female adults 29%. When population density is increased (0.9) and patience is decreased (1), the impact to travel time is further increased to 64% and 63% respectively. Finally, in a worst-case scenario with high population density (0.9) and high patience level (100), the percentage difference in travel times increases to 71% and 72% respectively. This demonstrates that population characteristics such as varied walking speeds need to be considered in the first instance when creating an agent-based model of an evacuation population. If further improvements are sought the inclusion of population density should be considered followed by a patience level for agents. Overall, this comparison shows that the microscale pavement model has successfully captured congestion within the model environment when compared to the 1.34m/s (3mph) model.

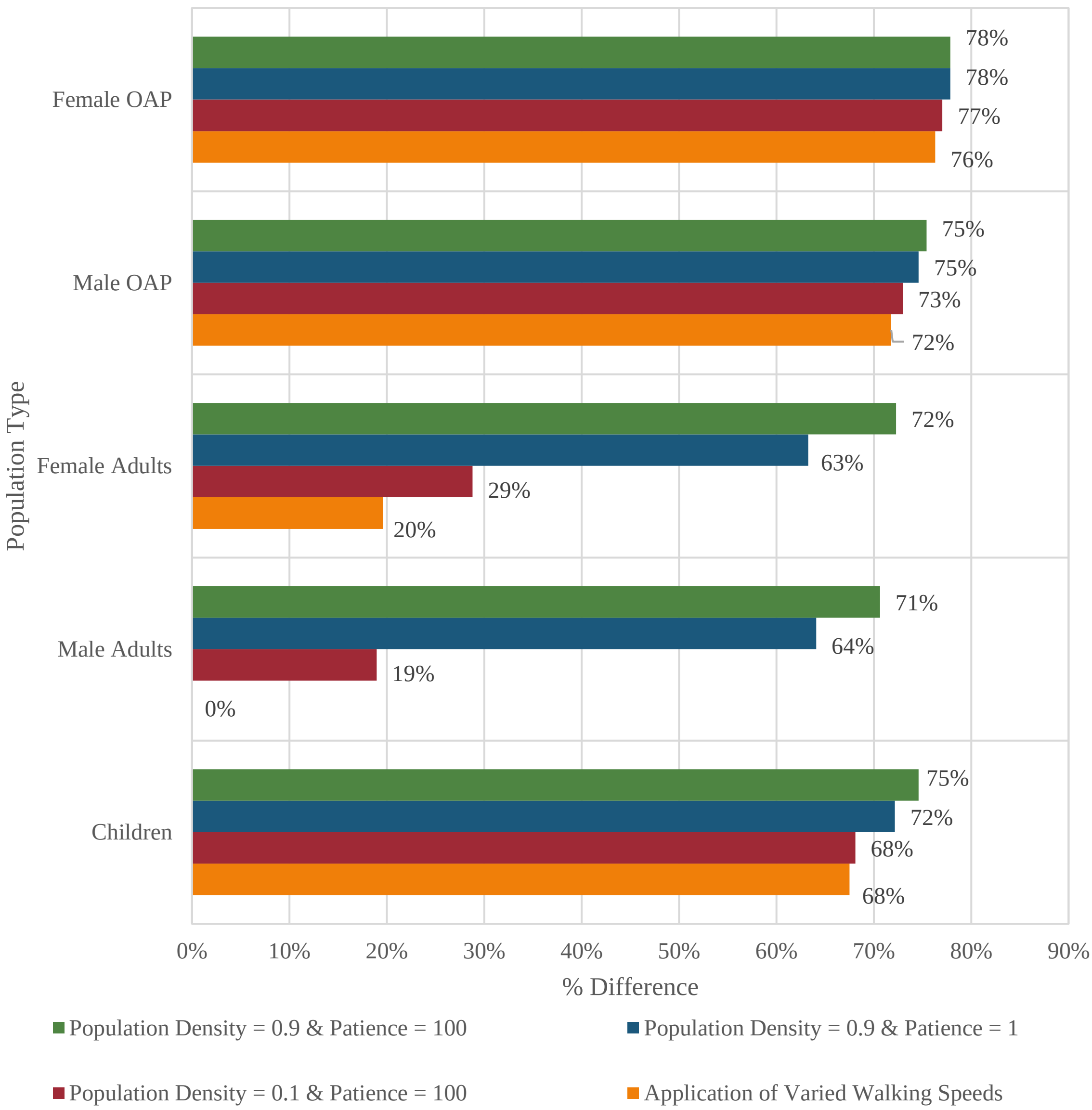


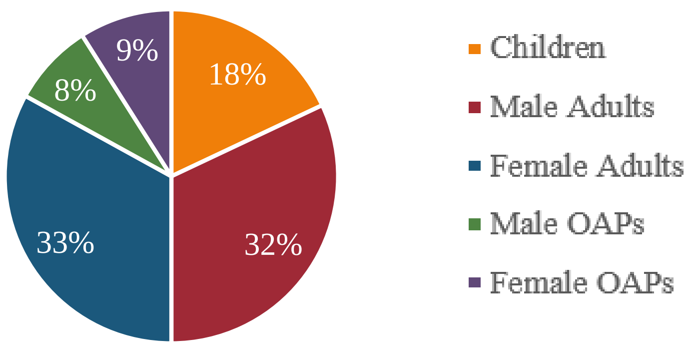
Figure 7-9 – Comparison to 1.34m/s (3mph) Calculated Model and Simulated Agent-Based Model Values, initially showing the introduction of varied walking speeds for different population types only, then the impact of varied walking speeds by population types combined with population density and patience levels

7.3 Crossroad Testing

7.3.1 Test Aim & Variables

The initial testing of the crossroads was based on the number of lanes in the crossroads, the population density, and the exit split percentage. The aim of these tests was to ascertain whether the: (1) number of lanes in the crossroads, (2) population density, and (3) exit split percentage had any effect on the travel time of agents over a given crossroad length of 500m. Within the test, two different scenarios were conducted to assess the overall impact on travel time: (1) all agents walk at the same speed (1.34m/s or 3mph) and (2) varied walking speeds by age and sex. These scenarios were run with several numbers of lanes to alter the crossroad width (3, 4 and 5 in each direction) referred to as Test 1, a range of population densities (0.1, 0.3, 0.5, 0.7 and 0.9) referred to as Test 2 and different exit split percentages (0, 25, 50, 75 and 100%) referred to as Test 3 (Table 7-5), the test variations have been set out in Figure 7-10. The comparison between the 1.34m/s (3mph) model and varied walking speeds is discussed in Test 4. For the crossroads, the patience level was maintained at a constant value of 2, this was informed by the pavement testing, which showed patience level could affect the travel time of agents and result in congestion in the model. In these tests, it was important to encourage agent reactions and therefore overtaking of each other, to ensure this occurred the patience level was kept at 2 throughout to yield good results. To understand the variability in the results, each set of variables and the varied walking speed scenario will have 10 realisations. This results in 750 sets of travel times per number of lanes in the north-south direction (3, 4 and 5), resulting in 2250 simulations in total in this test (Table 7-6), which can then be averaged for comparison purposes. The comparison to the 1.34m/s (3mph) model will be completed using calculated simulations using the distances travelled by agents rather than run as simulations.

Table 7-5 – Microscale Crossroads Model Variables for Test 1 (For the walking speeds: C = Children, MA = Male Adults, FA = Female Adults, MO = Male OAPs and FO = Female OAPs)

Variables	1.34m/s (3mph) Walking Speed	Varied Walking Speed by age and sex
Population Makeup	C = 18%, MA = 32%, FA = 33%, MO = 8% and FO = 9% 	

Population Density	0.1, 0.3, 0.5, 0.7, 0.9	
Walking Speed (Bosina & Weidmann, 2017)	All = 1.34 m/s (3mph)	C = 0.8 m/s (1.79mph) MA = 1.34 m/s (3mph) FA = 1.12 m/s (2.5mph) MO = 0.78 m/s (1.74mph) FO = 0.76 m/s (1.70mph)
Number of Lanes in North – South	3, 4, 5	
Number of Lanes in West – East	3, 4, 5	
Exit Split (%)	0, 25, 50, 75, 100	
Patience Level	2	

Table 7-6 – Total Number of Results Expected from Test 2

No of Lanes in N-S		**3 Lanes**															
No. of Lanes in E-W		**3 Lanes**					**4 Lanes**					**5 Lanes**					**Total**
Population Density		**0.1**	**0.3**	**0.5**	**0.7**	**0.9**	**0.1**	**0.3**	**0.5**	**0.7**	**0.9**	**0.1**	**0.3**	**0.5**	**0.7**	**0.9**	
Exit Split %	**0**	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	150
	25	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	150
	50	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	150
	75	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	150
	100	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	150
Total Number of Simulation Runs per Lane Configuration = 750 x 3 **Total Number of Simulation Runs = 2250**																	

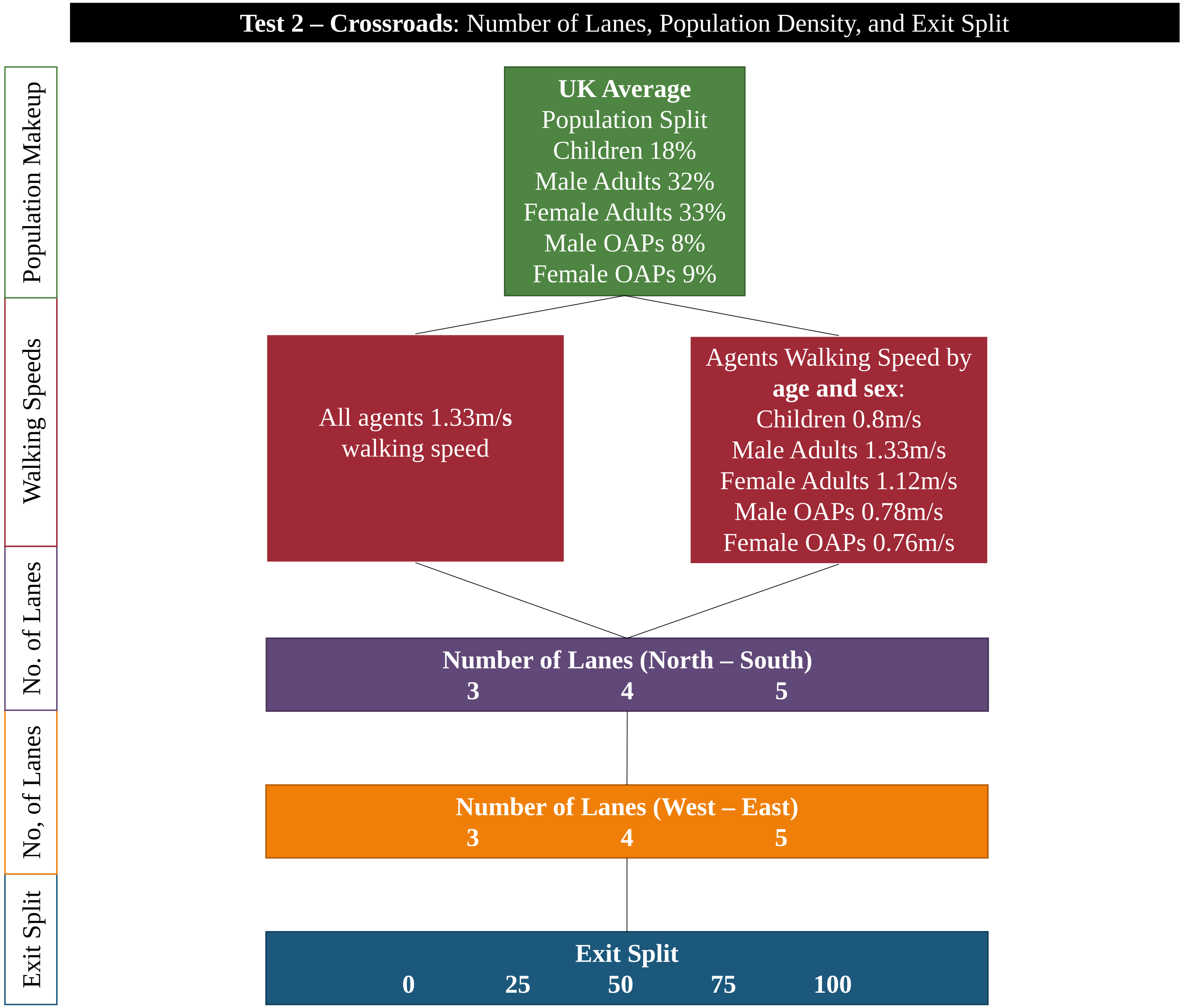


Figure 7-10 – Testing Regime for Test 2

7.3.2 *Average Travel Times*

After completing the simulations for the varied walking speeds by age and sex with the defined variables (crossroad configuration, population density and exit split percentage), the averaged evacuation times for each population type were compiled (Table 7-7). This showed that there were a range of travel times produced when the variables were considered, demonstrating that the model may be successfully reproducing congestion and agents considering the capacity of the crossroads. However, it was important to understand if this was an impact of population density, exit split percentage, the configuration of the crossroads or a combination of these factors. When walking speeds are all the same, there was little variation seen in the averaged travel times (standard deviation of 0.21 minutes). Unlike the varied walking speeds, which showed there was large variations for all agents but particularly for the male and female adults (approximately 70% difference between the minimum and maximum times recorded for adults and approximately 50% for children and OAPs), suggesting that the model has been impacted by the variables (Table 7-7). It is important to ascertain from this whether there is a primary variable influencing travel times or a combination required to produce congestion within the microscale crossroad model.

Table 7-7 – Average, Minimum, Maximum and Standard Deviations for each population type for all 2250 simulation runs with varied walking speeds compared to the Average, Minimum, Maximum and Standard Deviations for the calculated simulations with all walking speeds the same 1.34m/s (3mph)

Varied Walking Speeds by Age and Sex				
Population Type	**Minimum (minutes)**	**Average (minutes)**	**Maximum (minutes)**	**Standard Deviation (minutes)**
Children	9.39	11.62	18.77	2.24
Male Adults	5.53	9.20	17.90	2.85
Female Adults	6.79	10.49	23.68	3.29
Male OAPs	10.05	12.25	21.51	2.55
Female OAPs	9.26	11.39	18.46	1.85
All Walking Speeds the Same				
Population Type	**Minimum (minutes)**	**Average (minutes)**	**Maximum (minutes)**	**Standard Deviation (minutes)**
Children **Male Adults** **Female Adults** **Male OAPs** **Female OAPs**	5.22	5.86	6.22	0.21

A plot of all simulation travel times (2250 in total) was also compiled to show the variation. This shows the fluctuation in the times produced for all population types, the standard deviation for male adults is 2.85 minutes and female adults is 3.29 minutes, for the children, male and female OAPs, the standard deviations range from 1.85 – 2.55 minutes. This suggests the children and OAPs are successfully slowing the adult agent types and each other, causing congestion in the model (Figure 7-11) but there is a need to understand if there is a particular variable that influences the travel times or a combination required to cause congestion.

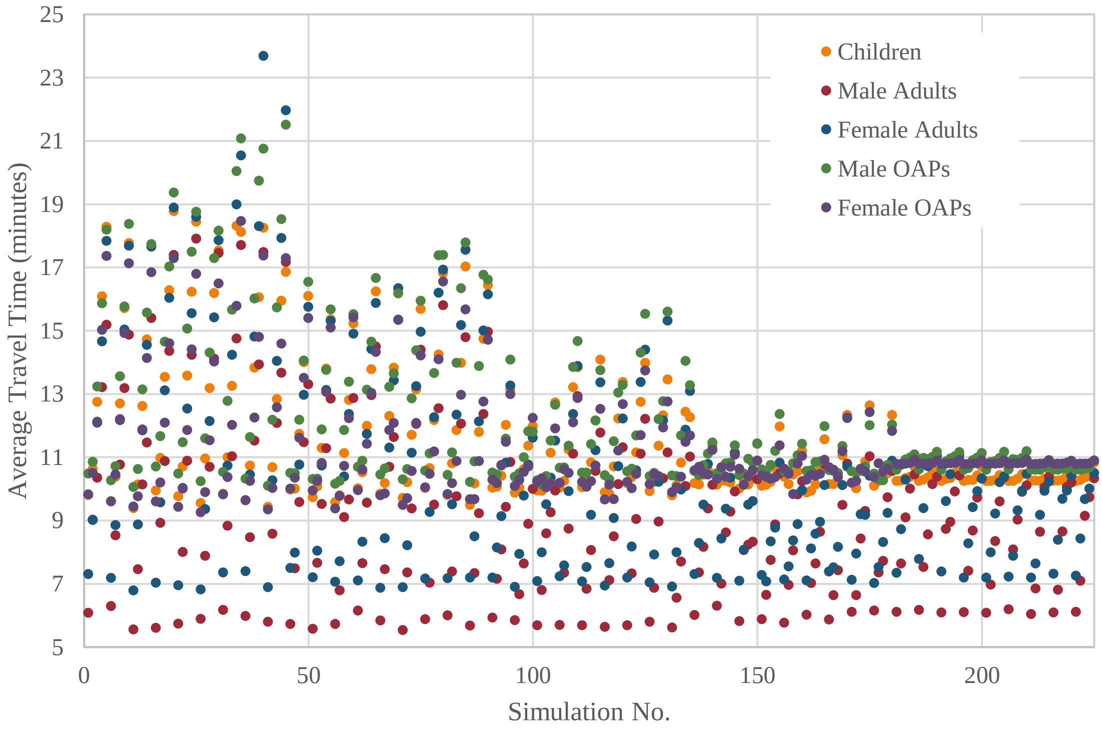


Figure 7-11 – Average Travel Time (minutes) for all Crossroad Simulations, Simulation No. is arbitrary (for each of the simulation numbers, there are 10 simulation runs averaged to produce a single value, equating to 2250 simulations in total), for each population type: mean (standard deviation), Children: 11.62 minutes (2.24 minutes), Male Adults: 9.20 minutes (2.85 minutes), Female Adults: 10.49 minutes (3.29 minutes), Male OAPs: 12.25 minutes (2.55 minutes) and Female OAPs: 11.39 minutes (1.85 minutes)

7.3.3 Test 1 – Effect of Crossroad Configuration

In this section, the effect of the crossroad configuration is examined, it has been demonstrated in Chapter 6 that a range of pavement widths can be anticipated in any city, which then form the two arms of a crossroads, and depending on the scenario any pavement can be split into a number of lanes. In this test, only crossroad arms of three to five lanes were considered, to mirror the number of lanes considered in the pavement model, but it is anticipated that crossroads may form as many as ten lanes in each direction during stress situations such as evacuations. In Figure 7-12, the average travel times for the 2250 simulations with varied walking speeds is presented by population type and the crossroad configuration. This shows that there is large variation between the population types, which was expected based on the results of Chapter 5, as it was shown that the introduction of varied walking speeds results in different travel times for the population types. However, there is also small variations between the crossroad configurations within each population type, with standard variations ranging from 0.21 – 0.41 minutes. Hence, it is suggested that the crossroad configuration has no significant impact on overall travel time and therefore the introduction of congestion into a microscale crossroad model. Other than the ability to create space for agent interactions such as overtaking and giving way to occur.

