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Replicating capacity and congestion in microscale agent-based simulations

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A R T I C L E I N F O

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A B S T R A C T

Disaster events cause detrimental impacts for communities across the globe, ranging from large numbers of fatalities and injuries, to the loss of homes and devastating financial impacts. Emergency professionals are faced with the challenge of providing sustainable solutions to mitigate these consequences and require tools to aid the assessment of potential impacts. Current modelling tools have either focused on modelling either the microscale (e.g. individual confined spaces such as buildings or stadiums) or the macroscale (e.g. city scale). The aim of this research is to create microscale agent-based modelling (ABM) tools, incorporating a realistic representation of human behaviours, which will help management professionals assess and improve their contingency plans for emergency scenarios. The focus has been on creating a microscale agent-based model of a pedestrian pavement and crossroads, to include overtaking and giving way, alongside the inclusion of varied population characteristics. This research has found that by improving pedestrian interactions (e.g. overtaking and giving way interactions) on pavements and at crossroads more robust travel time estimates can be achieved. To produce more realistic behaviour traits, microscale models should consider: (1) varied walking speed, (2) population density, (3) patience level and (4) an exit split percentage for crossroads. Comparisons to 1.34 m/s (3mph) models without additional variables show the travel times may be misrepresentative by up to 78% in pavements and 305% in crossroads for some population types. This has the potential to cause cascading effects such as a significant increase in fatalities or injuries as communities cannot reach safety in the anticipated time.

1. Introduction

Natural disasters affect communities across the globe, causing fatalities and injuries to many, significant economic impact, and loss of homes for communities (CRED, 2015). The prevalence of natural disasters is not increasing; however, the impacts of these events are (CRED, 2015). Therefore, there is a need to plan and prepare, to minimise the potential consequences and to provide solutions which are sustainable. Not all communities have the same ability to deal with events (Barnes, et al., 2019, Cutter, 2016, Aka, et al., 2017, Singh-Peterson, et al., 2015), leaving many in the developing world with ineffective solutions. In contrast to the developed world which has the resources to spend time and money on solutions, such as: risk registers (Glavovic, et al., 2010, Markovic, et al., 2016), early warning systems (Perera, et al., 2020, Becker, et al., 2020, Wenzel, et al., 2001, Durage, et al., 2013, Glade & Nadim, 2014), and emergency communication methods (Miao, et al., 2013, Lu & Xu, 2014). Imperative to all of this is the need to make appropriate decisions, which can be aided by the advancement of tools for emergency managers to help assess the consequences and to provide sustainable solutions.

There has been a focus previously on either creating modelling tools to assess the impacts on individual buildings or facilities such as stadiums to understand the movements of a crowd within a confined space (Shi, et al., 2009, Poulos, et al., 2018, Tan et al., 2015) or alternatively to look at the macroscale such as city scale modelling (Barnes, et al., 2021, Madireddy, et al., 2011, Liu & Lim, 2018, Mostafizi, et al., 2019, Loscos, et al., 2003). Both approaches have produced evacuation models to aid emergency professionals, however in both cases it can be argued that the representation of human behaviour has been poor and does not consider a wider enough range of behaviours, instead reducing individuals to crowds exhibiting the same behaviours with high levels of compliance. Barnes et al (2021) has demonstrated the merits of including additional population characteristics in macroscale city evacuation models, which showed evacuation times, that did not consider individual characteristics, were potentially misleading; meaning that the numbers of fatalities and injuries may be significantly underestimated due to the inability to evacuate in anticipated timings. Therefore, it is argued that if there are benefits of improving the representation of human behaviour at the macroscale, there are likely to also be benefits at the microscale.

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2. Literature review

2.1. Existing microscale models

There are many previous studies on simulating crowd behaviour available (Korhonen, et al., 2010, Low, 2000, Mehran, et al., 2009, Loscos, et al., 2003, Zaharia, et al., 2009, Akopov & Beklaryan, 2012). These studies show that 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. Some previous models have focused on treating crowds like fluids (i.e. the crowd moves as one continuous mass), resulting in the crowd becoming "*identical unthinking elements*" (Low, 2000). In reality, this is untrue 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 by Low (2000), a model created by Helbing et al (2000) is introduced. This model introduces the idea of individuals within a crowd, particularly during episodes of panic. 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. 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. The model also explored the idea of widening corridors, but again found this slowed the flow of the crowd, which is not what would be assumed (Low, 2000, Helbing, et al., 2000). 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. It is studies such as this that highlight the importance of reproducing realistic human behaviours on the microscale in buildings or walkways, for example. This is mostly in the form of congestion and capacity, which allows for the overtaking and giving way of agents as well as the ability to force agents to wait behind slower agents when space is unavailable. It can be argued that previous attempts at this have not fully captured these types of behaviours.

Existing microscale simulation software and simulations of pedestrians have often focused on transport interchanges or building environments and even within these models the representation of human behaviour has at times been standardised to eliminate intricate human traits such as giving way and overtaking (PTV Group, 2021; Simwalk, 2021; Oasys, 2021). Where evacuation simulations do exist these focus on the risk of fire and explosion, which are of greater risk in transport interchanges but not necessarily appropriate hazards for modelling evacuations of street environments. Graphically the standard of these simulations can be akin to that of gaming software and is visually appealing to users. However, if the fundamental rulesets guiding the human behaviour traits are flawed or misrepresentative then the simulations will not provide realistic and robust travel time estimates. For example. a simulation produced using software from SIMWALK, demonstrated a fire hazard in a bus interchange, the agents exhibited high levels of compliance (e.g. waiting at an appropriate crossing location and for a green light to cross roads even in a hazard scenario), were unaware of other agent's space (e.g. bumping into each other to force changes in direction), lacked distinction in walking speeds and agents travelled into the hazards pathway (Simwalk, 2012). It can be argued that these are not the typical behaviours expected during an evacuation simulation and that improvements need to be made to capture more realistic behaviour traits. Another simulation example, produced by the PTV Group in their Viswalk software of a transport interchange demonstrated the excellent graphics available but highlighted agent's movements were very rigid, conforming to walking in straight lines and that agents were unable to effectively manoeuvre around other agents to avoid congestion (PTV Group Traffic, 2012). This again demonstrates that human behaviour traits are not representative and there may be a need to improve these to enhance the simulation of evacuations.