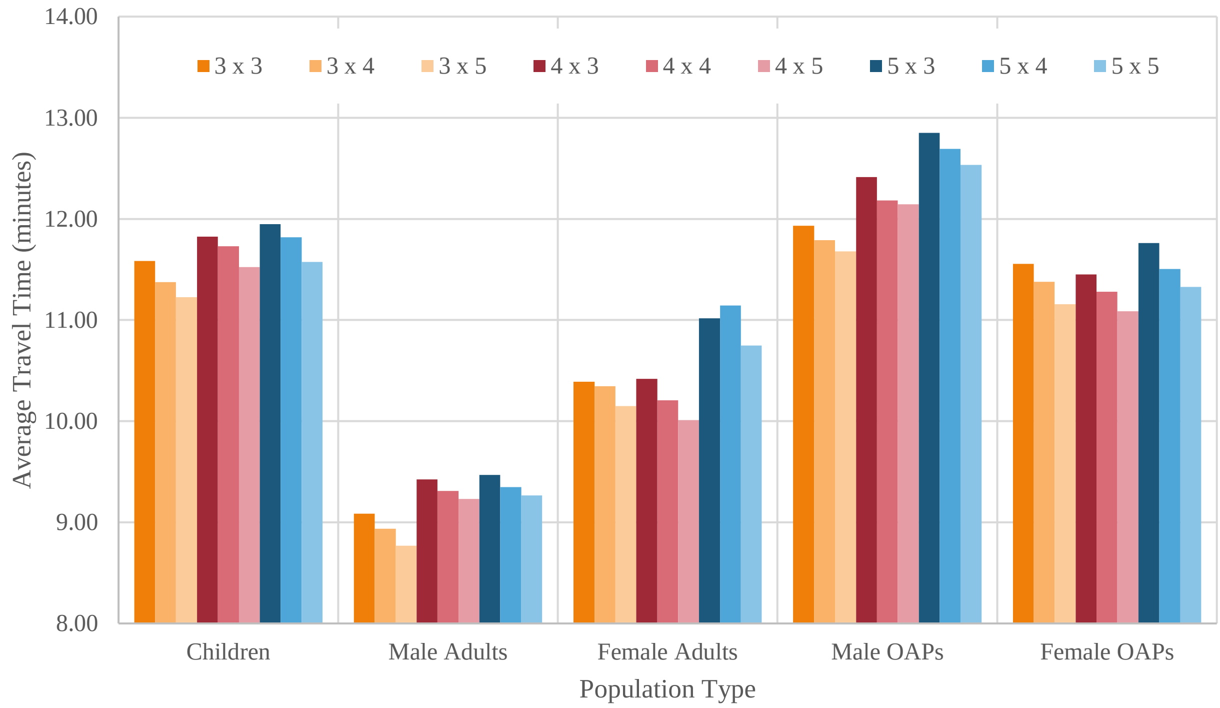


Figure 7-12 – Average Travel Times for each population type when considering the crossroad configuration between three and five lanes in each direction, for each population type: mean (standard deviation), Children:11.62 minutes (0.23 minutes), Male Adults: 9.20 minutes (0.23 minutes), Female Adults: 10.49 minutes (0.39 minutes), Male OAPs: 12.25 minutes (0.41 minutes) and Female OAPs: 11.39 minutes (0.21 minutes)

To explore the crossroad configuration further, the average travel times from the simulations were plotted in terms of population density and the exit split percentage (Figure 7-13 and Figure 7-14). In terms of population density, again the crossroad configuration produced little variation (standard deviation ranged from 0.09 – 0.50 minutes), as expected, but there were larger variations caused by population density (standard deviation ranged from 1.76 – 2.37 minutes), which could be a contributing factor to the introduction of congestion. When examining the exit split percentage, the crossroad configuration again had produced little variation (standard deviation ranged from 0.10 – 0.58 minutes), but larger variations appeared to have been caused by applying the exit split percentage (standard deviation ranged from 0.97 – 1.73 minutes), which could be aiding the introduction of congestion. The population density and exit split percentage will be explored further in subsequent sections to understand their impacts on travel time and capturing congestion in a microscale crossroad model.

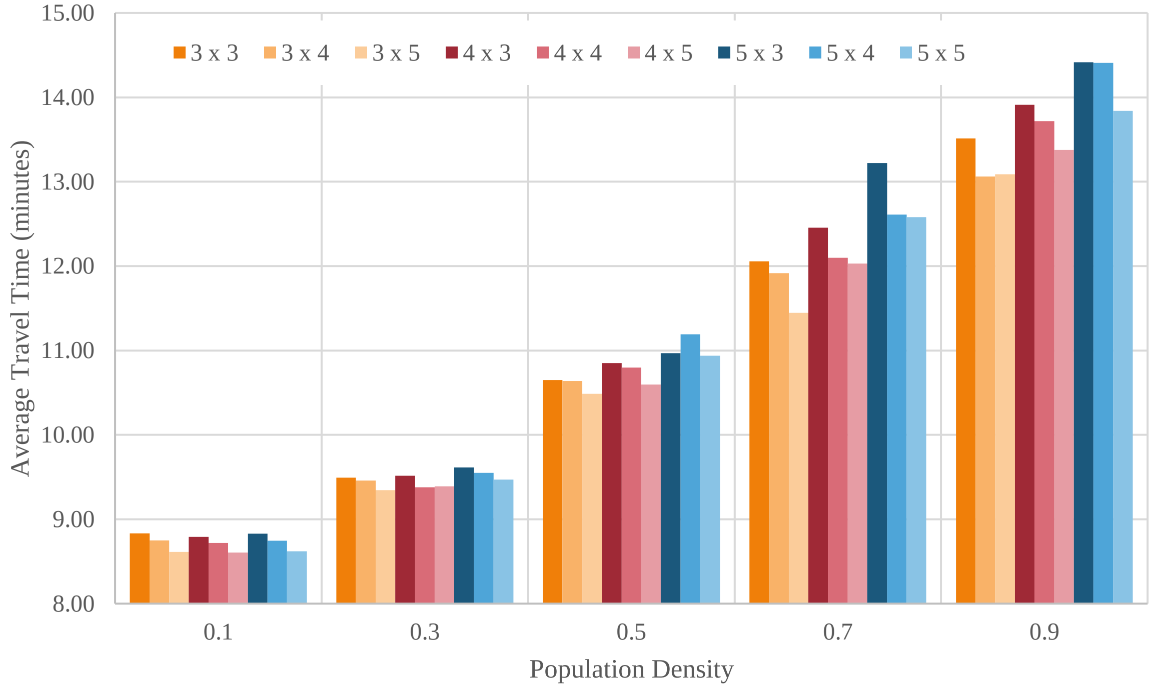


Figure 7-13 – Average Travel Time for each Population Density when considering the crossroad configuration between three and five lanes in each direction, for each population density: mean (standard deviation), 0.1: 8.72 minutes (0.09 minutes), 0.3: 9.47 minutes (0.09 minutes), 0.5: 10.79 minutes (0.22 minutes), 0.7: 12.27 minutes (0.51 minutes) and 0.9: 13.70 minutes (0.50 minutes)

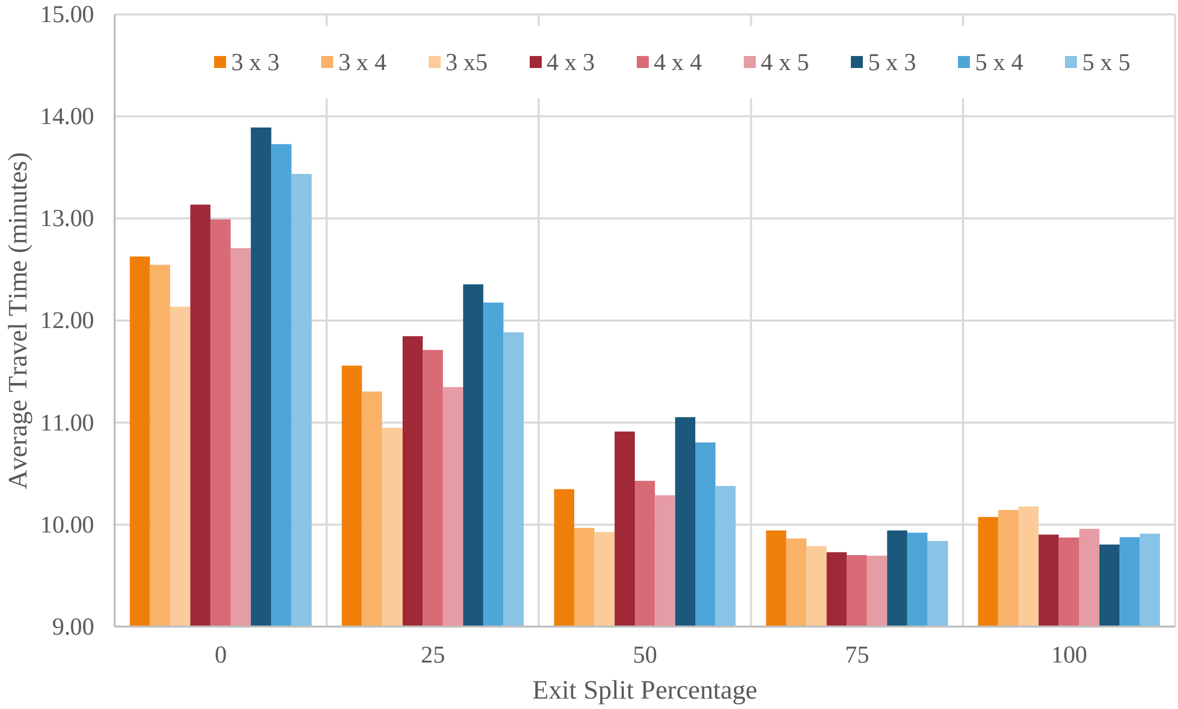


Figure 7-14 – Average Travel Time for each Exit Split Percentage when considering crossroad configuration between three and five lanes in each direction, for each Exit Split Percentage: mean (standard deviation), 0: 13.02 minutes (0.58 minutes), 25: 11.68 minutes (0.44 minutes), 50: 10.46 minutes (0.40 minutes), 75: 9.82 minutes (0.10 minutes), and 100: 9.97 minutes (0.13 minutes)

7.3.4 Test 2 – Effect of Population Density

A further plot has been compiled to show population density by population type from the 2250 simulations of varied walking speeds and altered variables (Figure 7-15). This shows that in general as population density increases the average travel time also increases, from an average of 8.72 minutes to 13.70 minutes. Another trend is that the travel times for population types are less varied as the population density increases, i.e. the travel times converge to a similar travel time, as reflected by the standard deviations at 0.1 population density, which is 2.06 minutes and at 0.9 it is 0.71 minutes. It can also be seen that the travel times for the slow agents (children and OAPs) are not as largely affected by increased population density as the faster adult population types. The standard deviation ranges from 1.38 – 1.71 minutes for children and OAPs whereas standard deviation ranges from 2.67 – 2.78 minutes for adults, demonstrating that the adult population is more greatly affected by the introduction of congestion than the slower agent types. It also suggests that all agent types are affected by the need to give way caused by the crossroads, which only increases further with a greater population density.

It was anticipated that travel times would increase with population density as the agents experience more congestion and opportunities to give-way as density increases. It would also be expected that the travel times would increase by population type with times reducing in variance as population density increases as the faster agents (adults) are impeded by the slower population types, but all agents are affected by the greater need to give-way. It can therefore be argued that the inclusion of population density is a requirement if a microscale crossroad model is to successfully replicate congestion and capacity in the model environment.

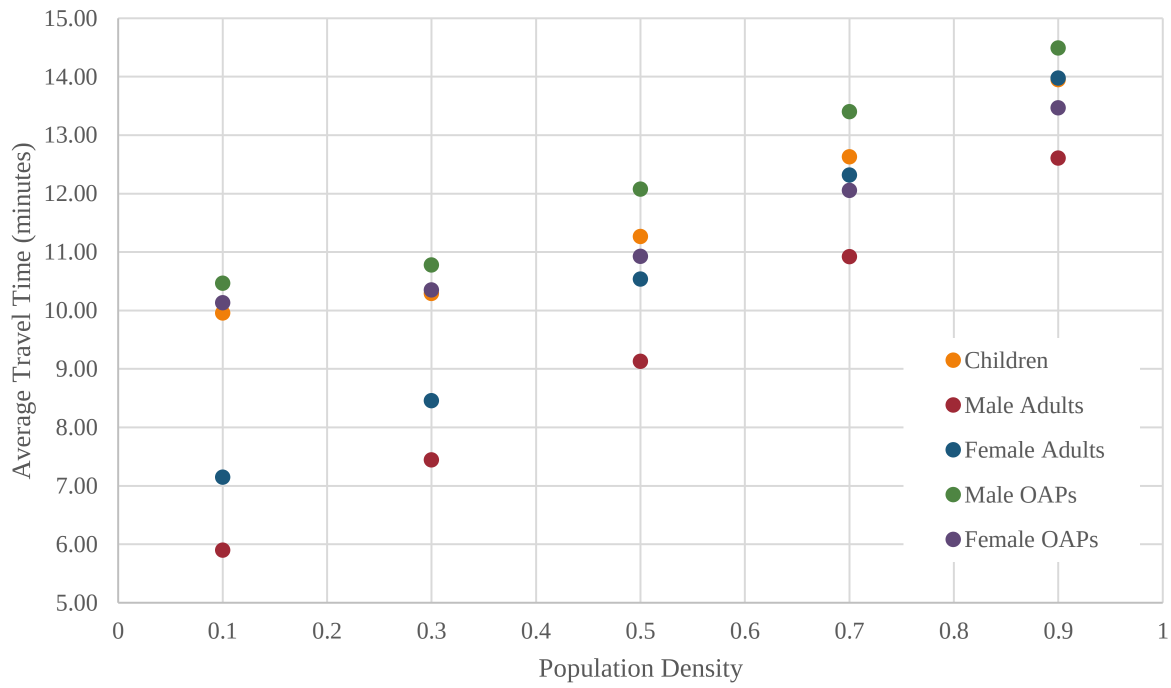


Figure 7-15 – Average Travel Times for each population type when considering population density between 0.1 and 0.9, for each population type: mean (standard deviation), Children:11.62 minutes (1.67 minutes), Male Adults: 9.20 minutes (2.67 minutes), Female Adults:10.49 minutes (2.78 minutes), Male OAPs: 12.25 minutes (1.71 minutes) and Female OAPs: 11.39 minutes (1.38 minutes)

7.3.5 Test 3 – Effect of Exit Split

It has been shown that the exit split percentage has influenced overall travel times of agents in the crossroad model. An additional plot has been completed to show the exit split percentage by population type for the 2250 simulations of varied walking speed and different variables (Figure 7-16). This shows that as the exit split percentage increases, which means more agents, are travelling south than East, the overall travel time decreases for each population type. For the slower agent types (children and OAPs) as exit split percentage increases the travel times converge, this is likely to be a result of an increased number of agents exiting in the same direction with a percentage increase, so there is less demand on overtaking and giving way to each other. Male and female adults have the fastest walking speeds within the model, and in terms of exit split percentage their travel times are always the fastest but decrease with an increase in exit split percentage. It is anticipated that this is again a result of the reduced demanded to cross paths with other agents as more agents are travelling in the first instance. The use of this variable has allowed the inclusion of varied exit pathways, which in this model are assigned at random. However, this may not always be the case so by including the exit split percentage, it has been possible to consider that all agents may exit in the same direction, which may be a necessity, for example, in an evacuation scenario a certain exit may be blocked with debris and the crowd must exit through one exit only. It therefore seems necessary to include exit split percentage within a microscale crossroads model if a robust representation of congestion and capacity is required.

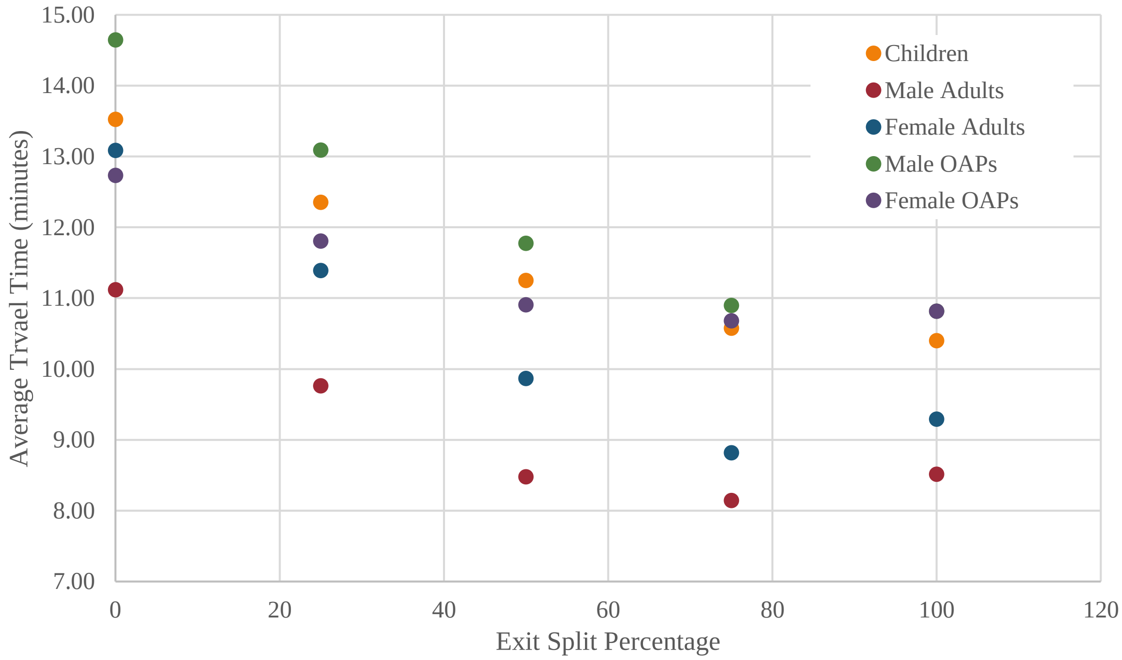


Figure 7-16 – Average Travel Times for each population type when considering exit split percentage between 0 and 100, for each population type: mean (standard deviation), Children: 11.62 minutes (1.32 minutes), Male Adults: 9.20 minutes (1.24 minutes), Female Adults: 10.49 minutes (1.74 minutes), Male OAPs: 10.82 minutes (1.62 minutes) and Female OAPs: 10.81 minutes (0.87 minutes)

A further plot was compiled to consider the exit split percentage and population density within the microscale crossroad model (Figure 7-17). This shows that as population density increases, travel time increases and that the largest travel time is attributed to the lowest exit split percentage each time. The slowest time is attributed to the lowest exit split percentage as this value causes an increase in agent interactions with all agents exiting to the east, which results in additional need to give way at the crossroads. It was also seen that when the population density increases, the travel time variance also increases, with initially the values converging to a similar value. This is likely to be caused by the fact that at low population densities there were fewer agent interactions, meaning the agent's exit pathways were clear, so their travel time was not impeded. However, as the population density increases, there were greater numbers of interactions caused and more overtaking was required, or if this was not possible, reductions in speed to the slowest agents, and this was heavily influenced by the exit split percentage. When exit split percentage was at 0%, so all agents need to exit east, there were greater numbers of interactions than at 100% when all agents exit south. This indicates that both exit split percentage and population density were having an impact on the model and should therefore both be considered for inclusion when a crossroad model needs to factor in congestion and capacity.

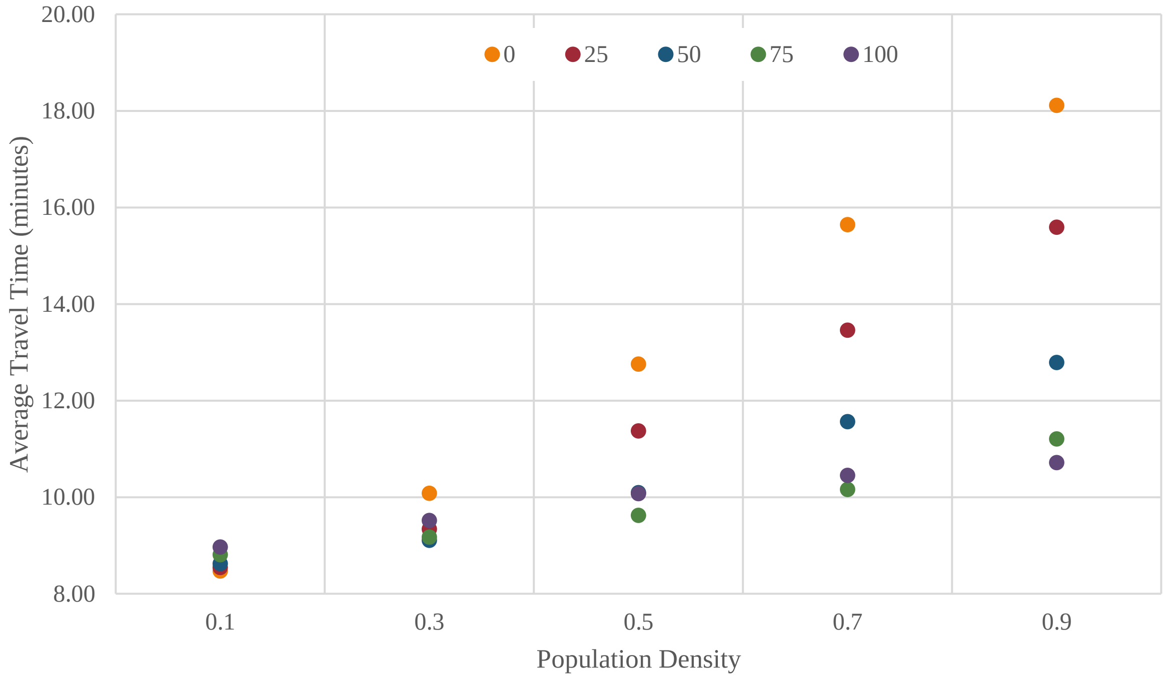


Figure 7-17 – Average Travel Times based on Population Density between 0.1 and 0.9 and Exit Split Percentage between 0 and 100, for each patience level: mean (standard deviation),0: 13.02 minutes (3.95 minutes), 25: 11.66 minutes (2.91 minutes), 50: 10.44 minutes (1.73 minutes), 75: 9.80 minutes (0.94 minutes) and 100: 9.95 minutes (0.71 minutes)

7.3.6 Test 4 – Comparison to 1.34m/s (3mph) Model

There was a need to understand if this microscale model of a crossroad differs from a calculated model with walking speeds of only 1.34m/s (3mph) with no additional variables included. The calculated travel times for the 1.34m/s (3mph) model were an average of 5.86 minutes. These calculated travel times were compared with the travel times produced through the 2250 simulations for varied walking speeds, this allowed a time difference to be estimated. It has been shown that for all population types, there is a travel time difference between the 1.34m/s (3mph) model and the simulated values.