To evaluate the impact of enhancing the representation of human behaviour traits relating to intricate human behaviours such as giving way and overtaking, two agent-based microscale models will be developed in this paper, one of a pavement and the second of a crossroads. Both models will focus on including more robust representations of human behaviour to enable patience, overtaking and population density to be captured accurately. It is anticipated that a more realistic representation of human behaviour will show that existing simulations of pavements and crossroads are producing misleading times and therefore the need to highlight this to improve computational evacuation modelling.

3. Data

3.1. Model characteristics

It has been identified that there is a need to improve the representation of human behaviour in microscale simulations, particularly of pavements and crossroads. Agent-based modelling is an effective tool as it allows the user to create a unique population of separate agents that change over time. 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). This is useful for this model as there is a reliance on movement and interactions between agents (Batty, 2012), which is suited to the replication of human behaviour where there are many unique agent decisions that are not necessarily binary in nature. 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).

The agent-based models, used in this paper, were set up using Netlogo, which is one of the freely available open-source agent-based programmes. Netlogo features a library of existing models, which were utilised to help form the basis of the model for the pavement and crossroads (Wilensky, 1997, Wilensky & Payette, 1998). 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 and, in this instance, has limited the agent movement as the model does not produce a true continuous space. Both models will need to consider (1) pavement characteristics e.g. dimensions, (2) population density and (3) overtaking behaviours.

3.2. Environment characteristics

It is important to ensure the pavement model is representative of pavements in real-life in both length and width. A standard pavement width in the UK is defined as 2 m wide and the minimum road width is 4.8 m (Department for Transport, 2007). It is assumed that pedestrians primarily use a pavement when available, however in stress situations such as evacuations, it is acknowledged that pedestrians are likely to move into using the road width to evacuate an area as quickly as possible. Consideration also needs to be given to preferred interpersonal distance, which is the distance between one person and another; this can be varied depending on the situation, familiarity, and culture.

As previously stated, the model is created in Netlogo, which is a grid-based cell system rather than continuous space. The grid-based system means that the agents need to have a series of defined pathways in the form of "lanes" to allow them to travel along the pavement or crossroads. This allows the number of lanes to be varied, to form different widths of pavements and crossroads (e.g. modelling a small lane to a large walkway). In order 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 in 1966 is used to find out the approximate number of lanes that would fit within a standard pavement and minimum road width (Hall, 1966, Baldassare & Feller, 1975, Sorokowska, et al., 2017). The lower estimate for each of the distance category's (personal (0.46 m), social (1.22 m) and public (2.10 m)) has been taken from Hall's interpersonal distances and does not consider the person's location. Using Hall's distances, the number of lanes can range from one to ten lanes, which was then taken to be the upper and lower bounds for the number of lanes variable in this model.

It is also important to identify an appropriate distance for the length of the pavement. In smaller UK cities such as Newcastle, the main shopping street (Northumberland Street) is approximately 400 m long measured from Google Maps, whereas larger cities like London (Oxford Street ≈ 1900 m), Manchester (Deansgate ≈ 1200 m) & Edinburgh (Princes Street ≈ 1200 m) are 1 km or longer (Google, 2021). Therefore, a 1 km length is used as a mid-point between shorter and longer shopping streets in the UK. It is also anticipated that this length will be sufficient to display the agent behaviours, such as overtaking and giving way.

3.3. Population characteristics

One of the advantages of agent-based modelling is the ability to simulate a unique population, but it is imperative to choose appropriate and accurate values to form the population base. The inclusion of unique population characteristics has been discussed in detail by Barnes et al (2021), who demonstrated the importance of a representative population distribution and varied walking speed by age and sex. In a similar manner, this model features five main population types: (1) children, (2) male adults, (3) female adults, (4) male Old Age Pensioners (OAPs) and (5) female OAPs. The population distribution of these types is based on UK average population data, from the Office for National Statistics (ONS) (2014), specifically: children (18%), male adults (32%), female adults (33%), male OAPs (8%) and female OAPs (9%). Within the model environment one of each of the population types is assigned to a static "home" square, in each simulation the same agent population type will start from the same "home" square (see Fig. 1 in Supplementary Data). This has a small knock-on effect on certain agent's travel times, primarily male OAPs, as their pathway to exit is marginally longer in distance when compared to the others. Each of these population types, has its own walking speed which has been determined by considering a number of studies (Bosina & Weidmann (2017), Rastogi et al (2011), Schimpl et al (2011) and Silva et al (2014)). The studies were used to produce average walking speed values by age for the selected population types. This equates to walking speeds of 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) and female OAPs 0.76 m/s (1.70mph).

3.4. Determining a patience level value

In this paper, 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 and give way. 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 walking in front of them, whilst others will seek the first possible opportunity to overtake and continue at their preferred (higher) speed. This can be interpreted as a level of patience; a person willing to wait will have a higher level of patience compared to the individual looking for the first opportunity to overtake. In stress situations, such as an evacuation, it can be assumed that the levels of patience would be decreased to zero, or very near.

To determine a patience level parameter, studies were considered to identify a method to produce a realistic representation. One study by Low (2000) proposed the idea that crowds can experience fear, panic, different directions of travel, stumbles and falls unlike previous studies which treated crowds as fluids, i.e. the crowd moves as one mass. Alternatively, a study by Pelechano & Badler (2006) suggested that crowds needed to include effective communication through the use of trained leaders, it was found that 40% of evacuees can escape without any communication, but with communication 100% of evacuees can escape in the same time. Finally, another 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 created by Helbing et al (2000) (i.e. a random numerical value assigned as a level of panic), the patience level is created within this model. To the best of the author's knowledge, there is no literature to guide the assigned patience level values and due to the scale and complexity of this task, this is outside the scope of this paper. We seek to consider the impact of this variable to overtaking behaviours and travel time, rather than derive the value itself. Therefore, we assign all agents with the same initial starting patience level, ranging from 1 to 100, which will then be affected differently depending on how many interactions an agent experiences and how densely populated the pavement is. In this paper, the patience level of the agents demonstrates the frustration an individual may experience. 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, and overtake, more often than an agent with a high patience level. To model this, the assigned level of patience starts to reduce to zero when an agent is walking 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 move lanes and accelerate back to their original chosen speed and reset their patience value (see Fig. 2 in Supplementary Data).

3.5. Determining an exit split percentage

To complement the previous pavement variables, one new variable is included in the crossroads model, termed as the 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 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 (between 1 and 100), if this number is lower than the south exit percentage then the agent will exit to the south and if greater than or equal to, to the east. This also ensures that the number of agents is approximately equivalent to the percentage exit split, with variation caused by the distribution of the random numbers and the initial agent placement (i.e. the agents have already passed the central zone).

An example of ten agents on a crossroads has been set out in Fig. 3 in the Supplementary Data 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 (Fig. 3(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 (Fig. 3(c)). When additional agents reach the centre of the crossroads, it creates additional congestion, and the agents must give way to each other (Fig. 3(d)). The agents continue along their desired paths, giving way to each other in the crossroads and overtaking when necessary to avoid slower agents (Fig. 3(e–k)) until reaching the exit location.

4. Methodology

4.1. Pavement model setup

The representation of the pavement is shown by patches of grass and grey patches marked with lines to delineate the pavement surface and different lanes (Fig. 4 in Supplementary Data), which was interpreted from existing Netlogo models available in the model library on traffic intersections (Wilensky, 1997; Wilensky & Payette, 1998). Population density can be varied by the user and in these simulations densities of 0.1, 0.3, 0.5, 0.7 and 0.9 (equivalent to 10%, 30%, 50%, 70% and 90%) are used to vary the "business" of the street environment. This resulted in differing numbers of agents in each simulation, for comparison see Table 1 in Supplementary Data. The population density is assigned based on the number of available road patches in the model and the user's defined population density value, effectively it is the number of occupied road cells divided by the total number of cells. Population density is set initially by the user and then changes over time as agents exit the model. The pavement is setup with an overall length of 1 km, as discussed in the Environment Characteristics section. An exit (safety) is marked by a line of red patches at the end of the 1 km stretch, once all agents have crossed into safety the simulation ends and the travel time of the different agent types placed on home squares are calculated.

4.2. Crossroads model setup

The crossroads ABM is similar to the pavement model, in that it is effectively two pavement models crossing at 90° to each other and is used to investigate the interactions of individuals when using a crossroads, specifically agents walking in two directions with the ability to overtake slower agents (Fig. 5 in Supplementary Data). The only major difference is the crossroads is a maximum length of 500 m rather than 1 km and the introduction of a new variable to determine the exit direction of each agent. An exit (safety) is marked by a line of red patches at the end of the East and South arms of the junction, again once all agents cross either of these safety zones the simulation ends, and the travel time of the different agent types placed on home squares are calculated. Population density can also be varied by the user and in these simulations densities of 0.1, 0.3, 0.5, 0.7 and 0.9 (equivalent to 10%, 30%, 50%, 70% and 90%) are used to vary the "business" of the street environment. This resulted in differing numbers of agents in each simulation, for comparison see Table 2 in Supplementary Data. An agent thought process (Fig. 6 in Supplementary Data) in the model environment has been detailed to aid the understanding of the agent's decisions during the simulation process, this is applicable in either the pavement or crossroad environment.

4.3. Initial model checks

It is important with any model that an attempt is made to calibrate, validate, and verify the anticipated results (Ngo & See, 2011; d'Aquino, et al., 2001). An initial calibration check was completed for each model to ensure that the travel times produced were realistic estimates and were not less than the minimum possible exit time of the model. Neither the pavement nor the crossroads were based on a specific real-life example; hence it was not possible to calibrate the model using real-life data. A visual check was also undertaken to confirm that agents were passing each other as anticipated. Several observations can be carried out, such as, (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.

4.4. Microscale model testing

After the validation model checks were completed, a series of tests were then undertaken to understand which variables primarily affected the travel times. The aim of this paper was to explore the impact on travel time of altering certain variables in the pavement and crossroad model environment (Table 3).

4.5. Number of simulations

To understand the variability in the pavement results, each set of variables and the varied walking speed scenario will have 100 realisations, resulting in 9000 sets of travel times, which can then be averaged for comparison purposes (Table 4 in Supplementary Data). In terms of the crossroads, again each set of variables had 100 realisations, which

Table 3
Proposed Testing Schedule.

No.	Variable(s) Tested	Research Questions
1	No of Lanes	- Does the width of the pavement/crossroads (number of lanes) influence the travel time of agents?
2	Population Density	- Does the population density influence the travel time of agents?
3	Patience Level (Pavement only)	- Does a varied patience level influence the overtaking occurring and effect overall travel time for agents?
4	Exit Split (Crossroads only)	- Does varying the exit split influence the number of agent interactions and effect overall travel time?
5	Comparison to the 1.34 m/s (3mph) Model	- Are there any travel time differences between a calculated model based on variables from current agent-based models of human behaviour and these models caused by the introduction of additional variables?

results in 7500 sets of travel times per number of lanes in the north-south direction (3, 4 and 5), resulting in 22,500 simulations in total that can then be averaged for comparison purposes (Table 5 in Supplementary Data).