The percentage time differences are greatest for the slower agent types when considering the application of varied walking speeds only, which was anticipated as their speeds had been reduced significantly compared to the 1.34m/s (3mph) value (Figure 7-18). However, when population density and south exit percentage are also considered, there are several conclusions which can be made. When the population density is low (0.1), none of the population types are significantly impacted and have a similar time differences to that of applying varied walking speed only regardless of the south exit percentage. This is a result of the reduction in the number of interactions occurring as the starting agents on their static "home" squares have an unhindered journey to their exit.

However, when population density is high, the south exit percentage plays a key role in governing the number of interactions that occur. All agent types are most severely hindered in their journey when the south exit percentage is low (0%), i.e. all agents are exiting to the East, the percentage time difference ranges from 209% - 238%. This means that the five agents from their static "home" squares will have to make a change of direction and will therefore but subject to the possibility of many opportunities to give way and overtake. This results in a significant time difference with the 1.34m/s (3mph) calculated model. When the south exit percentage is high (100%), e.g. all agents are exiting South, there are far fewer interactions for the five static "home" square agents and there is no change in direction required. In this instance the time difference percentage ranges from 73% - 81%. Demonstrating that these agents, in particular the male and female adults, are primarily affected by the population density and therefore the increased likelihood of congestion. When the south exit split is 50:50, i.e. an equal number of agents will exit in each direction, the time difference percentage ranges from 98% - 130% compared to the 1.34m/s (3mph) calculated model. This highlights that there are more interactions and congestion occurring than when all agents exit south. It is plausible in any evacuation scenario that any of these exit splits could occur, either due to a blockage in one direction or the need to evenly split a crowd through two exits. It is therefore vital that any agent-based evacuation model can consider the differences that may occur due to variances in the exit split. This comparison shows that this microscale crossroad model has successfully captured congestion and capacity within the model environment when compared to the 1.34m/s (3mph) model.

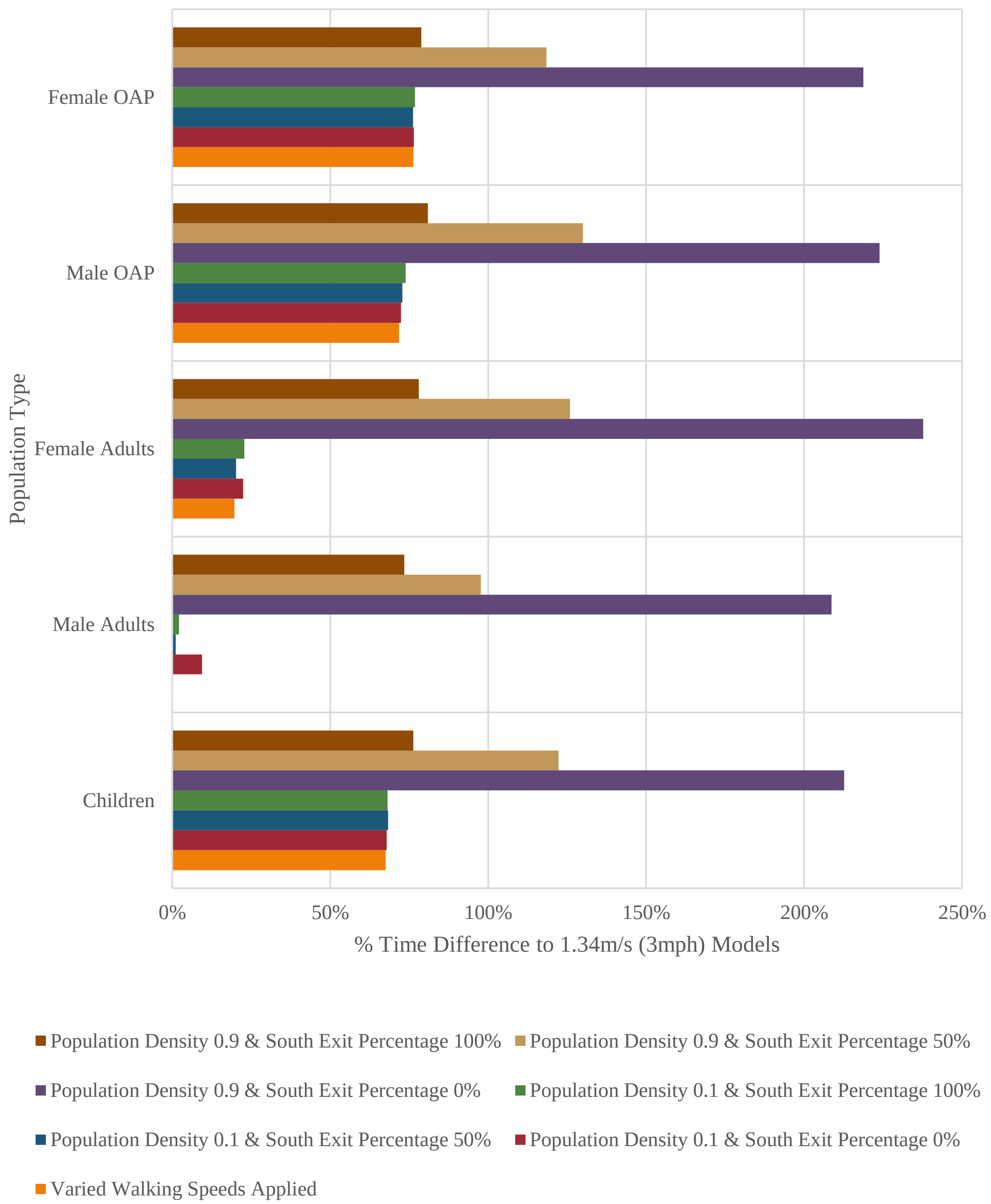


Figure 7-18 – Comparison to 1.34m/s (3mph) Calculated Model and Simulated Agent-Based Model Values, initially showing the introduction of varied walking speeds for different population types only, then the impact of varied walking speeds by population types combined with population density and south exit percentage

7.4 Microscale Model Testing Summary

The testing of the microscale pavement and crossroad models has demonstrated that including additional variables: population density, number of lanes, patience level and exit split percentage, alongside the previously defined population characteristics such as varied walking speeds by age and sex, improves the robustness of simulations when compared to existing models which contain fewer or none of these variables.

The first microscale model based on a pavement, has shown that the introduction of a range of variables improves the robustness of a computational simulation of a pavement environment. The variables need to be capable of altering the dimensions of the pavement, incorporating a range of population densities and including a patience level to replicate the desire to overtake slower individuals when walking on a pavement, in order to produce a realistic representation. When compared to a 1.34m/s (3mph) simulation of a pavement, it has been shown that there are large time differences when compared to this simulation of a pavement. The average time difference ranged from 40% – 77%, with a worst-case time difference increasing to a range of 73% - 78% (Table 7-8), this demonstrates that current simulations of pavements may be producing misleading travel times estimates and failing to include a range of behaviours.

The second microscale model of a pedestrian crossroads has shown that there is an additional variable that needs to be incorporated to produce a realistic simulation. This is an exit split percentage, which can control the exit directions of the agents, to alter the number of agent interactions. This must be included alongside the pavement variables to ensure a robust representation. When compared to a 1.34m/s (3mph) simulation of a crossroads, it has been demonstrated that there are again large time differences seen. The average time difference ranged from 63% - 102%, whilst the worst-case time difference increased to a range of 209% - 238% (Table 7-8), this highlights that current models of pedestrian crossroads are likely to be simulating misleading travel times and are incapable of producing human behaviours to demonstrate overtaking and giving way to each other at a junction.

Table 7-8 – Comparison of the Average and Worst-Case Results produced from Tests 1 and 2 with the Microscale Pavement and Crossroad Model based on the addition of population characteristics, walking speeds, grouping and a walking speed ratio

<table>
<tr><th></th><th colspan="6">Average Difference for all Population Types</th></tr>
<tr><th></th><th>Population Characteristics</th><th>No. of Lanes</th><th>Population Density</th><th>Patience Level</th><th>Exit Split Percentage</th><th>Compared to:</th></tr>
<tr><td>Newcastle (Pavement)</td><td colspan="4">Children: +70%
Male Adults: +40%
Female Adults: +47%
Male OAPs: +73%
Female OAPs: +77%</td><td></td><td rowspan="2">1.34m/s (3mph) Model</td></tr>
<tr><td>Newcastle (Crossroads)</td><td colspan="5">Children: +96%
Male Adults: +63%
Female Adults: +78%
Male OAPs: +102%</td></tr>
</table>

	Female OAPs: +98%		
	Worst Case Difference for all Population Types		
Newcastle (Pavement)	Children: +75% Male Adults: +73% Female Adults: +74% Male OAPs: +76% Female OAPs: +78%		1.34m/s (3mph) Model
Newcastle (Crossroads)	Children: +213% Male Adults: +209% Female Adults: +238% Male OAPs: +224% Female OAPs: +219%		

The two microscale models of a pavement and crossroads have successfully produced a series of travel time estimates with the inclusion of a range of new variables (number of lanes, population density, patience level and exit split percentage) to incorporate a robust representation of human interactions. This has resulted in large time differences with current simulations (ranging from 40% - 238% in worst case scenarios) as a realistic and robust representation of congestion and capacity has been incorporated into an agent-based model. This has captured the intricate human behaviours, such as overtaking on a pavement or giving way at a junction, that were not included within the macroscale city evacuation model. To further increase the robustness of the macro and microscale models, all the identified behaviours now need to be combined into a single model environment, the feasibility of this will be discussed further in Chapter 8.

7.5 Modelling Discussion

This thesis has presented three evacuation ABMs, one macroscale model of a city centre, one microscale model of a pavement and one further microscale model of a crossroads. These models have demonstrated that more robust evacuation timings can be produced when additional variables to simulate additional human behaviour traits have been included. The purpose of these models has been to capture complex social interactions and human behaviours within a model environment, the value of this is the ability to explore potential outcomes, which may or may not be predictable. The focus on this occasion has been on capturing quantitative population demographics and characteristics and does not full explore the behavioural changes which can occur during emergency scenarios such as panic and aggression.

The ultimate aim for these models is to be able to combine the two scales into one single model environment. This was not possible within the scope and timescale of this thesis but it was possible to explore ways in which this may be achieved. Currently it is plausible to run a macroscale simulation of a city centre that then identifies to the user the “pinch points” in the city’s pedestrian network where large volumes of congestion may occur. Initially, this can be seen from a visual inspection of the model simulation when running but it would also be possible to add counters into junctions to understand the volume of pedestrian traffic flowing through junctions. An emergency planner with good knowledge of their city could then identify either a pavement or crossroads model simulation to match the dimensions of the “pinch points” at the city scale. This data has then been captured in a series of lookup tables of standardised junction and pavement sizes, which indicates to the user a time difference compared to an unhindered journey using the junction. This allows emergency planers to understand the impacts of congestion on these junctions and to adjust their evacuation times accordingly. This is an initial step in addressing the issue of scalability between these three evacuation ABMs.

Another complex task when working with ABMs is the ability to validate models effectively. An attempt was made at both the macro and microscale to perform some validation, calibration, and verification checks but this needs to be improved further. The checks that were carried out were overall trivial and did not allow effective validation of the models. In the future, more effective validation should be sought through real-world data, there is lots of data becoming available on people movement and CCTV capture of city centre environments which could be utilised to understand how well the computational behaviours matched the real-world behaviours expected. This is outlined further in section 8.2.

Finally, it has not been possible to model all the behaviours set out in Chapter 3. In Chapter 3, 11 key behaviours were identified to be prioritised for inclusion within evacuation simulations. This thesis focused on making an initial improvement by including behaviours that were easily and reliably transformed into quantifiable rulesets to be used in an ABM. This resulted in several assumptions being made and some behaviours not being included. This includes no running in the model, only able-bodied agents, no additional transport models and no emerging leaders or higher-order agents such as Emergency Services being included. These decisions have been rationalised within this thesis, but it is important when moving forward with the improvement of evacuation simulations that these types of behaviour are included to explore their potential impact on evacuation timings.

Chapter 8. Conclusions and Further Work

8.1 Conclusions

Natural disasters affect communities globally, affecting 2.7 billion people between 2000 and 2011, resulting in high numbers of fatalities (estimated to be 1.1 million people over the same period), displacement of communities and negative financial implications with costs approximated as $1.3 trillion over 11 years (International Civil Defence Organisation, 2016). The aim of this thesis was to "improve the effectiveness of emergency planning" particularly focusing on the role of evacuations and how this can alleviate suffering for communities by ensuring people can reach safety successfully. Existing computational evacuation models are not fit for purpose, do not include a range of "real" human behaviours and those with human behaviour include oversimplified and standardised behaviours (Chapter 2, 3) (Objective 1 & 2). In conjunction with this, real-life exercises and table-top scenarios which are used to train emergency personnel during an emergency scenario, feature no public involvement, at best there may be some actors and dummies involved and therefore the exercises do not model the public's response. It is not possible to run "panicked" real-life simulations but without an understanding of the public's response this means that emergency personnel have little indication on how the public may react in any given scenario and how this may further impact their services. Hence, there is a need to close this gap and ensure that computational, real-life, and table-top simulations can work in conjunction and are more robust. In achieving this, disaster management personnel will gain a better understanding of how individuals react during hazards. Therefore, enabling them to plan and prepare more accurately to ensure their resources are directed to the most appropriate locations, thereby taking a proactive rather than reactive approach, which will reduce human suffering and in the short term has the potential to save lives (Objective 5).

This thesis has addressed this by introducing more robust human behaviour traits into numerical evacuation simulations (Objective 1 – 4). The advantage of using numerical simulations is the ability to produce numerous simulations without incurring large financial or resource costs, as well as the potential to add in new rulesets and behaviours without causing any harm or suffering to agents. Improving evacuation simulations will be beneficial for emergency management professionals when planning and preparing for hazard events. Especially given that current methods (table-top and real-life scenarios) cannot fully prepare emergency personnel due to the lack of human behaviours. On top of this, real-life simulations incur large financial and resource costs with an inability to run multiple simulations. Consequently, improved computational models will allow emergency planners to be better prepared, and for communities, which may ultimately result in saved lives as communities will be able to reach safety within the allotted time, a reduction in the levels of human suffering encountered and economic benefits (Objective 5). However, the problem with current models is that the human behaviour included is not representative and instead agents' behaviours have been oversimplified and standardised, in many cases resulting in agents that are exclusively male able-bodied adults (Objective 1). This thesis specifically created a modelling framework that utilised agent-based modelling to produce a more robust representation of human behaviour within an enhanced model environment (Objective 3 & 4).

This thesis identified six key human behaviour traits as key behaviour indicators (Chapter 3) (Objective 1). The focus of this thesis moved to those behaviours which could be easily quantified and as such the included behaviours concentrated on: (1) flee behaviour, (2) interpersonal distance, (3) crowd behaviour, (4) capacity, (5) route choice and (6) patience. Evacuations often occur at a city level, so the initial focus was on creating a macroscale evacuation model capable of evacuating a city centre location (Objective 3). This was based on a 2km x 3km area of the city of Newcastle (UK) with rulesets created to introduce population demographics (based on age and sex), varied walking speeds, grouping of agents and a walking speed ratio which met the flee behaviour, crowd behaviour and route choice behaviour traits previously identified.

The macroscale city evacuation model showed that there are demonstrable differences between current evacuation simulations and those that include more robust human behaviour representation (Chapter 4, 5). The addition of these rulesets (population demographics, varied walking speeds, groups, and a walking speed ratio) has increased average travel times by approximately 70%, resulting in the potential underestimation of evacuation times in city scale evacuation simulations, which may lead to additional fatalities and injuries as communities cannot reach safety in time (Objective 3). This identified the benefit of including supplementary model variables to capture human behaviour traits as current models are only fit for purpose if you are male able-bodied adult, with children and OAPs disproportionately affected. Hence, the difference in travel times could have significant impacts on evacuation planning and highlights that existing models are not fit for purpose (Objective 5). Using existing models could lead to communities not evacuating in the anticipated times, which may result in additional causalities and fatalities, it also means that planners may be placing resources and service personnel in the wrong locations (Objective 5). The inclusion of even basic characteristics (population demographics and varied walking speeds) demonstrated a 45%

increase in travel time, highlighting the need to remove standardised and oversimplified behaviours, which result in the production of misleading travel times and reduces agents in a model to male able-bodied adults only (Objective 3).

The macroscale model effectively captured flee behaviour, crowd behaviour and route choice but due to the scale it did not successfully capture the intricate human behaviours observed on pavements and at junctions, such as overtaking and giving way, as well as the influence of capacity in terms of available space. Therefore, to improve the evacuation simulations further, two microscale models were created of a pavement and crossroads, to address the representation of the additional behaviour traits (Chapter 6, 7) (Objective 4). To do this the two microscale models included additional variables to improve the simulation of human behaviour on a more intricate level, with the aim of replicating overtaking and giving way. The addition of these traits (population density, lane configuration, patience level and exit split percentage) improves the computational simulation of a pavement and crossroads environment.

For the pavement, it has been demonstrated that there are large time differences resulting from the introduction of these rulesets when compared to simpler simulations which focus on standardised speeds (Objective 4). The average time increase was approximately 40 – 70%, although in the worst-case scenarios (e.g. high population density and high patience levels), this was further increased. It should also be noted that the range of times converges as the fastest agent types are hindered by the congestion in the model. This improved pavement simulation demonstrates that current simulations of pavements may be producing misleading travel times estimates and failing to include the necessary behaviour traits to realistically simulate giving way, overtaking, capacity and congestion (Objective 5).

The second microscale model of a pedestrian crossroads has shown that there are again large time differences when compared to simpler junction simulations often operating at only one speed of 1.34m/s (3mph) (Objective 4). The average time difference ranged from 63% - 102% and if considering the worst-case scenario (high population density and large number of agent interactions) the time difference increased further because of the congestion created by the model and the need for agents to wait for a suitable gap to exit. This highlights that current models of pedestrian crossroads are likely to be simulating misleading travel times and are incapable of producing robust human behaviours to demonstrate pedestrian overtaking and giving way. Hence this has the potential to cause additional injuries and fatalities by underestimating the time to evacuate junctions, which can be numerous in city scale evacuations (Objective 5).

The models created in this thesis have successfully incorporated a wider range of human behaviour traits that could be quantified by literature to form the basis of model rulesets (Objective 1 – 4). This resulted in increases in travel time at both the macro and microscale and reinforces that current evacuation models are not fit for their intended purpose when focused on using standardised and oversimplified rulesets for human behaviour (Objective 5). Models cannot continue to assume that evacuees are able-bodied male adults and must broaden their human behaviour traits else run the risk of producing misleading simulation results. Ultimately without improvement, there is the potential for fatalities and injuries to increase as communities cannot reach safety within the allotted time. Improved evacuation simulation can be of great benefit for emergency professionals and can be effectively used in combination with existing table-top and real-life simulation exercises to allow for better preparation and planning (Objective 5).

8.2 Recommendations and Further Work

8.2.1 Recommendations

This thesis has demonstrated that there are benefits to including more robust representations of human behaviour within agent-based evacuation models. The inclusion of such behaviours has impacted on the time estimates produced by models and it can be argued that current models are likely to be producing misleading time estimates, which has the potential to result in significant additional injuries and fatalities as communities fail to reach safety within the predicted times. Hence, it is imperative that future models seek to include more robust representations of human behaviour to ensure that emergency planning professionals can make the most appropriate decisions when planning and preparing for events.

It has also been explored that computational modelling could significantly aid the testing of evacuation plans for governments. This would not alleviate the demand for real-life simulations (which provide a vital means of training ‘blue light’ personnel) but would ensure that the real-life simulations chosen were the most appropriate and target the worst-case scenarios. It would also provide more opportunities to consider the role of the public within scenarios, giving a range of probabilistic responses, without having to run “panicked” real-life simulations or over-simplified scenarios with actors and dummies. There would also be the option to test the emergency services in alternative scenarios depending on the public interaction rather than assuming the public will comply as requested. The inclusion of the public has the potential to change outcomes, but it is not viable to include them through the real-life scenarios, (and assume that they will respond accurately as their behaviours are often still prescribed or staged to them i.e. you are a casualty with head injuries, when in a situation of stress, it is unlikely the public know truly how they would react). It should be noted that the modelling in this thesis has focused on quantifiable behaviour traits and does not capture these behavioural changes which are anticipated to occur in times of stress, this will need to be addressed in future iterations of the model to be of the most benefit to emergency service personnel. However, it does highlight the strength of computational evacuation modelling in terms of their versatility and ability to replicate numerous scenarios with many different behaviours and outcomes, which will be beneficial for those planning for events.

8.2.2 Future Work

However, the models created within this thesis are not flawless and there are still improvements that could be included to further advance the model and its uses. This thesis set out to begin the process of identifying and creating human behaviour rulesets for agent-based models, but it was not possible to consider all possibilities. The scope of this PhD was large, and this has meant that in some cases, areas could not be thoroughly explored, and others could not be investigated at all. On top of this, as the models have been created and tested as well as literature explored, further ideas have arisen. It is hoped that some of the following suggestions could be explored further to carry on this work in the future.

Firstly, this thesis resulted in the creation of three different agent-based models, which are all capable of answering different questions due to their differing scales. Scalability in agent-based models is a widely acknowledged issue and one that has been tackled unsuccessfully numerous times. In the case of this thesis, if you wish to estimate the evacuation time for a city area then the macroscale city model should be used. This may then identify pinch points in the model where congestion needs to be explored in more detail. Exploring this detail would be suited to the microscale models of the pavement and crossroads. In an idealised scenario a hybrid of the three models would be created to allow a user to be able to consider the overall evacuation time of a city then "zoom in" to run microscale models of any pinch points to alleviate congestion and consider how agents may give way to each other. This was not possible during this thesis as the modelling software, Netlogo, had reached its limitations. Netlogo is a grid-based system, rather than continuous space, which means it is not possible to create true free movement for agents. The inclusion of free movement is a necessity to be able to combine the three models. It is anticipated that this would involve migrating the programming code to a new agent-based software, which can simulate free movement, prior to combining the three models.

This thesis considered a wide range of human behaviour traits, but could not include all possible individual human characteristics, and could not create rulesets for each possible characteristic. This is a large research task and would require a team including medical and psychology researchers to enable additional behaviours to be considered (e.g. level of compliance or panic behaviour). Consulting these experts, would also allow the patience level to be quantified in an alternative manner, with testing to ensure the proposed levels are valid. One way in which this could be done is by using CCTV data of pavements at different times of day, with large amounts of overtaking and giving way occurring, this would then allow the patience level of individuals to be tracked and a more robust estimation given on how long agents should wait. It should also be explored whether some of the included behaviours could be improved further, for example in terms of walking speed could a bell-curve of possible speeds be used rather than a single speed for each population type, the inclusion of larger group sizes and the addition of groups into the microscale models could also be considered.

The agent-based models were validated, calibrated, and verified where possible but this could be improved further. The microscale models were unspecific in their location but by collaborating with the Urban Observatory at Newcastle University, their data on streets across Newcastle could be utilised to validate, calibrate, and verify the model further. This could also explore the impact of street furniture in the model or the interactions with higher-order agents such as Police. Their data could also be utilised within the macroscale model by using data collected during largescale events such as a football match at St James Park, to compare the travel times produced with real-life data. There is also the potential to further improve pandemic modelling, particularly in relation to coronavirus, with the collaboration of this real-life data and the utilisation of more realistic human behaviour rulesets. This could be possible in two different ways, firstly to understand the change in capacity of spaces in cities such as pavements with the introduction and maintenance of social distancing and secondly the implications of congestion caused by the need to widen pavements and therefore the reduction in available road space.

Finally, the models need to be considered in a wider context, this could be done in several ways. In simple terms, the macroscale agent-based model could be tested to understand the impact of the addition of a hazard model and in terms of the number and location of evacuation points required to reduce evacuation times. It would also be beneficial to create several "test" cities, which cover the most common spatial layouts of major cities such as gridded or radial. This would make the models more widely applicable, and it would be possible to explore how the spatial layout influenced evacuation times, if at all. Ultimately, emergency planning professionals need to consider a wide range of issues and an emergency scenario as a whole. This demands the need to consider the logistics and supplies required to sustain a population in any given city after an evacuation or disaster event has occurred. Hence, it would be logical to examine the possibility of combining the current micro and macroscale models with a dynamic logistics model to further aid the planning and preparation of emergency scenarios. It is also imperative to consider the interaction of the pedestrian evacuation model with additional transport whether this be personal cars or the use of public buses to aid evacuation or logistics. Ultimately the most effective computational simulation for natural hazards, which will be of most benefit for emergency personnel, will be a multi-faceted approach that brings together as many diverse components in a single model environment. With the hope that emergency management professionals can successfully plan and prepare for events and run numerous scenarios without endangering the public and in due course reduce communities suffering and their risk of injury or death.

References

AEC Magazine, 2011. *Oasys MassMotion.* [Online]
Available at: http://aecmag.com/software-mainmenu-32/445-oasys-massmotion
[Accessed 4th January 2017].

Ainger, C. & Fenner, R., 2014. *Sustainable Infrastructure: Principle into Practice.* 1st ed. London: ICE Publishing.

Aka, F. T. et al., 2017. Disaster Prevention, Disaster Preparedness and Local Community Resilience within the Context of Disaster Risk Management in Cameroon. *Natural Hazards,* 86(1), pp. 57 - 88.

Altaweel, M., 2016. *Agent Based Modelling and GIS.* [Online]
Available at: https://www.gislounge.com/agent-based-modeling-gis/
[Accessed 4th January 2017].

American Council on Exercise, 2003. *ACE Personal Trainer Manual.* Third ed. San Diego: American Council on Exercise.

Anderson, J. & Nichols, N., 2010. *Spark People - The 1 Mile Walking Test - A DIY Fitness Assessment.* [Online]
Available at: http://www.sparkpeople.com/resource/fitness_articles.asp?id=1496
[Accessed 23rd June 2017].

Anitei, S., 2008. *Humans Really Behave Like Sheep in a Herd.* [Online]
Available at: http://news.softpedia.com/news/Humans-Really-Behave-Like-Sheep-in-a-Herd-78913.shtml
[Accessed 4th January 2017].

Autodesk, 2017. *Maya.* [Online]
Available at: https://www.autodesk.co.uk/products/maya/overview
[Accessed 14th September 2017].

Bae, Y.-H.et al., 2014. The Predicted Form of Clusters Using Inter-Person Distance and Angle: Evidence from a mock-up set at the Daegu subway station. *Transportation Research Procedia,* Volume 2, pp. 159 - 167.

Baker, C. R., 2014. Breakdowns of accountability in the face of natural disasters: The case of Hurricane Katrina. *Critical Perspectives on Accounting 25,* pp. 620 - 632.

Baldassare, M. & Feller, S., 1975. Cultural Variations in Personal Space. *Ethos,* Volume 3, pp. 481 - 503.

Balmer, M., Axhausen, K. W. & Nagel, K., 2006. Agent-Based Demand-Modelling Framework for Large-Scale Microsimulations. *Transportation Research Record: Journal of the Transportation Research Board,* 1985(1), pp. 125 - 134.

Barnes, B., Dunn, S. & Wilkinson, S., 2019. Natural hazards, disaster management and simulation: a bibliometric analysis of keyword searches. *Natural Hazards,* Volume 97, pp. 813 - 840.

Basefount, 2017 A. *Miarmy - Better Crowd Simulation for Maya.* [Online]
Available at: http://www.basefount.com/miarmy.html
[Accessed 14th September 2017].

Basefount, 2017 B. *Miarmy Case Studies.* [Online]
Available at: http://www.basefount.com/case-studies.html
[Accessed 14th September 2017].

Basefount, 2017 C. *Basefount Case Studies - War & Order (Mobile Game).* [Online]
Available at: http://www.basefount.com/war--order.html
[Accessed 12th December 2018].

Batty, M., 2012. Chapter 2 A Generic Framework for Computational Spatial Modelling. In: M. Batty, A. J. Heppenstall, A. T. Crooks & L. M. See, eds. *Agent-Based Modelling for Geographical Systems.* Dordrecht Heidelberg London New York: Springer, pp. 19 - 50.

Batty, M., Crooks, A. T., See, L. M. & Heppenstall, A. J., 2012. Chapter 1 Perspectives on Agent-Based Models and Geographical Systems. In: M. Batty, A. T. Crooks, A. J. Heppenstall & L. M. See, eds. *Agent-Based Models of Geographical Systems.* Dordrecht Heidelberg London New York: Springer, pp. 1 - 15.

BBC - Press Association, 2016. *Tube disaster exercise: "Tower collapses into station".* [Online]
Available at: https://www.bbc.co.uk/news/uk-35686269
[Accessed 22nd November 2018].

BBC, 2011. *New Zealand earthquake: 65 dead in Christchurch.* [Online]
Available at: http://www.bbc.co.uk/news/world-asia-pacific-12533291
[Accessed 11th May 2017].

BBC, 2015 A. *Paris Attacks: What happened on the night.* [Online]
Available at: https://www.bbc.co.uk/news/world-europe-34818994
[Accessed 6th December 2018].

BBC, 2015 A. *UK floods: Moment Tadcaster bridge collapsed.* [Online]
Available at: http://www.bbc.co.uk/news/uk-35195153
[Accessed 18th November 2016].

BBC, 2015 B. *Storm Desmond: Pooley Bridge collapses in Cumbria floods.* [Online]
Available at: http://www.bbc.co.uk/news/uk-35021614
[Accessed 18th November 2016].

BBC, 2015 B. *UK floods: Moment Tadcaster bridge collapsed.* [Online]
Available at: http://www.bbc.co.uk/news/uk-35195153
[Accessed 18th November 2016].

BBC, 2015 C. *Nepal earthquake: Hundreds die, many feared trapped.* [Online]
Available at: http://www.bbc.co.uk/news/world-asia-32461019
[Accessed 20th December 2016].

BBC, 2015 C. *Storm Desmond: Pooley Bridge collapses in Cumbria floods.* [Online]
Available at: http://www.bbc.co.uk/news/uk-35021614
[Accessed 18th November 2016].

BBC, 2015 D. *BBC - UK Floods: Moment Tadcaster bridge collapsed.* [Online]
Available at: https://www.bbc.co.uk/news/av/uk-35195153/uk-floods-moment-tadcaster-bridge-collapsed
[Accessed 4th May 2020].

BBC, 2015 E. *December storms' trail of destruction.* [Online]
Available at: https://www.bbc.co.uk/news/uk-35193682
[Accessed 22nd January 2019].

BBC, 2015. *Major counter-terrorism exercise in London.* [Online]
Available at: http://www.bbc.co.uk/news/uk-33315691
[Accessed 4th January 2017].

BBC, 2016 A. *BBC - Storm Desmond: Hundreds unable to go home one year on.* [Online]
Available at: http://www.bbc.co.uk/news/uk-england-cumbria-38194698
[Accessed 5th December 2016].

BBC, 2016 B. *BBC - Last winter's flooding 'most extreme on record' in UK.* [Online]
Available at: http://www.bbc.co.uk/news/uk-38204334
[Accessed 5th December 2016].

BBC, 2016 C. *Storms Desmond and Eva flooded 16,000 homes in England.* [Online]
Available at: https://www.bbc.co.uk/news/uk-35235502
[Accessed 22nd January 2019].

BBC, 2016. *BBC - Storm Desmond: Hundreds unable to go home one year on.* [Online]
Available at: http://www.bbc.co.uk/news/uk-england-cumbria-38194698
[Accessed 5th December 2016].

BBC, 2017 A. *Met officers hold mock terrorism exercise on River Thames.* [Online]
Available at: https://www.bbc.co.uk/news/uk-england-london-39320168
[Accessed 22nd November 2018].

BBC, 2017 B. *Gateshead MetroCentre used for anti-terror exercise.* [Online]
Available at: https://www.bbc.co.uk/news/uk-england-tyne-39978288
[Accessed 22nd November 2018].

BBC, 2018. *Presidential Alert: US mobile phones get test message.* [Online]
Available at: https://www.bbc.co.uk/news/technology-45730367
[Accessed 9th October 2018].

BBC, 2019. *BBC - Loyalty lottery for flood-hit Pooley Bridge Visitors.* [Online]
Available at: https://www.bbc.co.uk/news/uk-england-cumbria-49507785
[Accessed 4th May 2020].

Beake, N., 2017. *BBC News - Met officers hold mock terrorism exercise on River Thames.* [Online]
Available at: http://www.bbc.co.uk/news/uk-england-london-39320168
[Accessed 30th March 2017].

Bethelemy, M. & Louf, R., 2014. A typology of street patterns. *The Royal Society of Interface*, pp. 9 - 24.

Bing, 2018. *Bing Maps.* [Online]
Available at: https://www.bing.com/maps

Birkmann, J. et al., 2010. Extreme events and disasters: a window of opportunity for change? Analysis of organizational, institutional and political changes, formal and informal responses after mega-disasters. *Natural Hazards*, 55(3), pp. 637 - 655.

Blades, R., 2013. *Simulating Attrition: The Battlefields of Netlogo.* [Online]
Available at: https://www.hastac.org/blogs/rblades/2013/02/08/simulating-attrition-battlefields-netlogo
[Accessed 4th January 2017].

Boffey, D., 2016. *The Guardian - Russian hooligans were savage and organised, say England fans.*. [Online]
Available at: https://www.theguardian.com/football/2016/jun/12/russian-hooligans-savage-organised-england-fans-marseille-euro-2016#img-1
[Accessed 4th August 2017].

Bosina, E. & Weidmann, U., 2017. Estimating Pedestrian Speed using Aggregated Literature Data. *Physica A,* Volume 468, pp. 1 - 29.

Bruneau, M. et al., 2003. A Framework to Quanititatively Assess and Enhance the Seismic Resilience of Communities. *Earthquake Spectra,* 19(4), pp. 733 - 752.

Cabinet Office & National Security and Intelligence, 2010. *The National Security Strategy - A Strong Britain in an Age of Uncertainty.* [Online]
Available at:
https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/61936/national-security-strategy.pdf
[Accessed 14th March 2017].

Cabinet Office & National Security and Intelligence, 2013. *Emergency planning and preparednes: exercises and training.* [Online]
Available at: https://www.gov.uk/guidance/emergency-planning-and-preparedness-exercises-and-training
[Accessed 23rd November 2016].

Cabinet Office, 2008. *National Risk Register of Civil Emergencies.* [Online]
Available at:
https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/61934/national_risk_register.pdf
[Accessed 14th March 2017].

Cabinet Office, 2013. *Emergency response and recovery.* [Online]
Available at: https://www.gov.uk/guidance/emergency-response-and-recovery
[Accessed 23rd November 2016].

Cabinet Office, 2013. *Preparation and planning for emergencies: responsibilities of responder agencies and others.* [Online]
Available at: https://www.gov.uk/guidance/preparation-and-planning-for-emergencies-responsibilities-of-responder-agencies-and-others
[Accessed 23rd November 2016].

Cabinet Office, 2015. *National Risk Register for Civil Emergencies.* [Online]
Available at:
https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/419549/20150331_2015-NRR-WA_Final.pdf
[Accessed 14th March 2017].

Cai, X., Li, Y., Guo, X.-w. & Wu, W., 2014. Mathematical Model for Flood Routing Based on Cellular Automation. *Water Science and Engineering,* 7(2), pp. 133 - 142.

Canadian Business, 2016. *Fort McMurray, after the fire.* [Online]
Available at: http://www.canadianbusiness.com/fort-mcmurray-after-the-fire/
[Accessed 20th December 2016].

Carley, K. M., 1996. *Validating Computational Models (Working Paper),* Pittsburgh: Carnegie Mellon University.

Chang, S. E., 2014. Infrastructure Resilience to Disasters. *The Bridge,* 44(3), pp. 36 - 41.

CNN, 2016. *CNN - Hurricane Katrina Statistics Fast Facts.* [Online]
Available at: http://edition.cnn.com/2013/08/23/us/hurricane-katrina-statistics-fast-facts/
[Accessed 23rd November 2016].

Conn, D., 2017. *The Guardian - Hillsborough disaster: six people, including David Duckenfield, charged..* [Online]
Available at: https://www.theguardian.com/uk-news/2017/jun/28/hillsborough-six-people-including-two-senior-police-officers-charged
[Accessed 7th August 2017].

Cosgrave, J., Crawford, N. & Mosel, I., 2016. *ODI - 10 things to know about refugees and displacement.* [Online]

Available at: https://www.odi.org/publications/9916-10-things-know-about-refugees-and-displacement
[Accessed 19th December 2016].

Costa, M., 2010. Interpersonal Distances in Group Walking. *Nonverbal Behaviour,* Volume 34, pp. 15 - 26.

Council for Science and Technology (CST), 2009. *A National Infrastructure for the 21st Century,* London: Council for Science and Technology.

CRED, 2015. *The Human Cost of Natural Disasters 2015 - A Global Perspective,* Brussels: CRED & UNISDR.

Cridland, J., 2007. *Flickr.* [Online]
Available at: https://www.flickr.com/photos/18378655@N00/613445810
[Accessed 10th July 2017].

Crooks, A. T., Castle, C. J. E. & Batty, M., 2008. Key challenges in agent-based modelling for geo-spatial simulation. *Computers, Environment and Urban Systems,* 32(6), pp. 417 - 430.

Crooks, A. T. & Heppenstall, A. J., 2012. Introduction to agent-based modelling. In: *Agent-based models of geographical systems.* Dordrecht: Springer, pp. 85 - 105.

Cutter, S. L., 2016. The Landscape of Disaster Resilience Indicators in the USA. *Natural Hazards,* 80(2), pp. 741 - 758.

Daamen, W. & Hoogendoorm, S. P., 2003. Experimental Research of Pedestrian Walking Behaviour. *Transportation Research Record,* Volume 1828, pp. 20 - 30.

d'Aquino, P. et al., 2001. *Agent-Based Models of Land-Use and Land-Cover Change.* Irvine, California, Proceedings of an International Workshop.

Dawson, R. J., Peppe, R. & Wang, M., 2011. An agent-based model for risk-based flood incident management. *Natural Hazards,* Volume 59, pp. 167 - 189.

Department for Environment, F. &. R. A. & Environment Agency, 2016. *Long-term action plan to reduce flood risk in Cumbria.* [Online]
Available at: https://www.gov.uk/government/news/long-term-action-plan-to-reduce-flood-risk-in-cumbria
[Accessed 22nd January 2019].

Department for Transport , 2007. *Manual for Streets,* London: Thomas Telford Publishing.

desinventar - Disaster Information Management System, 2016. *Definition of disaster types.* [Online]
Available at: http://www.desinventar.net/definitions.html#letter-g
[Accessed 16th December 2016].

Dow, K. & Cutter, S. L., 2000. Public orders and personal opinions: household strategies for hurricane risk assessment. *Environmental Hazards 2*, Volume 2, pp. 143 - 155.

Durage, S. W., Wirasinghe, S. C. & Ruwanpura, J., 2013. Comparison of the Canadian and US Tornado Detection and Warning Systems. *Natural Hazards*, 66(1), pp. 117 - 137.

EM-DAT, 2016. *Disasters Database - Advanced Search.* [Online]
Available at: http://www.emdat.be/advanced_search/index.html
[Accessed 10th March 2017].