5. Model results & discussion

5.1. Test 1 – Effect of width

In this section, the effect of the pavement and crossroad width is explored, it has been demonstrated that a range of widths can be anticipated in any city and depending on the scenario any pavement can be split into several lanes. In this test, only configurations 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 Fig. 7, the average travel times for the pavement simulations with varied walking speeds is presented by population type and the number of lanes. In Fig. 8, the average travel times for the crossroad simulations with varied walking speeds is presented by population type and the crossroad configuration. This shows that in both cases there is variation between the population types, which was expected as it has been previously demonstrated that the introduction of varied walking speeds results in different travel times for the population types (Barnes, et al., 2021). However, there is little variation between the number of lanes within each individual population type, for example on the pavement, the three values for varying lane configuration for children have a standard deviation of only 0.01 min and three male adults' times have the largest variation at 0.14 min. In terms of the crossroads the standard deviation ranges from 0.23 to 0.42 min (calculated from nine average values) across all the population types. Hence, it can be argued that the width of the pavement or the crossroads 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 giving way interactions to occur in.

5.2. Test 2 – Effect of population density

Two plots have been compiled to show population density by population type for the 9000 pavement simulations (Fig. 9) and for the 22,500 crossroad simulations (Fig. 10), when including varied walking speeds and altered variables. These show that in general as population density increases the average travel time also increases, from an average of 18.43 min to 21.16 min on the pavement and from 8.34 min to 13.26 min on the crossroads.

Another trend is that the travel times for population types are less varied as the population density increases, i.e. the travel times converge.

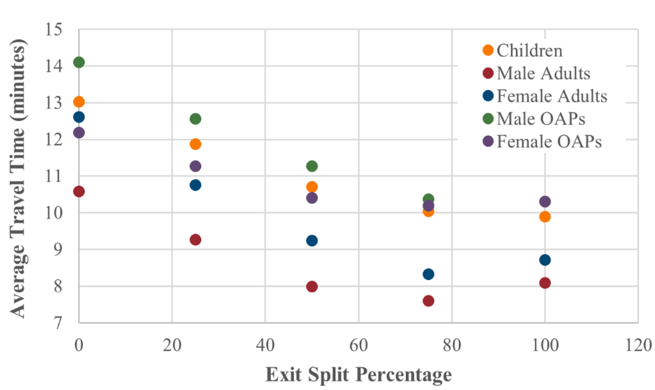

Fig. 7. Average Travel Times for each population type when considering the width of the pavement between three and five lanes, for each population type: mean (standard deviation), children:20.95 min (0.01 min), male adults: 17.10 min (0.14 min), female adults: 17.95 min (0.09 min), male OAPs: 21.34 min (0.00 min) and female OAPs: 21.87 min (0.00 min).

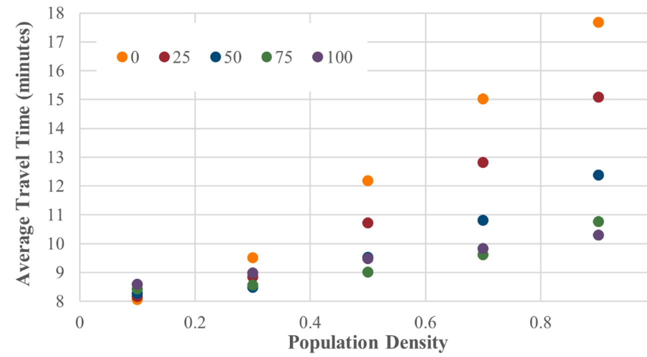

Fig. 8. Average Travel Times for each population type when considering the crossroad configuration between three and five lanes in each direction, for each population type: mean (standard deviation), children:11.10 min (0.24 min), male adults: 8.70 min (0.23 min), female adults: 9.93 min (0.42 min), male OAPs: 11.72 min (0.39 min) and female OAPs: 10.87 min (0.23 min).

For example, on the pavement, the standard deviations of the five averaged values at 0.1 population density is 4.00 min and at 0.9 it is 0.65 min. This is also seen on the crossroads where the standard deviations at 0.1 population density is 2.06 min and at 0.9 it is 0.69 min (calculated from five averaged values). It can also be seen on the pavement and crossroads that the travel times for the slow agents (children and OAPs) only make small changes with population density compared with the faster adults, demonstrating that the adult population is more greatly affected by the introduction of congestion than the slower agent types. On the pavement children and OAPs have standard deviations ranging from 0.04 to 0.25 min for the five average values, whereas adult types have standard deviation ranging from 2.18 to 2.89 min. On the crossroads, this is also reflected as the standard deviation ranges (calculated from five averaged values) from 1.41 to 1.70 min for children and OAPs compared with 2.65 – 2.70 min for adults. One point of interest in the crossroad simulation is the effect of the static "home" square positioning, in that the female OAPs have lower travel times than the male OAPs despite the male OAP agents having the faster walking speed. This is a result of the male OAPs having a slightly increased distance to travel from their "home" square compared with their female counterpart.

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 robustly vary the "business" of a street environment within a model.

5.3. Test 3 – Effect of patience level (pavement only)

An additional plot has been completed to show the patience level by population type for the simulations of varied walking speed and different variables in the pavement model (Fig. 11). 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 to 0.05 min for five averaged values. 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 min to 18.19 min and for the female adults from 17.24 min to 18.85 min. 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 factors similar to patience level within a microscale pavement