EM-DAT, 2016. *EM-Dat Frequently Asked Questions.* [Online]
Available at: http://www.emdat.be/frequently-asked-questions
[Accessed 20th December 2016].

Environment Agency, 2018. *Estimating the economic costs of the 2015 to 2016 winter floods,* Bristol: Environment Agency.

Featherston, C. R. & Doolan, M., 2012. *A Critical Review of the Criticisms of System Dynamics.* Canberra, The 30th International Conference of the System Dynamics Society.

FEMA, 2015. *Information Sheet - National Preparedness Goal, Second Edition: Overview.* [Online]
Available at: https://www.fema.gov/media-library-data/1443624338930-32e9ed3ac6cf8e95d7d463ed9b9685df/NationalPreparednessGoal_InformationSheet_2015.pdf
[Accessed 20th March 2017].

FEMA, 2016. *National Preparedness Goal.* [Online]
Available at: https://www.fema.gov/national-preparedness-goal
[Accessed 20th March 2017].

FEMA, 2017. *About the Agency - Mission.* [Online]
Available at: https://www.fema.gov/about-agency#
[Accessed 20th March 2017].

Forrester, J. W., 2003. *Economic Thoery for the New Millennium.* New York, The Twenty-First Annual Conference of the System Dynamics Society.

Galea, E., 2003. Passenger Behaviour in Emergency Situations. In: R. Bor, ed. *Passenger Behaviour.* Ashgate, Aldershot: Routledge, pp. 128 - 183.

GAMMA UNC, 2015. *YouTube - GAMMA UNC.* [Online]
Available at: https://www.youtube.com/gammaunc
[Accessed 1st September 2017].

GAMMA, 2016. *Crowd and Multi-agent Simulation.* [Online]
Available at: http://gamma.web.unc.edu/research/crowds/
[Accessed 1st September 2017].

Gardoni, P. & Murphy, C., 2020. Society-based design: promoting societal well-being by designing sustainable and resilient infrastructure. *Sustainable and Resilient Infrastructure,* 5(1 - 2), pp. 4 - 19.

Getty Images, 2015. *Mass Evacuations: How to Flee a Disaster Area.* [Online]
Available at: http://www.safebee.com/travel/mass-evacuations-how-to-flee-disaster-area
[Accessed 10th July 2017].

Glade, T. & Nadim, F., 2014. Early Warning Systems for Natural Hazards and Risks. *Natural Hazards,* 70(3), pp. 1669 - 1671.

Glavovic, B. C., Saunders, W. S. A. & Becker, J. S., 2010. Land-use planning for natural hazards in New Zealand: the setting, barriers, ‘burning issues’ and priority actions. *Natural Hazards,* 54(3), pp. 679 - 706.

Google Maps, 2020. *Google Maps.* [Online]
Available at: https://www.google.com/maps/@54.9832002,-1.5737299,13.5z
[Accessed 11th June 2020].

Google, 2018. *Google Maps.* [Online]
Available at: https://www.google.co.uk/maps

Gray, B. H. & Herbert, K., 2007. Hospitals in Hurricane Katrina: challenges facing custodial institutions in a disaster. *J Health Care Poor Undeserved,* 18(2), pp. 283 - 298.

Guha-Sapir, D., Below, R. & Hoyois, P., 2016. *EM-DAT: The CRED/OFDA International Disaster Database.* [Online]
Available at: http://www.emdat.be/database
[Accessed 8th December 2016].

Guha-Sapir, D., Hoyois, P. & Below, R., 2016. *Annual Disaster Statistical Review 2015: The Numbers and Trends,* Brussels: Centre for Research on the Epidemiology of Disasters (CRED).

Haigh, D. R., 2011. *Diasaster Management Cycle.* [Online]
Available at: http://www.orbee.org/images/5cc-resource-files/1314112213_Introduction%20to%20Disaster%20Management%20Lifecycle.pdf
[Accessed 18th November 2016].

Hall, E. T., 1966. *The Hidden Dimension,* New York: Doubleday.

Harris, C. D. & Ullman, E. L., 1945. The Nature of Cities. *The Annals of the American Academy of Political and Social Science,* 242(1), pp. 7 - 17.

Hawken, P., Lovins, A. & Lovins, H., 1999. *Natural Capitalism: Creating the Next Industrial Revolution.* 1st ed. Boston, MA: Little, Brown and Company.

Helbing, D., Farkas, I. & Vicsek, T., 2000. Simulating Dynamical Features of Escape Panic. *Nature,* Volume 407, pp. 487 - 490.

Horocajuelo, G. & EPA, 2016. *The Guardian - Russian Hooligans were savage and oragnised, say England fans..* [Online]
Available at: https://www.theguardian.com/football/2016/jun/12/russian-hooligans-savage-organised-england-fans-marseille-euro-2016#img-1
[Accessed 4th August 2017].

HR Wallingford & BC Hydro, 2016. *About Life Safety Model.* [Online]
Available at: http://www.lifesafetymodel.net/about_lsm.html
[Accessed 14th September 2017].

HR Wallingford, BC Hydro, Tagg, A. & Lumbroso, D., 2016. *Life Safety Model.* [Online]
Available at: http://www.lifesafetymodel.net/index.html
[Accessed 14th September 2017].

Imamura, F. & Anawat, S., 2012. *Damage due to the 2011 Tohoku earthquake tsunami and its lessons for future mitigation.* Tokyo, Japan, Proceedings of the International Symposium on Engineering Lessons Learned from the 2011 Great East Japan Earthquake.

Insight Maker, 2016. *Agent Based Disease Simulation.* [Online]
Available at: https://insightmaker.com/insight/2846/Agent-Based-Disease-Simulation
[Accessed 4th January 2017].

Institution of Professional Engineers New Zealand (IPENZ), 2012. *A Safer New Zealand - Reducing Our Exposure to Natural Hazards,* Wellington: IPENZ.

International Civil Defence Organisation, 2016. *Natural Disasters / Earthquakes.* [Online]
Available at: http://www.icdo.org/en/disasters/natural-disasters/earthquakes
[Accessed 19th December 2016].

International Federation of Red Cross and Red Crescent Societies, 2016. *What we do - What is a disaster?.* [Online]
Available at: http://www.ifrc.org/en/what-we-do/disaster-management/about-disasters/what-is-a-disaster/
[Accessed 19th December 2016].

Ismail-Zadeh, A. & Takeuchi, K., 2007. Preventative Disaster Management of Extreme Natural Events. *Natural Hazards,* 42(3), pp. 459 - 467.

Jackson, M. C., 1991. *Systems Methodology for the Management Sciences.* 1st ed. New York: Plenum Publishers.

Jenkins, N., 2008. *Fotolibra.* [Online]
Available at: http://www.fotolibra.com/gallery/419442/flock-of-sheep-brecon-beacons/
[Accessed 10th July 2017].

Kassam, A., 2016. *The Guardian - Canada wildfires: worst of blazes 'still to come' after Fort McMurray evacuated.* [Online]
Available at: https://www.theguardian.com/world/2016/may/04/canada-wildfire-evacuation-fort-mcmurray
[Accessed 20th December 2016].

Kates, R. W., Colten, C. E., Laska, S. & Leatherman, P., 2006. Reconstruction of New Orleans after Hurricane Katrina: A research perspective. *Proceeedings of National Academy of Sciences of the USA,* 103(40), pp. 14653 - 14660.

Kates, R. W., Colten, C. E., Laska, S. & Leatherman, S. P., 2006. Reconstruction of New Orleans after Hurricane Katrina: A research perspective. *Proceedings of the National Academy of Sciences of the United States of America,* 103(40), pp. 14653 - 14660.

Kazama, M. & Noda, T., 2012. Damage statistics (Summary of the 2011 off the Pacfic Coast of Tohoku Earthquake damage). *The Japanese Geotechnical Society - Soils and Foundations,* pp. 780 - 792.

Klugl, F., 2008. *A validation methodology for agent-based simulations.* New York, Proceedings of the 2008 ACM Symposium on Applied Computing - Advances in Computing Simulation.

Kretz, T., Lohmiller, J. & Schlaich, J., 2015. The Social Force Model and its Relation to the Kladek Formula. *Transportation Research Board - PTV Group,* pp. 1 - 14.

Lane, D. C., 2000. Should System Dynamics be Described as 'Hard' or 'Deterministic' Systems Approach?. *Systems Research and Behavioral Science,* Volume 17, pp. 3-22.

Life Safety Model, 2002. *Life Safety Model - Welcome.* [Online]
Available at: http://www.lifesafetymodel.net/
[Accessed 4th January 2017].

Lindell, M. K. & Prater, C. S., 2003. Assessing Community Impacts of Natural Disasters. *Natural Hazards Review,* 4(4), pp. 176 - 185.

Live Science, 2013. *Live Science - A History of Destruction: 8 Great Hurricanes.* [Online]
Available at: http://www.livescience.com/37265-worst-hurricanes-america-hurricane-katrina.html
[Accessed 23rd November 2016].

London Fire Brigade, 2016. *Europe's biggest ever disaster training exercise begins today.* [Online]
Available at: https://www.london-fire.gov.uk/news/2016-news/europe-s-biggest-ever-disaster-training-exercise-begins-today/
[Accessed 15th November 2018].

London Resilience Partnership, 2017. *London Risk Register,* London: London Resilience.

London Resilience Team, 2014. *London Resilience Partnership Mass Evacuation Framework,* London: Greater London Authority.

Lo, S. M., Wang, W. L., Liu, S. B. & Ma, J., 2014. Using Agent-Based Simulation Model for Studying Fire Escape Process in Metro Stations. *Procedia Coumputer Science,* Volume 32, pp. 388 - 396.

Low, D. J., 2000. Following the Crowd. *Nature,* Volume 407, pp. 465 - 466.

Lubkowski, Z., da Silva, J., Hicyilmaz, K. & Grant, D., 2009. Review of Reconstruction in Aceh following the 2004 Boxing Day Tsunami. *Science of Tsunami Hazards,* 28(5), pp. 272 - 282.

Lu, Y. & Xu, J., 2014. The progress of emergency response and rescue in China: a comparative analysis of Wenchuan and Lushan earthquakes. *Natural Hazards,* 74(2), pp. 421 - 444.

Macomber, J. D., 2016. *Harvard Business Review - The 4 Types of Cities and How to Prepare Them for the Future.* [Online]
Available at: https://hbr.org/2016/01/the-4-types-of-cities-and-how-to-prepare-them-for-the-future#
[Accessed 18th November 2016].

Malamud, B. D. & Turcotte, D. L., 2002. Cellular-automata models applied to natural hazards. *Computing in Science & Engineering,* 2(3), pp. 42 - 51.

Markovic, V. et al., 2016. Assessing drought and drought-related wildfire risk in Kanjiza, Serbia: the SEERISK methodology. *Natural Hazards,* 80(2), pp. 709 - 726.

Markusoff, J., Macdonald, N. & Gills, C., 2016. *Fort McMurray Fire The Great Escape.* [Online]
Available at: http://www.macleans.ca/fort-mcmurray-fire-the-great-escape/
[Accessed 20th December 2016].

Markusoff, J., MacDonald, N. & Gills, C., 2016. *Fort McMurray Fire The Great Escape.* [Online]
Available at: http://www.macleans.ca/fort-mcmurray-fire-the-great-escape/
[Accessed 19th December 2016].

Mas, E., Suppasri, A., Imamura, F. & Koshimura, S., 2012. Agent-Based Simulation of the 2011 Great East Japan Earthquake/Tsunami Evacuation: An Integrated Model of Tsunami Inundation and Evacuation. *Journal of Natural Disaster Science,* 34(1), pp. 41 - 57.

McKie, R., 2015. *The Guardian - Why was the earthquake in Nepal such a devastating event?.* [Online]
Available at: https://www.theguardian.com/world/2015/apr/25/science-of-earthquakes
[Accessed 3rd November 2020].

Miao, X., Banister, D. & Tang, Y., 2013. Embedding resilience in emergency resource management to cope with natural hazards. *Natural Hazards,* 69(3), pp. 1389 - 1404.

Milken Institute, 2005. *The Economic Impact of Hurricane Katrina.* [Online]
Available at: http://www.milkeninstitute.org/events/associates/view/134
[Accessed 18th November 2016].

Moir, S. & Carter, K., 2012. *Diagrammatic Representations of Sustainability - A Review and Synthesis.* Edinburgh, Association of Researchers in Construction Manangement (ARCOM) Conference.

Monirul Qader Mirza, M., 2003. Climate change and extreme weather events: can developing countries adapt?. *Climate Policy,* 3(3), pp. 233 - 248.

Moussaid, M. et al., 2010. The Walking Behaviour of Pedestrian Social Groups and its Impact on Crowd Dynamics. *PLoS ONE,* 5(4).

NetLogo, 2016. *NetLogo Home Page.* [Online]
Available at: https://ccl.northwestern.edu/netlogo/
[Accessed 3rd May 2017].

NetLogo, 2017. *NetLogo User Manual Version 6.0.1.* [Online]
Available at: https://ccl.northwestern.edu/netlogo/faq.html
[Accessed 3rd May 2017].

Newcastle City Council, 2014. *Resilient Newcastle.* [Online]
Available at: https://www.newcastle.gov.uk/environment-and-waste/emergencies/resilient-newcastle
[Accessed 23rd November 2016].

Ng, M., Diaz, R. & Behr, J., 2016. Inter- and intra-regional evacuation behaviour during Hurricane Irene. *Travel Behaviour and Society 3,* pp. 21 - 28.

Ng, M., Diaz, R. & Behr, J., 2016. Inter- and Intra-regional evacuation behaviour during Hurricane Irene. *Travel Behaviour and Society,* Volume 3, pp. 21 - 28.

Ngo, T. A. & See, L., 2011. Chapter 10 Calibration and Validation of Agent-Based Models of Land Cover Change. In: A. T. C. L. M. S. M. B. Alison J. Heppenstall, ed. *Agent-Based Models of Geographical Systems.* Dordrecht Heidelberg London New York: Springer Science & Business Media, pp. 181 - 197.

Northumbria Local Resilience Forum, 2014 . *The Northumbria Local Resilience Forum Community Risk Register*, Morpeth: Northumberland County Council.

Northumbria Local Resilience Forum, 2014. *Community Risk Register for the Northumbria Local Resilience Forum.* [Online]
Available at: http://www.northumberland.gov.uk/WAMDocuments/90643B93-8332-48F1-B8F7-BA1BDE72459D_1_0.pdf?nccredirect=1
[Accessed 23rd November 2016].

NPCC, 2017. *National Police Chiefs' Council (NPCC) - Stay Safe.* [Online]
Available at: http://www.npcc.police.uk/NPCCBusinessAreas/WeaponAttacksStaySafe.aspx
[Accessed 4th August 2017].

Ntinas, V. G., Moutafis, B. E., Trunfino, G. A. & Sirakoulis, G. C., 2016. Parallel Fuzzy Cellular Automata for Data-Driven Simulation of Wildfire Spreading. *Journal of Computational Science*, Article in Press(Article in Press), p. 17.

Office for National Statistics (ONS), 2016. *UK Population by Country of Birth and Nationality Grouping, by Sex and Age: 2014.* [Online]
Available at:
https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/internationalmigration/adhocs/005561ukpopulationbycountryofbirthandnationalitygroupingbysexandage2014

Office for National Statistics, 2014. *UK Population by country of birth and nationality grouping, by sex and age: 2014.* [Online]
Available at:
https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/internationalmigration/adhocs/005561ukpopulationbycountryofbirthandnationalitygroupingbysexandage2014
[Accessed 29th August 2018].

Office for National Statistics, 2016. *Familes and Households in the UK: 2016.* [Online]
Available at:
https://www.ons.gov.uk/peoplepopulationandcommunity/birthsdeathsandmarriages/families/bulletins/familiesandhouseholds/2016#average-household-size-remains-stable-over-the-decade-to-2016

Office for National Statistics, 2017. *Families and households in the UK: 2017.* [Online]
Available at:
https://www.ons.gov.uk/peoplepopulationandcommunity/birthsdeathsandmarriages/families/bulletins/familiesandhouseholds/2017
[Accessed 30th May 2018].

Olshansky, R. B., 2006. Planning After Hurricane Katrina. *Journal of the American Planning Association,* 72(2), pp. 147 - 153.

Ordnance Survey, 2020. *Ordnance Survey OpenData.* [Online]
Available at: https://www.ordnancesurvey.co.uk/opendatadownload/products.html
[Accessed 12th March 2020].

Osborne, H., 2016. *International Business Times - 2011 Japan earthquake and tsunami: Facts about devastating event that killed 15,800.* [Online]
Available at: http://www.ibtimes.co.uk/2011-japan-earthquake-tsunami-facts-about-devastating-event-that-killed-15800-1547423
[Accessed 18th November 2016].

Oskin, B., 2017. *Japan Earthquake & Tsunami of 2011: Facts and Information.* [Online]
Available at: https://www.livescience.com/39110-japan-2011-earthquake-tsunami-facts.html
[Accessed 18th January 2019].

Oslen, L., 2005. *Houston Chronicle - New Orleans strayed from evacuation plan.* [Online]
Available at: http://www.chron.com/news/hurricanes/article/New-Orleans-strayed-from-evacuation-plan-1491205.php
[Accessed 18th November 2016].

Oxford Dictionary, 2016 A. *Definition of War.* [Online]
Available at: https://en.oxforddictionaries.com/definition/war
[Accessed 16th December 2016].

Oxford Dictionary, 2016 B. *Definition of Terrorist.* [Online]
Available at: https://en.oxforddictionaries.com/definition/terrorist
[Accessed 16th December 2016].

PA, 2015. *The Guardian.* [Online]
Available at: https://www.theguardian.com/environment/live/2015/dec/06/storm-desmond-uk-severe-flooding-and-extreme-weather-live-blog
[Accessed 10th July 2017].

Palm III, W. J., 2012. Chapter 1 Introduction. In: B. Stenquist, ed. *System Dynamics.* New York: McGraw-Hill, pp. 2 - 26.

Palm III, W. J., 2012. Preface. In: B. Stenquist, ed. *System Dynamics.* New York: McGraw-Hill, pp. vii - xi.

Pan, X., Han, C. S., Dauber, K. & Law, K. H., 2007. A multi-agent based framework for the simulation og human and social behaviours during emergency evacuations. *AI & Soc,* Volume 22, pp. 113 - 132.

Parker, D. C. et al., 2002. Multi-agent systems for the simulation of land-use and land-cover change: A review. *Annals of the Association of American Geographers,* Volume 93, pp. 314 - 337.

Parkin, S., 2003. Sustainable Development: the concept and practical challenges. *Proceedings of the ICE - Civil Engineering,* 138(6), pp. 3 - 8.

Paton, E. & Warrell, H., 2015. *Financial Times - Simulated terror attack to test London emergency services.* [Online]
Available at: https://www.ft.com/content/2e11646c-1ef9-11e5-ab0f-6bb9974f25d0
[Accessed 4th January 2017].

Pelechano, N. & Badler, N. I., 2006. Modelling Crowd and Trained Leader Behaviour during Building Evacuation. *IEEE Computer Society,* pp. 80 - 86.

Pilot, S., 2016. What is a Fault Tree Analysis?. *Quality Progress,* 49(1), p. 43.

RAC, 2018. *RAC Route Planner.* [Online]
Available at: https://www.rac.co.uk/route-planner/

Rafferty, J. P., 2016. *Nepal Earthquake of 2015.* [Online]
Available at: https://www.britannica.com/topic/Nepal-earthquake-of-2015
[Accessed 19th December 2016].

Rastogi, R., Thaniarasu, I. & Chandra, S., 2011. Design Implications of Walking Speed for Pedestrian Facilities. *Journal of Transportation Engineering,* 137(10), pp. 687 - 696.

Raworth , K., 2012. *A Safe and Just Space for Humanity: Can we live within the doughnut?,* Oxford: Oxfam International.

Reuters, 2011. *TIME - London Riots: Why the violence is spreading across England..* [Online]

Available at: http://content.time.com/time/world/article/0,8599,2087701,00.html
[Accessed 10th July 2017].

Reynolds, P., 2005. *BBC News.* [Online]
Available at: http://news.bbc.co.uk/1/hi/4216508.stm
[Accessed 18th November 2016].

Riebeek, H., 2005. *The Rising Cost of Natural Disasters.* [Online]
Available at: http://earthobservatory.nasa.gov/Features/RisingCost/rising_cost5.php
[Accessed 18th November 2016].

Ro, M., Bhalerao, A. & Na, P., 2011. *What is the assumed walking speed in Google Maps time estimates?.* [Online]
Available at: https://www.quora.com/What-is-the-assumed-walking-speed-in-Google-Mapss-time-estimates

Rosenberg, M., 2015. *About Education - The Disaster Cycle.* [Online]
Available at: http://geography.about.com/od/hazardsanddisasters/a/The-Disaster-Cycle.htm
[Accessed 18th November 2016].

Rowlatt, J., 2016. *Nepal earthquake: Patience wearing thin one year on.* [Online]
Available at: http://www.bbc.co.uk/news/world-asia-36102058
[Accessed 20th December 2016].

Sadiq, A.-A., Tharp, K. & Graham, J. D., 2016. FEMA versus local governments: influence and reliance in disaster preparedness. *Natural Hazards,* 82(1), pp. 123 - 138.

Schimpl, M. et al., 2011. Association between Walking Speed and Age in Healthy, Free-Living Individuals Using Mobile Accelerometry - A Cross-Sectional Study. *PLoS ONE,* 6(8), pp. 1 - 7.

Science Daily, 2008. *Sheep in human clothing: Scientists reveal our flock mentality.* [Online]
Available at: https://www.sciencedaily.com/releases/2008/02/080214114517.htm
[Accessed 4th January 2017].

Shen, Y. et al., 2014. Evacuation Processes of Different Genders in Different Visbility Conditions - An Experimental Study. *Procedia Engineering,* Volume 71, pp. 65 - 74.

Silva, A. M. C. B., Cunha, J. R. R. d. & Silva, J. P. C. d., 2014. Estimation of Pedestrian Walking Speeds on Footways. *Municipal Engineer,* 167(ME1), pp. 32 - 43.

SimWalk, 2017 A. *SimWalk - About.* [Online]
Available at: http://www.simwalk.com/about/index.html
[Accessed 14th September 2017].

SimWalk, 2017 A. *SimWalk Case Studies - Crowd and Pilgrimage Control in Mecca, Saudi Arabia.* [Online]
Available at: http://www.simwalk.com/downloads/simwalk_casestudy_tawaf_e.pdf
[Accessed 8th January 2019].

SimWalk, 2017 B. *SimWalk - Clients.* [Online]
Available at: http://www.simwalk.ch/clients/index.html
[Accessed 14th September 2017].

SimWalk, 2017 B. *SimWalk Case Studies - Sport Stadium. Simulation of Normal Operations and Evacuation.* [Online]
Available at: http://www.simwalk.com/downloads/simwalk_casestudy_lucerne_e.pdf
[Accessed 8th January 2019].

SimWalk, 2017 C. *SimWalk - Projects.* [Online]
Available at: http://www.simwalk.ch/projects/index.html
[Accessed 14th September 2017].

SimWalk, 2017 C. *SimWalk Case Studies - Football Stadium. Evacuation Simulation Study Verified..* [Online]
Available at: http://www.simwalk.com/downloads/simwalk_casestudy_penn_e.pdf
[Accessed 8th January 2019].

SimWalk, 2017 D. *SimWalk Price List.* [Online]
Available at: http://www.simwalk.ch/downloads/pricelist_simwalk.pdf
[Accessed 14th September 2017].

Singh-Peterson, L., Salmon, P., Baldwin, C. & Goode, N., 2015. Deconstructing the Concept of Shared Responsibility for Disaster Resilience: A Sunshine Coast Case Study, Australia. *Natural Hazards,* 79(2), pp. 755 - 774.

Sorokowska, A. et al., 2017. Preferred Interpersonal Distances: A Global Comparison. *Journal of Cross-Cultural Psychology,* 48(4), pp. 577 - 592.

Spielauer, M., 2011. What is Social Science Microsimulation?. *Social Science Computer Review,* 29(1), pp. 9 - 20.

Sterman, J. D., 2000. *Business Dynamics: Systems Thinking and Modeling for a Complex World.* 1st ed. New York: McGraw-Hill / Irwin.

Stewart, A., 2018. *The National - Seven years on, how far has Japan come after its earthquake and tsunami?.* [Online]
Available at: https://www.thenational.ae/world/asia/seven-years-on-how-far-has-japan-come-after-its-earthquake-and-tsunami-1.711944
[Accessed 17th January 2019].

Tanaka, H., Fan, L. T., Lai, F. S. & Toguchi, K., 1983. Fault-Tree Analysis by Fuzzy Probability. *IEEE Transactions on Reliability*, R-32(5), pp. 453 - 457.

TerraME, 2016. *TerraME: Multiparadigm Modeling Toolkit.* [Online]
Available at: http://www.terrame.org/doku.php
[Accessed 4th January 2017].

Thapa, T., 2018. *Human Rights Watch - Lessons for Nepal, Three Years After Deadly Earthquake.* [Online]
Available at: https://www.hrw.org/news/2018/04/25/lessons-nepal-three-years-after-deadly-earthquake
[Accessed 11th October 2018].

The Canadian Press, 2016. *Huffpost Alberta Canada - Fort McMurray Fire Could Last Months: Officials.* [Online]
Available at: http://www.huffingtonpost.ca/2016/05/07/fort-mcmurray-fire_n_9863188.html
[Accessed 19th December 2016].

The Chronicle - Hannah Graham, 2017. *See inside the Metrocentre as police stage majo 'terror attack' training.* [Online]
Available at: https://www.chroniclelive.co.uk/news/north-east-news/see-inside-metrocentre-police-stage-13063548
[Accessed 22nd November 2018].

The Guardian, 2016. *The Guardian - Last winter's floods 'most extreme on record in UK', says study.* [Online]
Available at: https://www.theguardian.com/environment/2016/dec/05/last-winters-floods-most-extreme-on-record-uk-study
[Accessed 5th December 2016].

The Guardian, 2016. *The Guardian - Last winter's floods 'most extreme on record in UK', says study.* [Online]
Available at: https://www.theguardian.com/environment/2016/dec/05/last-winters-floods-most-extreme-on-record-uk-study
[Accessed 5th December 2016].

The Guardian, 2017. *Hundreds of armed police stage terror drill on Thames tourist ship.* [Online]
Available at: https://www.theguardian.com/uk-news/2017/mar/19/massive-anti-terrorism-drill-on-thames-cruise-ship
[Accessed 22nd November 2018].

The Kathmandu Post, 2018. *Costs of Reconstruction.* [Online]
Available at: https://kathmandupost.ekantipur.com/news/2018-04-25/costs-of-reconstruction.html
[Accessed 11th October 2018].

The World Bank, 2018. *Databank - Population Estimates and Projections.* [Online]
Available at: http://databank.worldbank.org/data/reports.aspx?source=population-estimates-and-projections

Tingsanchali, T., 2012. Urban flood disaster management. *Procedia Engineering,* Volume 32, pp. 25 - 37.

Toya, H. & Skidmore, M., 2007. Economic development and impacts of natural disasters. *Economic Letters,* Volume 94, pp. 20 - 25.

Troitzsch, K. G., 2004. *Validating simulation models.* Magdeburg, Proceedings of the 18th European Simualtion Multi-conference.

Twitter (Alix Long), 2017. *Alix Long Twitter Account.* [Online]
Available at: https://twitter.com/long_alix
[Accessed 10th July 2017].

Twitter (GM Police), 2017. *G M Police Account.* [Online]
Available at: https://twitter.com/gmpolice
[Accessed 10th July 2017].

Twitter (JesyRae), 2017. *JesyRae Twitter Account.* [Online]
Available at: https://twitter.com/iamjesyrae
[Accessed 10th July 2017].

U.S. Homeland Security and Counterterrorism, 2006. *The Federal Response to Hurricane Katrina Lessons Learned.* 1st ed. Washington D.C.: U.S. Government Printing Office.

UK Government, 2004. *Civil Contingencies Act.* London: UK Government.

UK Population, 2020. *Newcastle Popualtion 2020.* [Online]
Available at: www.ukpopulation.org/newcastle-population
[Accessed 31st March 2020].

UNHCR - The UN Refugee Agency, 2015. *Worldwide displacement hits all-time high as war and persecution increase.* [Online]
Available at: http://www.unhcr.org/uk/news/latest/2015/6/558193896/worldwide-displacement-hits-all-time-high-war-persecution-increase.html
[Accessed 19th December 2016].

UNISDR, 2009. *United Nations Office for Disaster Risk Reduction - Terminology.* [Online]
Available at: https://www.unisdr.org/we/inform/terminology
[Accessed 28th March 2017].

UNISDR, 2016. *Who Are We - History.* [Online]
Available at: https://www.unisdr.org/who-we-are/history
[Accessed 30th March 2017].

United Nations, 1987. *Report of the World Commission on Environment and Development: Our Common Future - Brundtland Report,* Oslo: Oxford University Press.

United Nations, 2010. *Environmental Indicators - Natural Disasters: Hydrological Disasters.* [Online]
Available at: http://unstats.un.org/unsd/environment/Hydro_disasters.htm
[Accessed 16th December 2016].

United Nations, 2016. *World Humanitarian Summit.* [Online]
Available at: https://www.worldhumanitariansummit.org/
[Accessed 22nd December 2016].

United Nations, 2020. *What is the Sendai Framework for Disaster RIsk Reduction?.* [Online]
Available at: https://www.undrr.org/implementing-sendai-framework/what-sendai-framework
[Accessed 23rd July 2021].

Univeristy of Leeds, 2008. *Sheep in human clothing - scientists reveal our flock mentality.*
[Online]
Available at:
http://www.leeds.ac.uk/news/article/397/sheep_in_human_clothing__scientists_reveal_our_flock_mentality
[Accessed 4th January 2017].

US Department of Homeland Security, 2015. *National Preparedness Goal, Second Edition,* Washington D.C: US Departmenet of Homeland Security.

Van, K. N. D., 2019. *2011 Tohoku Earthquake.* [Online]
Available at: https://storymaps.arcgis.com/stories/94f15bfe999c497288c582f7db46e3de
[Accessed 4th May 2020].

Vega, N., 2018. *New York Post - Trump's 'presidential alert' system will buzz 200 million phones.* [Online]
Available at: https://nypost.com/2018/10/03/trumps-presidential-alert-system-will-buzz-200-million-phones/
[Accessed 2nd March 2020].

Walkit The Urban Route Planner, 2018. *FAQs - How do you Calculate Your Walking Times?.*
[Online]
Available at: https://walkit.com/faq/#walking-times

Walkit, 2018. *Walkit Route Planner.* [Online]
Available at: https://walkit.com/

Warfield, C., 2002. *The Disaster Management Cycle.* [Online]
Available at: http://www.gdrc.org/uem/disasters/1-dm_cycle.html
[Accessed 18th November 2016].

Wenzel, F. et al., 2001. Potential of Earthquake Early Warning Systems. *Natural Hazards,* 23(2), pp. 407 - 416.

Whitehead, J. C. et al., 2000. Heading for higher ground: factors affecting real and hypothetical hurricane evacuation behaviour. *Environmental Hazards 2,* Volume 2, pp. 133 - 142.

Wilensky, U., 1997. *Netlogo Traffic Basic Model, Center for Connected Learning and Computer-Based Modelling, Northwestern University, Evanston, IL.*. [Online]
Available at: http://ccl.northwestern.edu/netlogo/models/TrafficBasic.
[Accessed 16th February 2018].

Wilensky, U., 1997. *Netlogo Wolf Sheep Predation Model.* [Online]
Available at: http://ccl.northwestern.edu/netlogo/models/WolfSheepPredation.
[Accessed 12th December 2018].

Wilensky, U., 1999. *NetLogo.* [Online]
Available at: http://ccl.northwestern.edu/netlogo/.
[Accessed 31st August 2017].

Wilensky, U. & Payette, N., 1998. *Netlogo Traffic Two Lanes Model, Center for Connected Learning and Computer Based Modelling, North Western University, Evanston, IL.*. [Online]
Available at: http://ccl.northwestern.edu/netlogo/models/Traffic2Lanes
[Accessed 16th February 2018].

Windrum, P. F., Fagiolo, G. & Moneta, A., 2007. Empirical validation of agent-based models: Alternatives and prospects. *Journal of Artifical Societies and Social Simulation,* 10(2), p. 8.

Wolfram, S., 1984. Cellular Automata as Models of Complexity. *Nature,* 311(4), pp. 419 - 424.

Wolfram, S., 1985. Twenty Problems in the Theory of Cellular Automata. *Physica Scripta (Proceedings of the 59th Nobel Symposium),* Volume T9, pp. 170 - 183.

Wood, N. et al., 2016. Pedestrian flow-path modelling to support tsunami evacuation and disaster relief planning in the U.S. Pacific Northwest. *International Journal of Disaster Risk Reduction,* Volume 18, pp. 41 - 55.

Wu, H.-C., Lindell, M. K. & Prater, S. C., 2012. Logistics of hurricane evacuation in Hurricanes Katrina and Rita. *Transportation Research Part F 15,* pp. 445 - 461.

Yang, J. et al., 2006. Modelling Pedestrians' Road Crossing Behaviour in Traffic System Micro-Simulation in China. *Transportation Research Part A: Policy and Practice,* 40(3), pp. 280 - 290.

Young, M. J., 2006. *Typical Uses of Cellular Automata.* [Online]
Available at: http://www.mjyonline.com/CellularAutomataUses.htm
[Accessed 27th February 2017].

Youtube, 2009. *Aggregate Dynamics for Dense Crowd Simulation - GAMMA UNC.* [Online]
Available at:
https://www.youtube.com/watch?v=pqBSNAOsMDc&list=PLD56A0C7765234DCD&index=12
[Accessed 12th December 2018].

Youtube, 2010. *An agent based model of flood evacuation - Richard Dawson (Newcastle University).* [Online]
Available at: https://www.youtube.com/watch?v=o0EOlc5n9O8
[Accessed 12th December 2018].

Youtube, 2013. *SimWalk 2D/3D Bus Terminal Scenario - SimWalk.* [Online]
Available at: https://www.youtube.com/watch?v=RA5qllqRB6M
[Accessed 12th December 2018].

Youtube, 2014. *Miarmy 3.5 Crowd DEMO 10 EN - Basefount.* [Online]
Available at: https://www.youtube.com/watch?v=P8RZUpZluQA
[Accessed 12th December 2018].

Youtube, 2016. *Metro Station Simulation with SimWalk 5 - SimWalk.* [Online]
Available at: https://www.youtube.com/watch?v=0r5mF2EBwvY
[Accessed 12th December 2018].

Yun, N. Y. & Hamada, M., 2012. *A Study on Evacuation Behaviours in the 2011 Great Japan Earthquake.* Lisbon, Portugal, 15th World Conference on Earthquake Engineering (15WCEE).

Zare, M. & Ghaychi Afrouz, S., 2012. Crisis Management of Tohoku: Japan Earthquake and Tsunami, 11 March 2011. *Iranian Journal of Public Health,* 41(6), pp. 12 - 20.

Zhong, M. et al., 2008. Study of the Human Evacuation Simulation of Metro Fire Safety Analysis in China. *Journal of Loss Prevention in the Process Industries,* 21(3), pp. 287 - 298.

Appendix A – Test 2: World Population & Walking Speeds

A. Test 2 – World Population & Walking Speeds

A.1 Test Aim & Variables

To aid comparison, it was decided that the model would simulate several international populations, where population extremes are often higher and to allow comparison with the UK evacuation times produced. The data for the varied walking speeds by age and sex was gathered as part of the literature review and was the same data as used in the UK simulations. Global population data was used to form real-life population groups. As before, the aim of this test, was to ascertain whether using varied walking speeds had any effect on the evacuation time of the case study area, including whether the population data needed to include the age and sex of the population or just the age. Within the test, the model ran three scenarios to understand the effect on overall evacuation time: (1) all agents travelling at 1.34m/s (3mph), (2) agents travelling at varied walking speeds by age only and (3) agents travelling at varied walking speeds by age and sex. Each simulation was completed for four different total population sizes (1000, 2000, 5000 and 10000) and population extremes based on different International locations (Table A-1), the test variations have been set out in Figure A-1. The four different population make-ups are the World average, Tokyo, Japan which has a larger OAP population, Johannesburg, South Africa which has a larger number of children and Seoul, South Korea which has a larger adult population (The World Bank, 2018) (Figure A-2). To get an indication on variability in the results, each set of variables and walking speed scenarios will have five realisations; this will result in 240 sets of evacuation times for this test, which equates to 60 results per location (Table A-2).

Table A-1 – Macroscale City Evacuation Model Variables for Test 2 (For the walking speeds: C = Children, MA = Male Adults, FA = Female Adults, MO = Male OAPs and FO = Female OAPs)

Variables	1.34m/s (3mph) Walking Speed	Varied Walking Speed by age only	Varied Walking Speed by age and sex
No of Evacuees	1000 or 2000 or 5000 or 10000		
Population Makeup	See Figure A-2		
Walking Speed (Bosina & Weidmann, 2017)	All = 1.34 m/s (3mph)	C = 0.8m/s (1.79mph) MA & FA = 1.34 m/s (3mph) MO & FO = 0.78 m/s (1.74mph)	C = 0.8 m/s (1.79mph) MA = 1.34 m/s (3mph) FA = 1.12 m/s (2.5mph) MO = 0.78 m/s (1.74mph) FO = 0.76 m/s (1.70mph)

Table A-2 – Total Number of Results Expected from Test 2

	World Average	Tokyo	Johannesburg	Seoul	Total Tests
	All Walking Speeds the Same				
1000	5	5	5	5	80
2000	5	5	5	5	
5000	5	5	5	5	
10000	5	5	5	5	
	Varied Walking Speed by age only				
1000	5	5	5	5	80
2000	5	5	5	5	
5000	5	5	5	5	
10000	5	5	5	5	
	Varied Walking Speed by Age and Sex				
1000	5	5	5	5	80
2000	5	5	5	5	
5000	5	5	5	5	
10000	5	5	5	5	