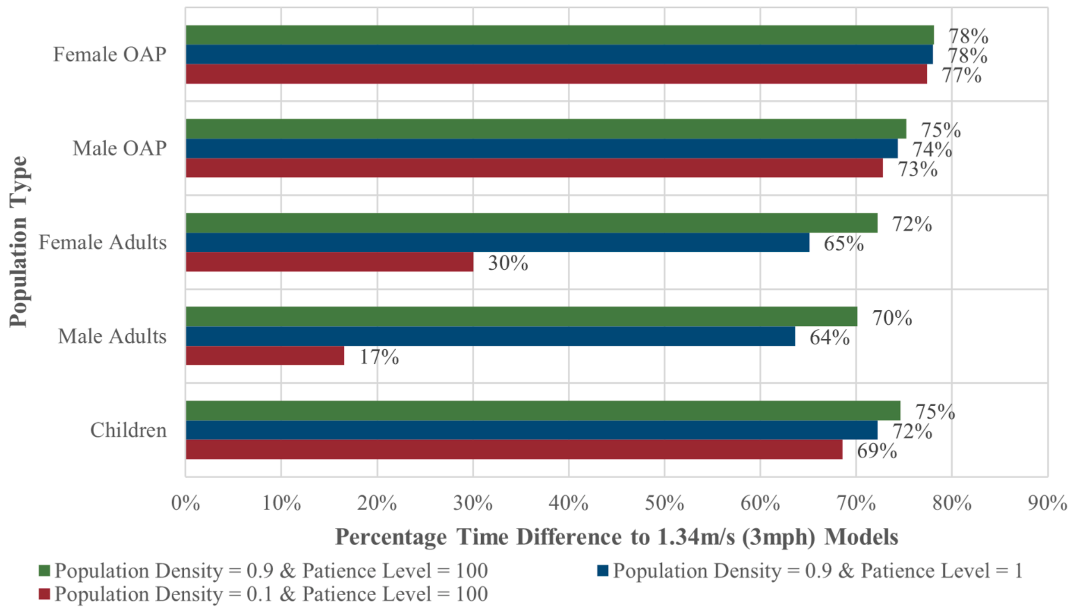

Fig. 9. Average Travel Times for each population type when considering population density between 0.1 and 0.9, for each population type: mean (standard deviation), children:20.95 min (0.25 min), male adults: 17.10 min (2.89 min), female adults:17.95 min (2.18 min), male OAPs: 21.34 min (0.10 min) and female OAPs: 21.87 min (0.04 min).

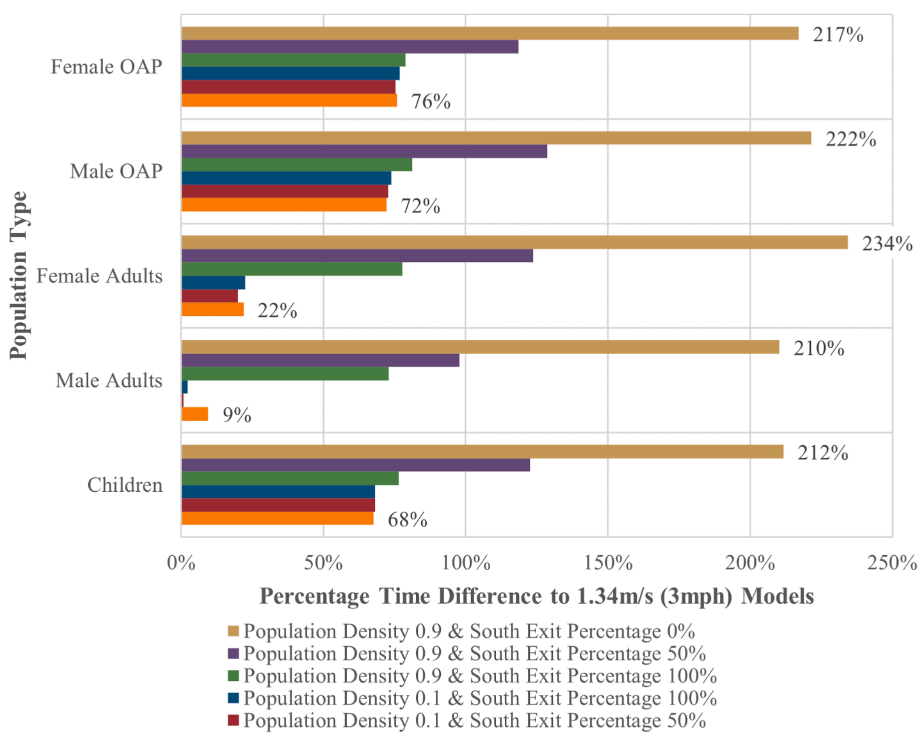

Fig. 10. Average Travel Times for each population type when considering population density between 0.1 and 0.9, for each population type: mean (standard deviation), children:11.10 min (1.68 min), male adults: 8.70 min (2.65 min), female adults:9.93 min (2.70 min), male OAPs: 11.72 min (1.70 min) and female OAPs: 10.87 min (1.41 min).

model if a robust representation of congestion is required.

A further plot was compiled to consider the patience level and population density within the microscale pavement model (Fig. 12). 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.

5.4. Test 4 – Effect of exit split (crossroads only)

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 (Fig. 13). For this paper, five different exit

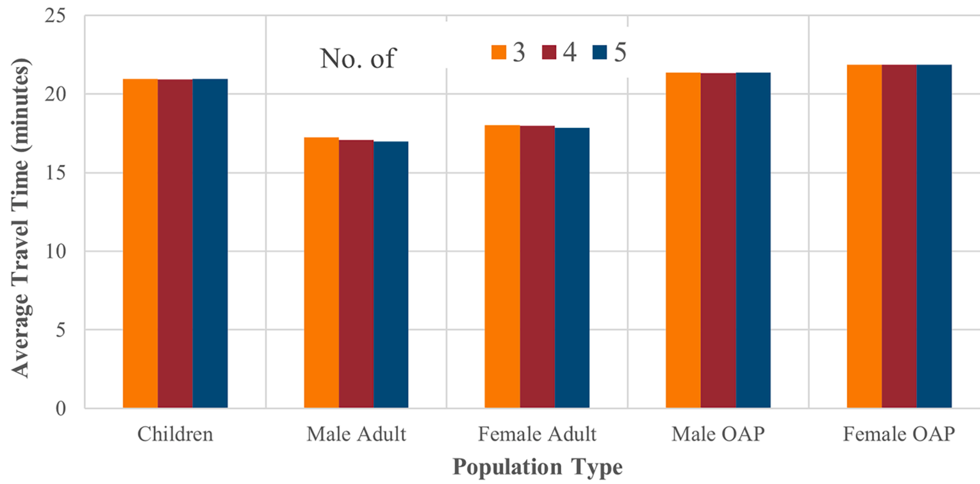

Fig. 11. Average Travel Times for each population type when considering patience level between 1 and 100, for each population type: mean (standard deviation), children: 20.95 min (0.05 min), male adults: 17.10 min (0.70 min), female adults: 17.95 min (0.60 min), male OAPs: 21.34 min (0.01 min) and female OAPs: 21.87 min (0.00 min).