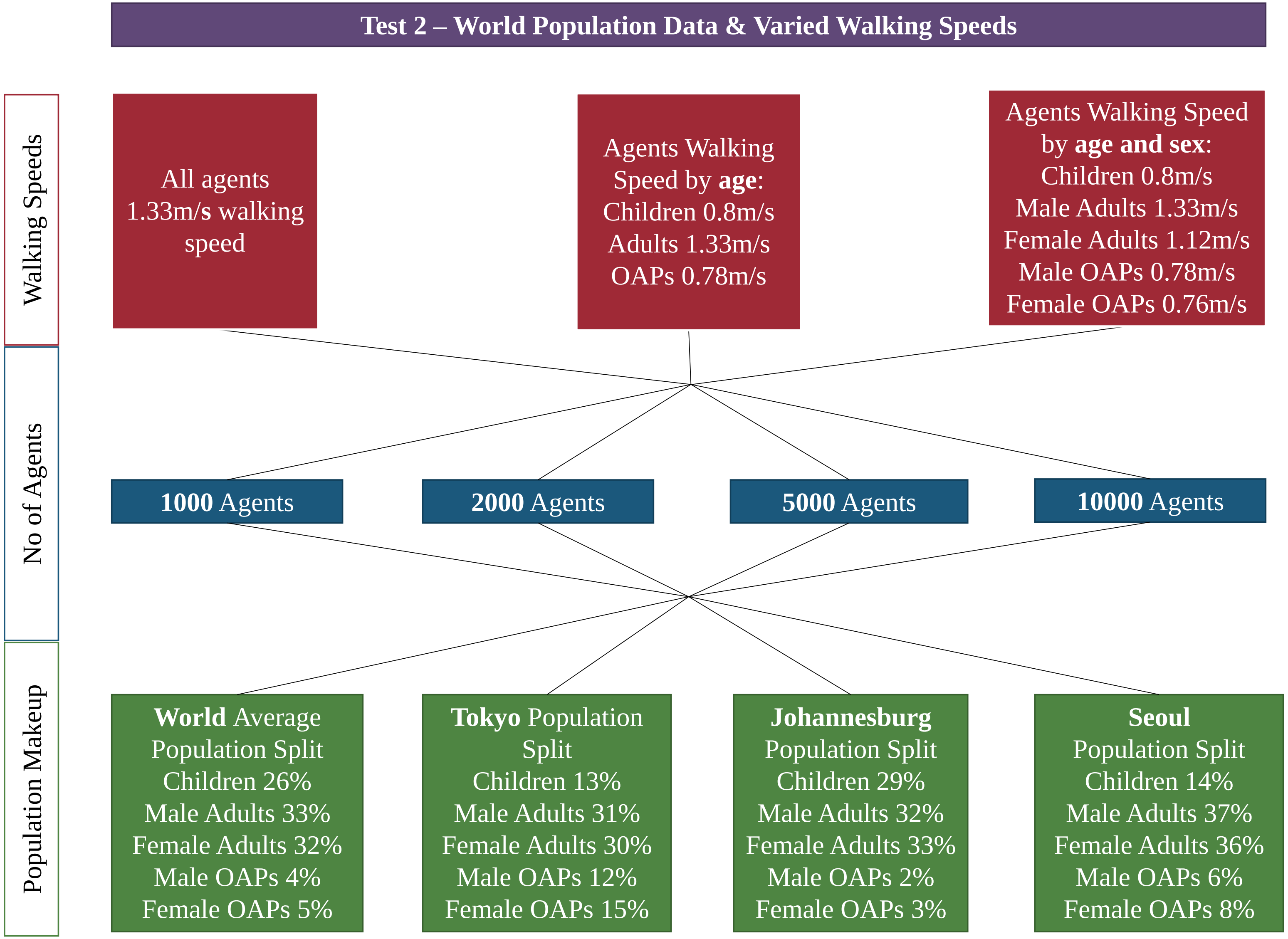
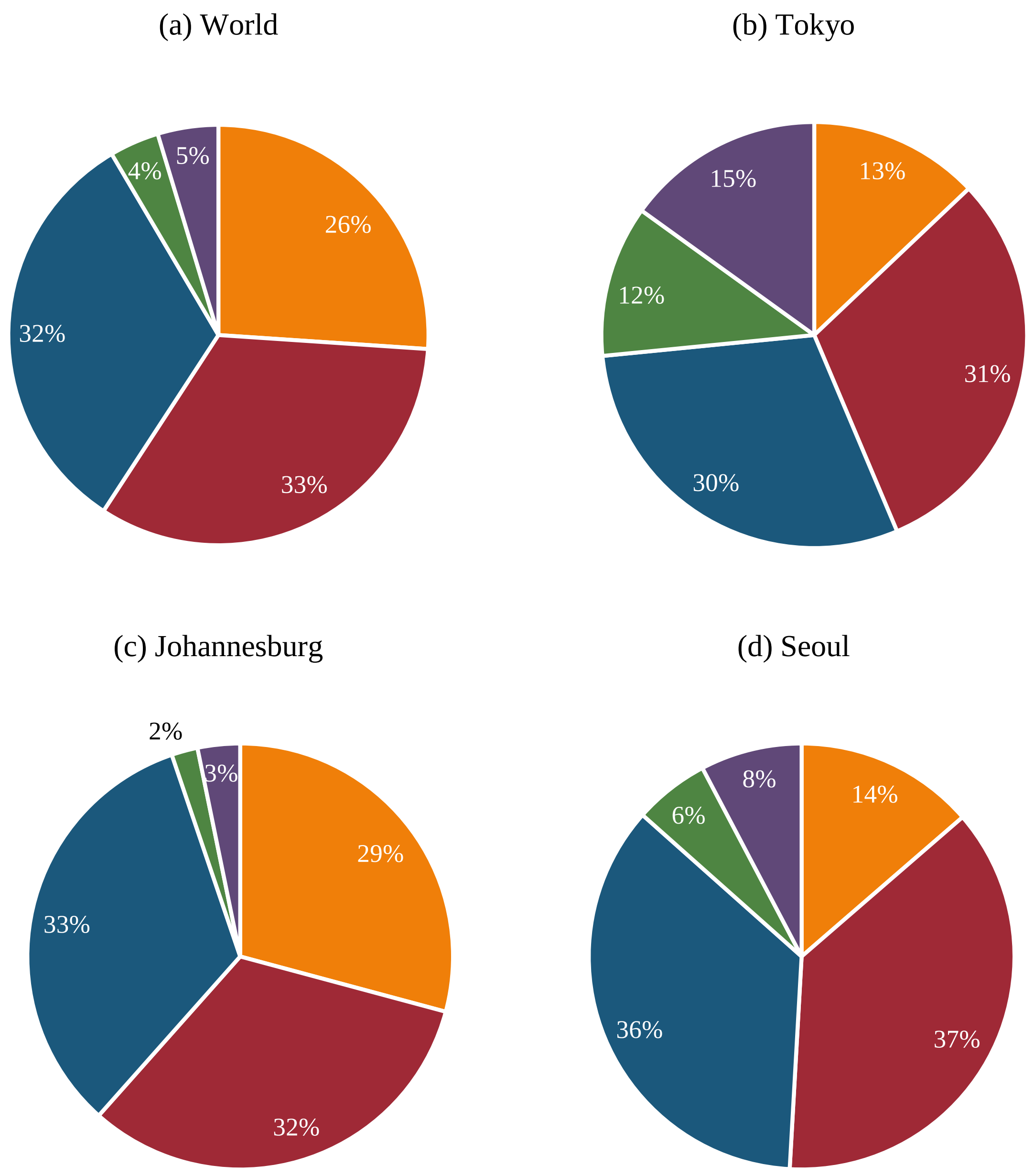


Figure A-1 – Testing Regime for Test 2



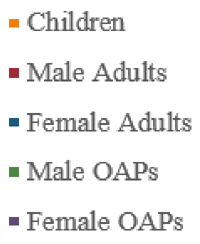


Figure A-2 – Population Breakdown of World Locations – (a) World Average, (b) Tokyo, Japan – high OAP population, (c) Johannesburg, South Africa – high child population, (d) Seoul, South Korea – high adult population (The World Bank, 2018)

A.2 Initial Evacuation Times

After completing the simulations at different global locations and with varied walking speeds, the averaged evacuation times for each population type were compiled (Table A-3). This showed that there were a range of evacuation times produced by considering the demographics of the crowd, demonstrating that there may be an impact of including population characteristics. However, it was important to understand whether this was a factor of the total population size, the population distribution of different agent types or the inclusion of varied population characteristics (by age and/or sex) or a combination of these factors, and to check this did not differ from the results collated from the UK data.

When walking speed was the same for all population types, there was little variation seen in the averaged evacuation times for the different locations (e.g. Tokyo, Johannesburg etc.) (Table A-3). The introduction of varied walking speed by age only showed that the slowest agent types (OAPs and children) have an increased average evacuation time compared with the adults, approximately 70% slower, whereas adults by only approximately 2% (Table A-3). Finally, the introduction of varied walking speed by age and sex demonstrated that the average evacuation times for adult females increased by approximately 20% whilst other agents had similar evacuation times to the previous tests (Table A-3).

Table A-3 – Average Global Evacuation Times (minutes) for different regions across the world, showing (in the third column) average evacuation times when all agents walk at 1.34m/s, (in the fourth column) when agents of different age have different walking speeds and (in the fifth column) when both age and sex are considered in walking speeds

<table>
<tr><th colspan="2">Variables</th><th colspan="3">Evacuation Times (minutes)</th></tr>
<tr><th></th><th>Population</th><th>1.34m/s (3mph) Model (minutes)</th><th>Varied Walking Speeds by age only (minutes)</th><th>Varied Walking Speeds by age and sex (minutes)</th></tr>
<tr><td rowspan="5">Tokyo, Japan (Large OAP population)</td><td>Children</td><td rowspan="5">69.4</td><td>117.7</td><td>114.9</td></tr>
<tr><td>M Adults</td><td rowspan="2">69.7</td><td>69.0</td></tr>
<tr><td>F Adults</td><td>85.7</td></tr>
<tr><td>M OAPs</td><td rowspan="2">115.9</td><td>116.6</td></tr>
<tr><td>F OAPs</td><td>120.5</td></tr>
<tr><td rowspan="5">Johannesburg, South Africa (Large Child population)</td><td>Children</td><td rowspan="5">67.3</td><td>116.9</td><td>116.2</td></tr>
<tr><td>M Adults</td><td rowspan="2">70.8</td><td>69.4</td></tr>
<tr><td>F Adults</td><td>84.5</td></tr>
<tr><td>M OAPs</td><td rowspan="2">107.7</td><td>106.8</td></tr>
<tr><td>F OAPs</td><td>112.9</td></tr>
<tr><td rowspan="2">Seoul, South Korea (Large</td><td>Children</td><td rowspan="2">68.9</td><td>112.4</td><td>114.4</td></tr>
<tr><td>M Adults</td><td>70.1</td><td>70.3</td></tr>
</table>

Adult population)	F Adults			82.8
	M OAPs		113.6	114.7
	F OAPs			116.4
World	Children	68.5	117.7	116.3
	M Adults		71.4	70.9
	F Adults			84.0
	M OAPs		112.9	110.0
	F OAPs			116.9

A.3 Effect of Total Population Size

It was not expected that the population size would have a significant impact on the evacuation times as it had not with the UK population data, however, it was still important to check that the larger populations did increase evacuation time in the same manner. When all agents travelled at 1.34m/s (3mph), but the population was broken down by age and sex, it showed that as the total population size increased, the overall evacuation time also increased (Figure A-3). The difference in evacuation time was approximately 3 – 6.5 minutes between a population of 1000 compared to 10000. For the populations with varied walking speed by age only and for age and sex, a similar increase in evacuation time with increased population size was observed. For varied walking speeds by age only, the difference in evacuation time was approximately 8.5 –12.5 minutes (Figure A-4) between a population of 1000 compared to 10000. For varied walking speeds by age and sex, the difference in evacuation time was approximately 4 – 16 minutes (Figure A-5) between a population of 1000 compared to 10000.

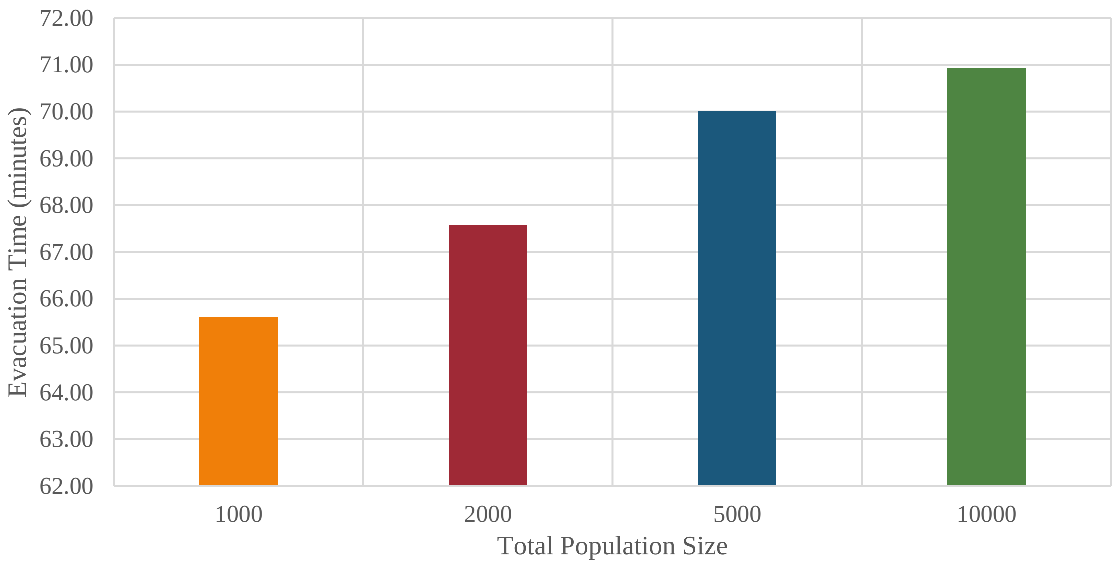


Figure A-3 – Comparison of Population Size for all Global population data locations (e.g. Tokyo, Johannesburg etc.) with 1.34m/s (3mph) walking speed for all population types, approximate difference in evacuation times 3 – 6.5 minutes as total population size increases, mean of 68.53 minutes and standard deviation of 2.41 minutes

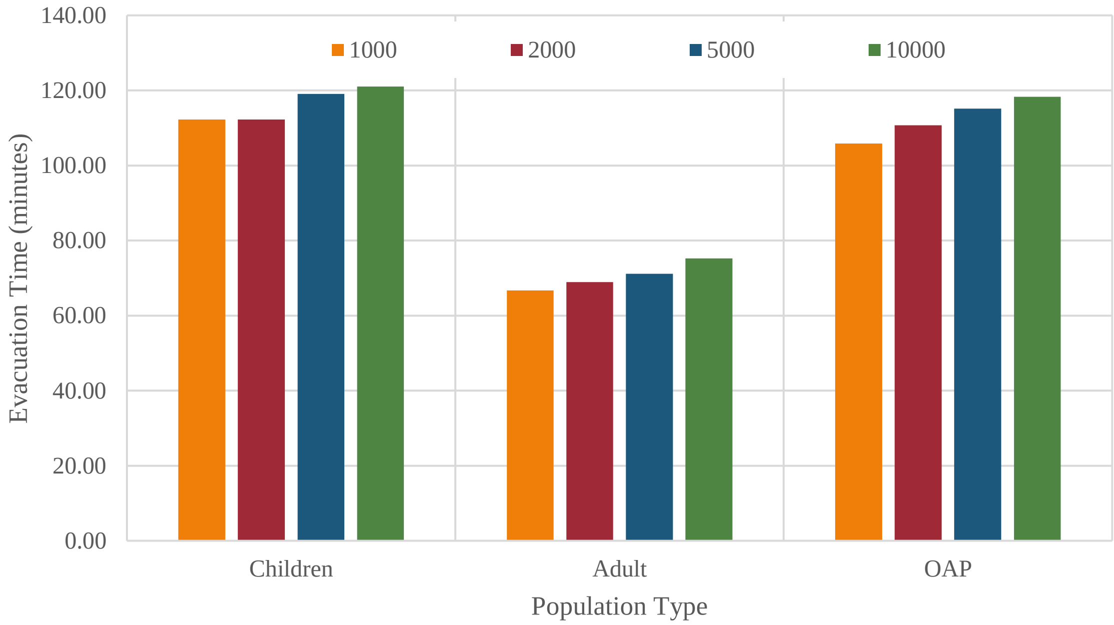


Figure A-4 – Comparison of Population Size for all Global population data locations (e.g. Tokyo, Johannesburg etc.) with varied walking speed for population types by age only, approximate difference in evacuation times 8.5 – 12.5 minutes as total population size increases, for each population type: mean (standard deviation), Children: 116.17 minutes (4.58 minutes), Adults: 70.51 minutes (3.61 minutes) and OAPs: 112.53 minutes (5.43 minutes)

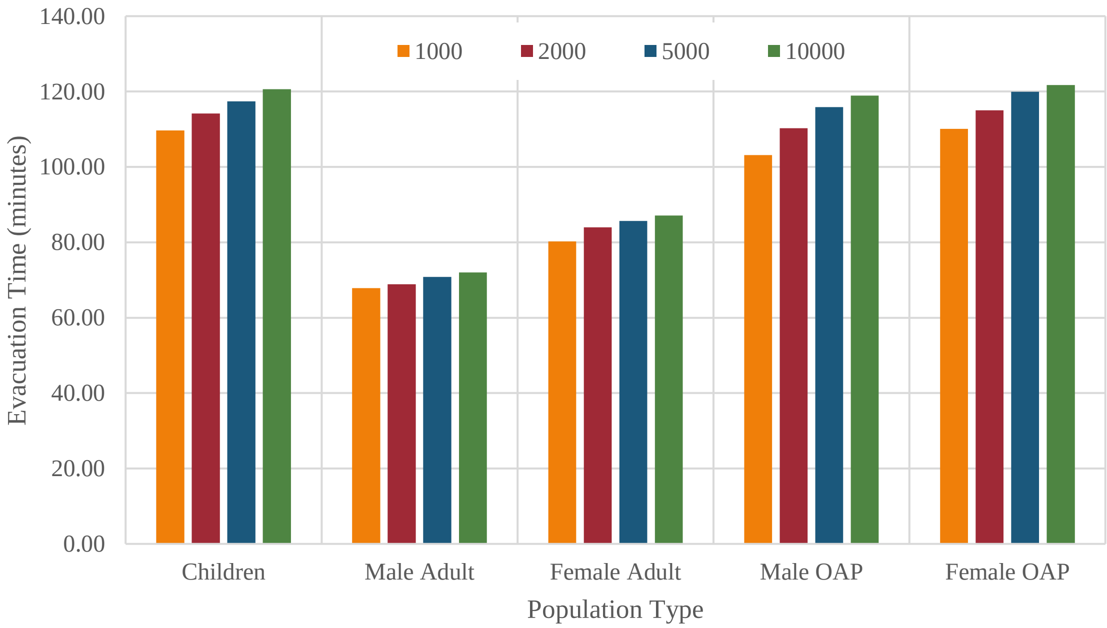


Figure A-5 – Comparison of Population Size for all Global population data locations (e.g. Tokyo, Johannesburg etc.) with varied walking speed for all different population types by age and sex. Approximate evacuation time difference 4 – 16 minutes as total population size increases. For each population type: mean (standard deviation), Children: 115.44 minutes (4.87 minutes), Male Adults: 69.57 minutes (2.40 minutes), Female Adults 84.25 minutes (2.97 minutes), Male OAPs 112.05 minutes (6.93 minutes) and Female OAPs 116.69 minutes (5.23 minutes)

A comparison was made between the UK and World data (Table A-4), which showed overall the time differences were similar. It is assumed that this time difference was a result of the spatial variability in the model and that when the total population size increased, it was more likely that there was an agent at the extents than when the population was smaller. It was also more probable that the slower agents were found at the extents as population size increased. The only larger time difference was seen in the World data when the varied walking speeds were added into the model by both age and sex, it was anticipated that this difference was more likely to be attributed to the population characteristics rather than the large total population size.

Table A-4 – Comparison of Time Difference by Population Size between UK and World Population Data for total population size of 1000 and 10000, showing (in the second column) when all agents walk at 1.34m/s, (in the third column) agents adopting varied walking speed by age only and (in the fourth column) agents adopting varied walking speed by age and sex

	1.34m/s (3mph) Model (minutes)	**Varied Walking Speeds by age only (minutes)**	**Varied Walking Speeds by age and sex (minutes)**
UK Data	5.6 – 6.5	7.0 – 12.1	5.6 – 9.6
Time Difference	0.90	5.10	4.00
World Data	2.85 – 6.3	8.5 – 12.5	4.1 – 15.8
Time Difference	3.45	4.00	11.70

A.4 Effect of Population Extremes

Across the globe there are further examples of population extremes, which are more pronounced than the UK data. Hence, further checks were carried out on the implications of simulating populations with larger numbers of slower agents present. A comparison was made of the various global locations, which had population extremes (e.g. larger number of children or OAPs) with varied walking speeds by age and sex, which showed that there was only a small difference in evacuation time for each of the slower population types (Figure A-6). The largest difference was for the male OAPs, the time difference was 9.7 minutes between the slowest and fastest evacuation time, the largest evacuation time was seen where the OAP population was highest (Tokyo) and vice versa for the smallest evacuation time (Johannesburg). In comparison, for the children the evacuation time difference was 1.9 minutes and female OAPs was 7.6 minutes. It was apparent that the population characteristics were influencing evacuation time through the varied walking speeds rather than the total number of any one agent type, hence highlighting the importance of capturing a range of traits.