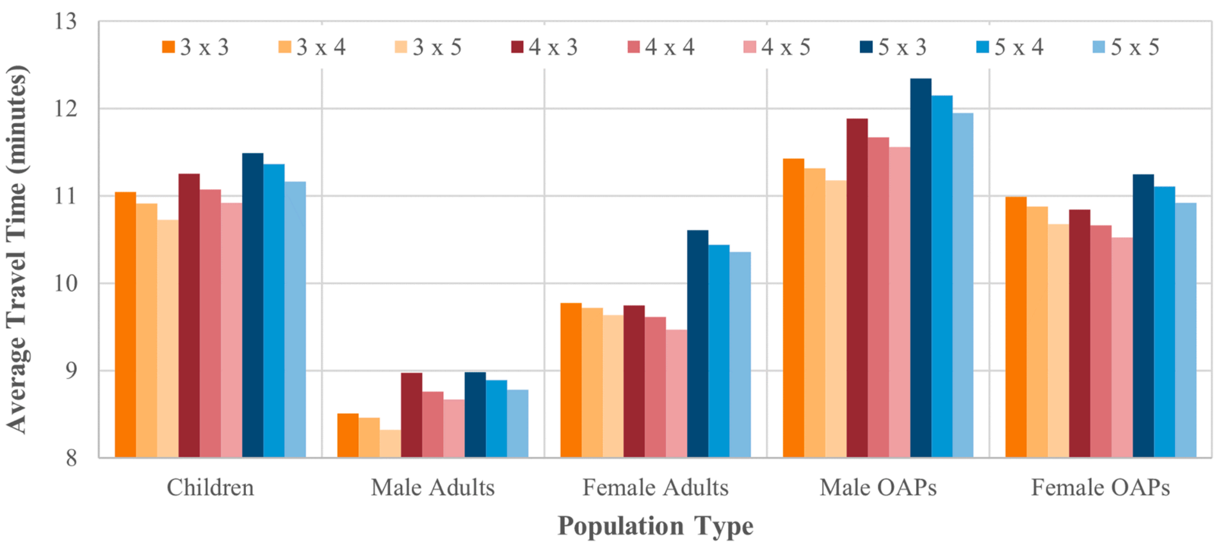

Fig. 12. Average Travel Times based on Population Density between 0.1 and 0.9 and Patience Level between 1 and 100, for each patience level: mean (standard deviation),1: 19.52 min (1.08 min), 5: 19.64 min (1.13 min), 10: 19.71 min (1.14 min), 25: 19.89 min (1.11 min), 50: 20.03 min (1.05 min) and 100: 20.26 min (0.98 min).

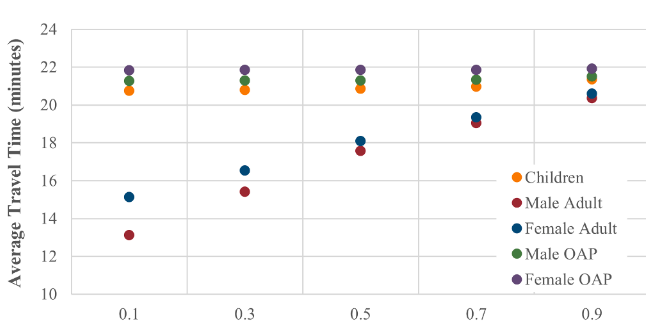

Fig. 13. Average Travel Times for each population type when considering exit split percentage between 0 and 100, for each population type: mean (standard deviation), children: 11.10 min (1.33 min), male adults: 8.70 min (1.22 min), female adults: 9.93 min (1.76 min), male OAPs: 11.72 min (1.61 min) and female OAPs: 10.87 min (0.85 min).

splits have been tested to understand the implications of exit direction on overall travel time: (1) 0% east, 100% south, (2) 25% east, 75% south, (3) 50% east, 50% south, (4) 75% east, 25% south and (5) 100% east, 0% south.

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, 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 same direction 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.

A further plot was compiled to consider the exit split percentage and population density within the microscale crossroad model (Fig. 14). 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. 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.

5.5. Test 5 – Comparison to 1.34 m/s (3mph) agent-based models

There is a need to understand if these microscale models of a pavement and crossroads differ from a calculated model with walking speeds of only 1.34 m/s (3mph) with no additional variables included. The calculated travel times for the 1.34 m/s (3mph) pavement model were an average of 12.26 min and for the crossroads an average of 5.86 min. These calculated travel times were compared with the travel times produced through the 9000 pavement and 22,500 crossroad simulations with additional variables, allowing a time difference to be estimated. It has been shown in both microscale models that for all population types, there is a travel time difference between the calculated 1.34 m/s (3mph) model and the simulated values (Fig. 15) and (Fig. 16).

In the case of the pavement, 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 17% and female adults 30%. When population density is increased (0.9) and patience is decreased (1), the impact to travel time is further increased to 64% and 65% 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 70% and 72% respectively.

In the case of the crossroads, 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 difference 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 210% – 234%. 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 1.34 m/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% – 129% compared to the 1.34 m/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.

By comparing the simulations with a calculated standardised model, it highlights that additional variables such as varied walking speed, patience level and exit split percentage can have an impact on travel times. Visual inspection showed in these simulations that overtaking and

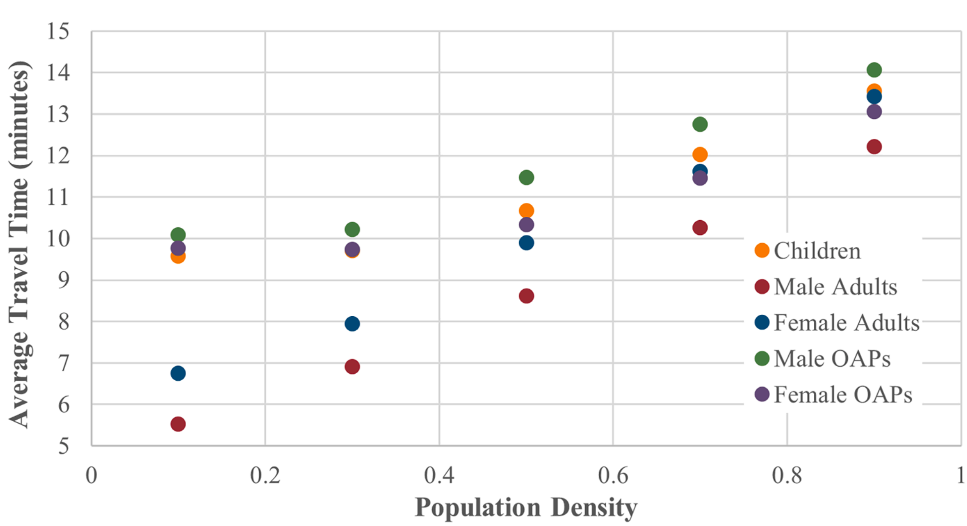

Fig. 14. Average Travel Times based on Population Density between 0.1 and 0.9 and Exit Split Percentage between 0 and 100, for each patience level: mean (standard deviation),0: 12.50 min (3.93 min), 25: 11.13 min (2.85 min), 50: 9.90 min (1.71 min), 75: 9.28 min (0.95 min) and 100: 9.44 min (0.68 min).

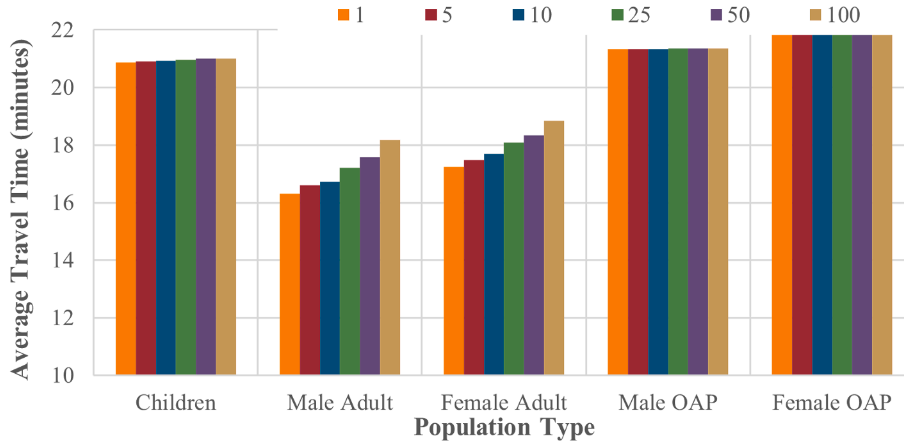

Fig. 15. Comparison to 1.34 m/s (3mph) Calculated Model and Simulated Agent-Based Model Values, initially showing the impact of varied walking speeds by population types combined with population density and patience levels.

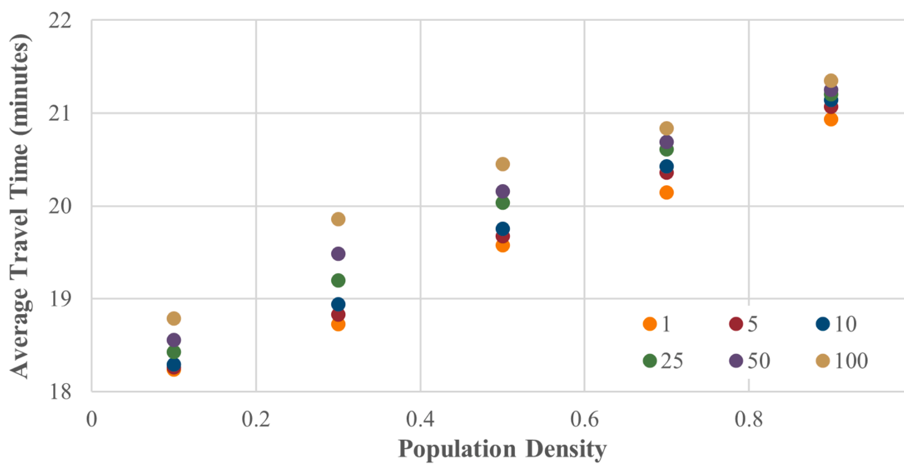

Fig. 16. Comparison to 1.34 m/s (3mph) Calculated Model and Simulated Agent-Based Model Values, initially showing the impact of varied walking speeds by population types combined with population density and south exit percentage.

giving way was occurring between agents and in the future microscale models should look to include similar variables to enhance the representation of human behaviour traits in pedestrian simulations, with the aim of incorporating giving way and overtaking.

5.6. Testing discussion

The microscale model based on a pavement, has shown that the introduction of a range of variables (population density, number of lanes and patience level) improves the robustness of a computational simulation of a pavement environment. The simulation incorporates agents overtaking and giving way to each other, which can be observed in any real-life pavement and should be incorporated into computational simulations of them. The variables need to be capable of altering the dimensions of the pavement, incorporating a range of population densities, and including a patience level or similar to replicate the desire to overtake slower individuals when walking on a pavement, in order to produce an improved representation. When compared to a calculated 1.34 m/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% to 78%, with a worst-case time difference increasing to a range of 71% – 78% (Table 4), this demonstrates that some existing simulations of pavements may be producing misleading travel time estimates and failing to include a range of robust and realistic behaviours to simulate overtaking and giving way.