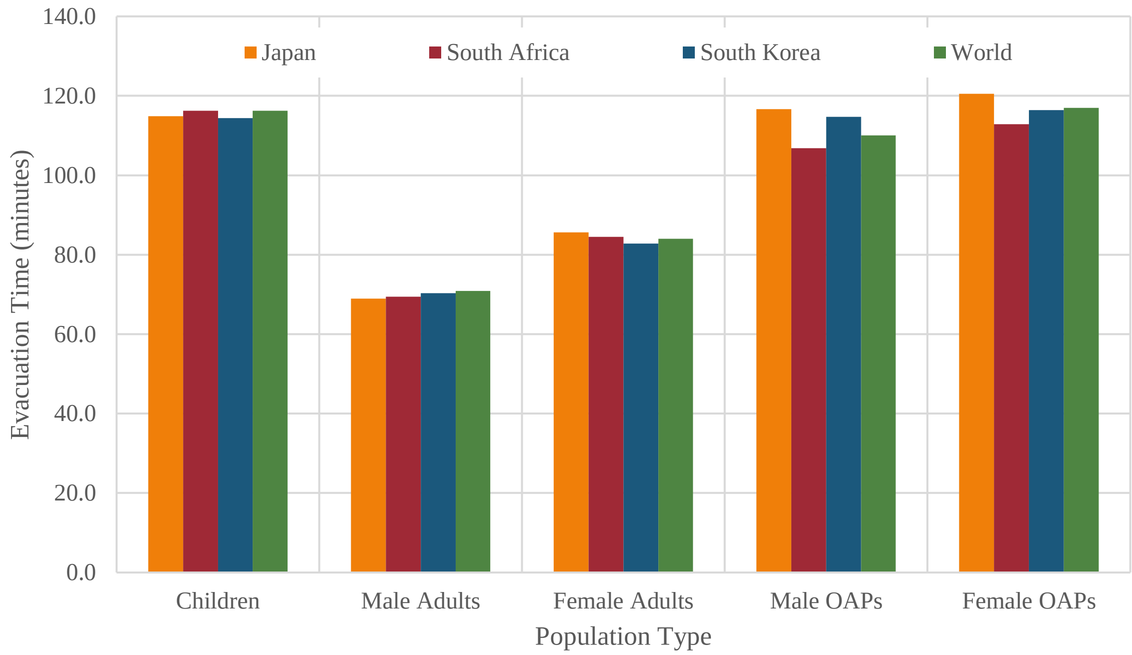


Figure A-6 – Comparison of Different Global Locations and Average Evacuation Times in terms of Population Extremes (Japan – large OAP population, South Africa – large child population and South Korea – large adult population)with varied walking speed by age and sex, for each population type: mean (standard deviation), Children: 115.4 minutes (0.96 minutes), Male Adults: 69.9 minutes (0.87 minutes), Female Adults: 84.2 minutes (1.20 minutes), Male OAPs: 112.1 minutes (4.44 minutes) and Female OAPs: 116.7 minutes (3.14 minutes)

A.5 Minimum & Maximum Times

To further compare the evacuation times produced for the population extremes, the minimum and maximum times were plotted (Figure A-7), this information was taken from all the available simulations. However, the maximum times were all found to be produced from simulations, which included a greater number of population characteristics whereas the minimum times were all produced from simulations with agents only walking at 1.34m/s (3mph). The results show that there were only small variations in the minimum and maximum times produced for each location, for the maximum times the time difference was 3.5 minutes and for the minimum times the time difference was 9.2 minutes. This again contributed to the idea that there was no need to simulate the model at a population extreme. A further plot was completed to identify the population type for each of the minimum and maximum evacuation times (Figure A-8). This showed that the all the maximum times were caused by slower agent population types but that the minimum was also attributed to the slower agent types. The maximum times generally tally with the largest percentage of slower agents as it more probable that one of the agents was at the model extents and therefore took a longer time to exit the model. The converse of this was true when the model runs at 1.34m/s (3mph), in that there were far fewer of the slower agent types to exit the model and all agents were travelling at the same speed, which results in a faster evacuation time overall.

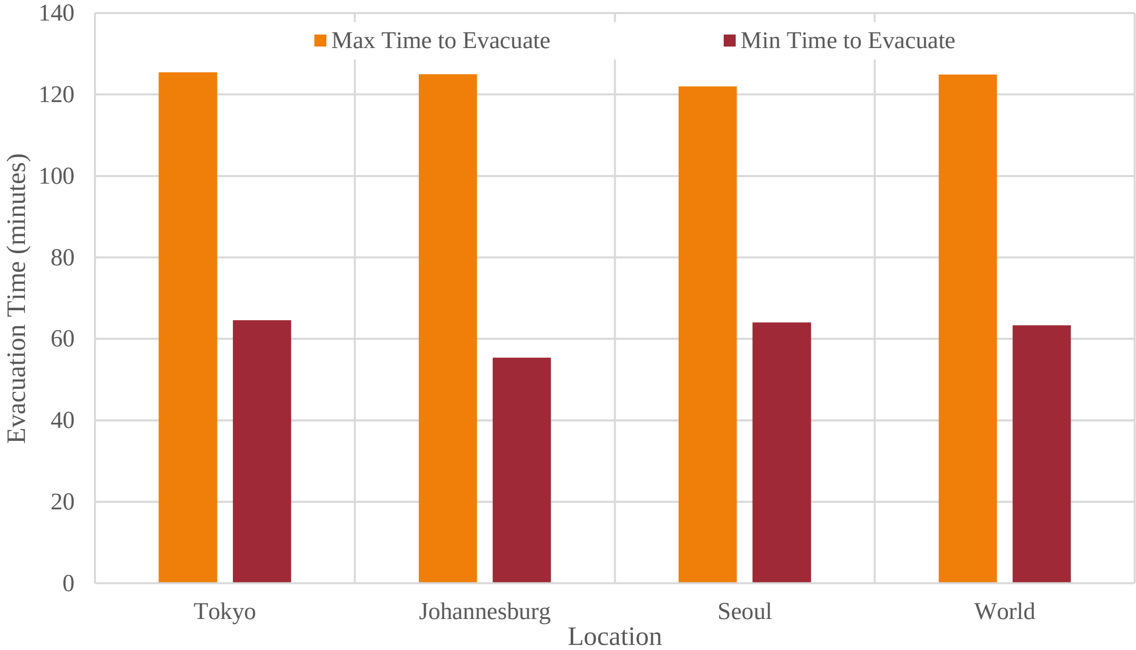


Figure A-7 – Minimum and Maximum Evacuation Times (minutes) at Worldwide Locations, time difference for maximum times approximately 3.5 minutes, time difference for minimum times approximately 9.2 minutes

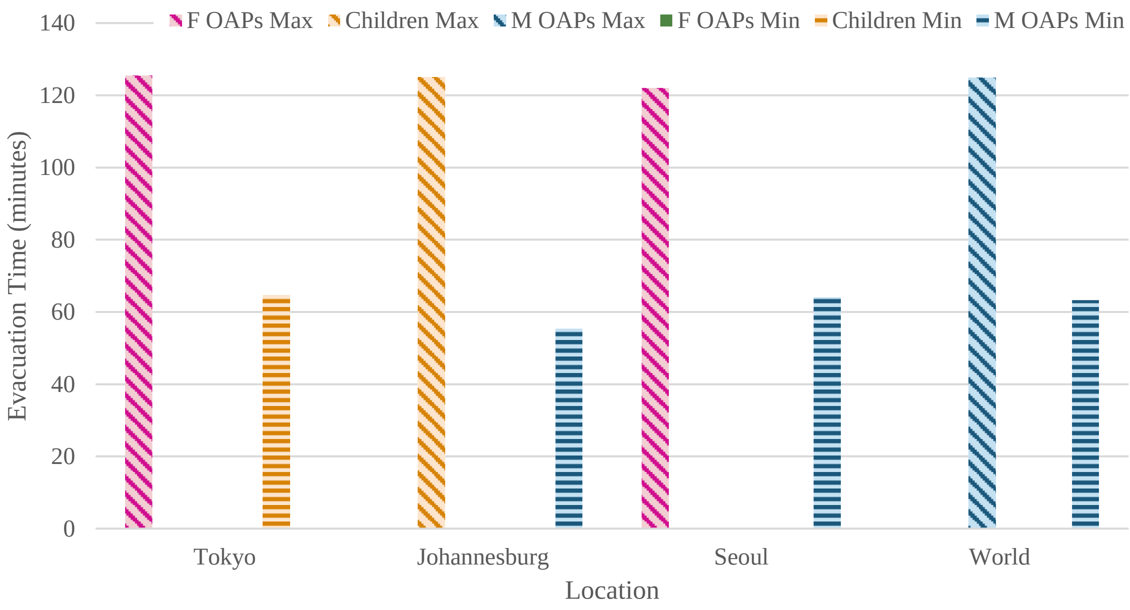


Figure A-8 – Minimum and Maximum Evacuation Times (minutes), depicting the different population types at various international locations, Tokyo: maximum time by Female OAP, minimum time by child, Johannesburg: maximum time by child and minimum time by Male OAP, Seoul: maximum time by Female OAP and minimum time by Male OAP, and the World: maximum time by Male OAP and minimum time by Male OAP

A.6 Effect of Population Characteristics

As previously, with the UK data neither the total population size nor the population extremes seemed to significantly affect the differences in evacuation time, which means that the inclusion of population characteristics were having an impact on evacuation time. A comparison was made between the model considering only walking speeds of 1.34m/s (3mph) and the inclusion of varied walking speeds based on age as well as age and sex (Table A-5). This showed that there were some large time differences between the model simulations, an average of 31.15 minutes when walking speeds were added by age and sex and an average of 27.65 minutes when walking speeds were added by age only. This resulted in large percentage time differences and was particularly seen with the slower agent types. For varied walking speeds by age and sex in South Korea, the children had 66% time difference, male OAPs had 75% time difference and female OAPs had 76% time difference when compared with a 1.34m/s (3mph) model (Figure A-9). For varied walking speeds by age only, the children had 63% time difference and the OAPs had 73% time difference (Figure A-10). These large time differences again demonstrate that the current evacuation models including only agents walking at 1.34m/s (3mph) are producing inaccurate evacuation times by failing to consider a range of walking speeds.

Table A-5 – Comparison between World Average Evacuation Times (minutes) and Simulations for different international locations, showing (in the third column) the difference in average evacuation times between all agents walking at 1.34m/s and agents adopting walking speeds based on their age only and (in the fourth column) the difference in evacuation times between all agents walking at 1.34m/s and agents adopting walking speeds based on their age and sex

<table>
<tr><th></th><th>Population</th><th>1.34m/s (3mph) Model vs. Varied Walking Speed by age only (minutes)</th><th>1.34m/s (3mph) Model vs. Varied Walking Speed by age and sex (minutes)</th></tr>
<tr><td rowspan="5">Tokyo, Japan (Large OAP population)</td><td>Children</td><td>49.0</td><td>46.2</td></tr>
<tr><td>M Adults</td><td rowspan="2">-1.4</td><td>-1.9</td></tr>
<tr><td>F Adults</td><td>14.3</td></tr>
<tr><td>M OAPs</td><td rowspan="2">50.0</td><td>50.9</td></tr>
<tr><td>F OAPs</td><td>54.5</td></tr>
<tr><td rowspan="5">Johannesburg, South Africa (Large Child population)</td><td>Children</td><td>48.1</td><td>47.5</td></tr>
<tr><td>M Adults</td><td rowspan="2">-0.3</td><td>-1.4</td></tr>
<tr><td>F Adults</td><td>13.2</td></tr>
<tr><td>M OAPs</td><td rowspan="2">41.8</td><td>41.2</td></tr>
<tr><td>F OAPs</td><td>46.8</td></tr>
<tr><td rowspan="5">Seoul, South Korea (Large Adult population)</td><td>Children</td><td>43.6</td><td>45.6</td></tr>
<tr><td>M Adults</td><td rowspan="2">-1.0</td><td>-0.5</td></tr>
<tr><td>F Adults</td><td>11.4</td></tr>
<tr><td>M OAPs</td><td rowspan="2">47.8</td><td>49.0</td></tr>
<tr><td>F OAPs</td><td>50.4</td></tr>
<tr><td colspan="2">Average Time Difference</td><td>27.65</td><td>31.15</td></tr>
<tr><td colspan="2">Average % Difference</td><td>40%</td><td>45%</td></tr>
</table>

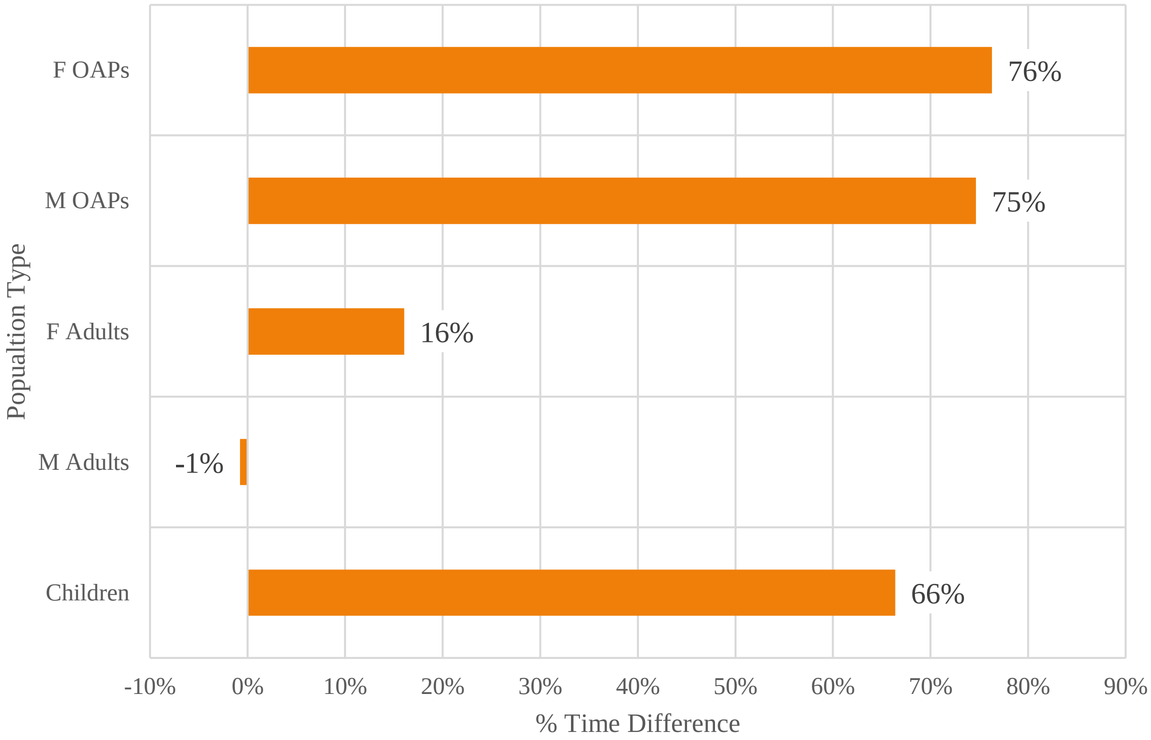


Figure A-9 – Comparison of World Average Population Data to South Korea Population Data for 1.34m/s (3mph) Walking Speed vs. Varied Walking Speeds for All Population Types by Age and Sex, Mean Time. Difference of 27.4 minutes and Standard Deviation of 26.0 minutes.

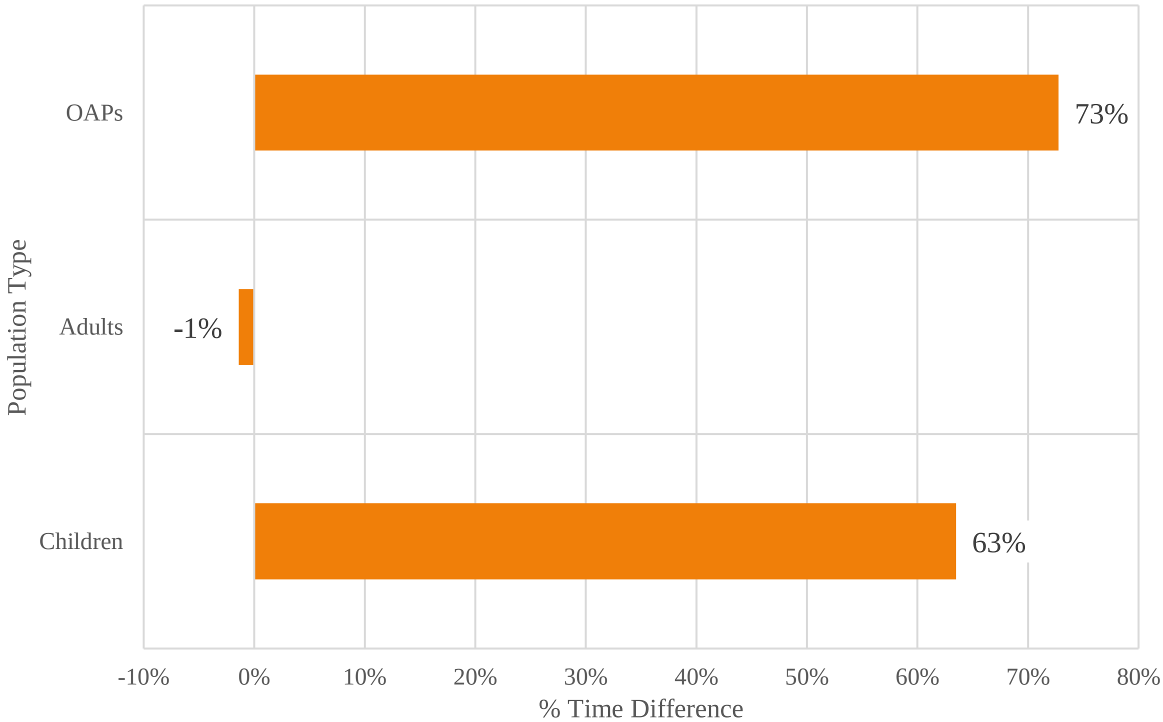


Figure A-10 – Comparison of World Average Population Data to South Korea Population Data for 1.34m/s (3mph) Walking Speed vs. Varied Walking Speeds for All Population Types by Age only, Mean Time Difference of 30.1 minutes and Standard Deviation of 27.0 minutes

A.7 Comparison of UK and World Data Evacuation Times

Evaluation of the UK and then World population data combined with the introduction of additional population characteristics into the agent-based model environment has shown that current models are producing inaccurate estimates for evacuation times. The average difference in evacuation time when walking speeds were varied by age and sex was 40% and when walking speed was by age only, the difference was 39.5%. However, for the slower population types, the time difference may be as high as 66% (female adults with varied walking speeds by age and sex) (Table A-6). Such large evacuation time differences could cause detrimental impacts for communities with increased fatalities and injuries caused by the inability to evacuate in the allotted time frame. The results so far have also shown that if a user has a lack of computational power then there were only small differences between including walking speeds varied by age and sex compared with those just by age so the number of variables could be reduced to increase computational efficiency.

The macroscale evacuation model has successfully produced a range of evacuation times with many variants in Test 1 and 2. However, it was difficult to replicate scenarios when using small numbers of agents as agents were randomly placed across the entire model, meaning the starting positions were often vastly different and slow agent types were not always placed at the model extents. This means spatial variability affected the minimum and maximum evacuation times produced. In the future, consideration should be given to the introduction of population density into the model, which would reduce the spatial variability by ensuring that all pathways were similarly populated.

Also, within the model, agents were not fully capable of reacting to each other, agents calculated a shortest path to the evacuation point, this occurred regardless of the rest of the population i.e. agents did not make an alternative route choice if there was congestion present. Further to this, agents were able to “pass” over each other e.g. if there was a slower agent ahead the agent manoeuvred around the agent rather than being held at a slower speed behind it. This may be a plausible scenario, but the model was not considering the capacity of the pathways being used and instead assuming that agents were always able to pass each other. Hence, there is a need to consider capacity and the “passing” of agents within the model environment, to improve the accuracy of the time estimates.

Table A-6 – Comparison of UK (columns 2 – 5) and World (columns 6 – 8) Population Data with 1.34m/s (3mph) simulation vs. Varied Walking Speeds by age and sex simulation (rows 3 – 8) and age only simulation (rows 10 – 13), showing % difference in evacuation times

	Newcastle	South Devon	Slough	Tower Hamlets	Tokyo	Johannesburg	Seoul	AVG
	1.34m/s (3mph) vs. Varied Walking Speed by age and sex							
Children	67%	68%	74%	69%	67%	69%	66%	**60%**
Male Adults	-2%	-4%	-1%	-5%	-3%	-2%	-1%	**-2%**
Female Adults	19%	17%	17%	21%	20%	18%	16%	**16%**
Male OAPs	68%	72%	63%	60%	78%	63%	75%	**60%**
Female OAPs	75%	81%	75%	67%	83%	71%	76%	**66%**
Average	**45%**	**47%**	**46%**	**42%**	**49%**	**44%**	**47%**	
	1.34m/s (3mph) Model vs. Varied Walking Speed by age only							
Children	65%	67%	67%	71%	71%	70%	63%	**59%**
Adults	-1%	-1%	-1%	-1%	-2%	0%	-1%	**-1%**
OAPs	70%	73%	67%	62%	76%	64%	73%	**61%**
Average	**45%**	**46%**	**44%**	**44%**	**48%**	**44%**	**45%**	