The microscale model of a pedestrian crossroads has shown that there is an additional variable that needs to be incorporated to produce an improved simulation. This is an exit split percentage, which can control the exit directions of the agents, which helps to alter the number of agent interactions occurring. These interactions need to be included alongside the pavement variables to produce a more robust representation of human behaviour traits. When compared to a calculated 1.34

Table 6
Comparison of the Average and Worst-Case Results produced from Tests on the Microscale Pavement and Crossroads Model based on the addition of population characteristics, varied walking speeds, number of lanes, population density, patience level and exit split percentage (crossroads only) when compared to a calculated model using standardised speeds of 1.34 m/s (3mph).

	Pavement		Crossroads	
	Average Difference	Worst-Case Difference	Average Difference	Worst-Case Difference
Children	70%	75%	96%	219%
Male Adults	40%	71%	63%	229%
Female Adults	47%	73%	78%	305%
Male OAPs	73%	75%	102%	268%
Female OAPs	78%	78%	98%	230%

m/s (3mph) simulation of a crossroads, it has been demonstrated that there are again large time differences. The average time difference ranged from 63% − 102%, whilst the worst-case time difference increased to a range of 219% − 305% (Table 6), this highlights that some existing models of pedestrian crossroads are likely to be simulating misleading travel times as they are incapable of producing human behaviours that feature agents overtaking and giving way to each other at a junction.

6. Conclusion

This paper has developed two microscale agent-based models (one of a pavement, the other a crossroads) to assess the impact of including additional agent (individual) characteristics on travel time and whether the characteristics result in a more robust representation of human interactions in a street model environment. This study has created two generic representations of a pavement and crossroads in an agent-based environment, with the inclusion of several variables to represent human behaviour traits. The model included: (1) five different population types (children, male adults, female adults, male OAPs, and female OAPs), (2) varied walking speeds by age and sex, (3) varied pavement or crossroad dimensions, (4) a patience level and for the crossroads only (5) a south exit percentage.

For the pavement, it has been established that there are large time differences due to the introduction of these agent characteristics when compared to simpler calculated simulations which focus on standardised speeds. The average travel time increased by approximately 40 – 78%, however in the worst-case, for example when there was high population density and high patience levels, travel times further increased. The range of travel times also converged as the fastest agent types were hindered by the congestion in the model. This improved pavement simulation demonstrated that some of the current simulations of pavements may be producing misrepresentative travel times estimates and failing to include the rulesets to robustly simulate giving way, overtaking, capacity and congestion in a pavement environment.

Secondly, the simulation of a crossroads has shown that again there were large travel time differences when compared to simpler calculated junction simulations featuring standardised speeds of 1.34 m/s (3mph). The average time difference ranged from 63% − 102% and in the worst-case with high population density and therefore a large number of agent interactions, the travel time increased further due to the congestion created by the model and the necessity for agents to wait for an appropriate gap to exit. This highlights that some current models of pedestrian junctions are likely to be simulating ambiguous travel times and are unable to produce robust human characteristics to demonstrate pedestrian interactions such as overtaking and giving way. Hence, when simplified evacuation simulations of pedestrian environments are used by emergency planners to estimate travel time without effective human behaviour representation, it is plausible that times will be underestimated. Therefore, it is possible that communities will not be able to reach a place of safety in the allotted time, which has the potential to cause additional injuries and fatalities by underestimating the time to evacuate pavements and junctions, which can be numerous in city scale evacuations.

These microscale models have focused on the representation of intricate human behaviours in a street and junction model environment. It can be argued that microscale pedestrian simulations need to address the inclusion of intricate behaviour traits such as giving way and overtaking, and this paper has provided one way in which this may be achieved. However, these models are not flawless and can be further improved. During the simulations visual observations allowed the user to see overtaking and giving way occurring but this could not be validated against real-life data as the models created were generic representations of a street and junction environment. One way of tackling this could be utilising CCTV data of street environments throughout the day, where giving way and overtaking is anticipated to occur. Patience levels of individuals could then be tracked, and a more realistic estimate of how long agents will wait behind one another made. The walking speed values assigned could also be validated and tailored to specific locations or population demographics if necessary.

Effective computational simulation has the ability to aid emergency management professionals as numerous simulations can be completed without the large financial and resource costs of real-life simulation and without causing harm to participants to facilitate multiple outcomes. Simulations such as the ones created in this paper could significantly influence emergency professional's planning particularly of city evacuations due to the potentially large differences in travel times estimated, and also by providing the link between microscale simulation of confined spaces (e.g. buildings) and macroscale city evacuations. In the future, the incorporation of these models at the two differing scales (macro and microscale) should be considered to produce an effective tool for emergency planners. However, the issue of scalability, i.e. transferring between a macro and microscale simulation is large and complex. Scalability has not been successfully resolved within agent-based models to date and is a widely acknowledge issue. In an idealised scenario, a planner would be able to simulate a city-scale evacuation, which could highlight "pinch" points in the pedestrian environment, microscale models like the ones in this paper could then be utilised to alleviate congestion and consider how agents can effectively interact with each other. However, Netlogo has reached its limitations in these simulations due to its grid-based system, which does not create true free movement for agents. It is reasoned that the inclusion of free movement is necessary to incorporate models at differing scales to produce one hybrid model.

In the future, agent-based simulations of pavements and crossroads need to continue improving the representation of human behaviour, else run the risk of representing only male able-bodied adults within simulations. This begins with the introduction of the variables such as those suggested in this study: varied walking speeds, population density, patience level and an exit split percentage for crossroads. In addition, further traits should be pursued to continue the improvement of the model environment as well as the introduction of real-life data to ensure the models are truly representative. Furthermore, to increase the robustness of the macro and microscale models, a hybrid model environment incorporating all the rulesets should be established to link up the modelling of a single confined space with a larger scale city evacuation model.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tbs.2022.07.006.

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