

## **EVALUATION OF GUIDANCE SYSTEMS AT DYNAMIC PUBLIC TRANSPORT HUBS USING CROWD SIMULATION**

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### **ABSTRACT**

A key challenge in the implementation of novel public transport systems is to maintain usability over a broad spectrum of potential users. Transport systems that increasingly emphasise dynamic adjustment to changing passenger numbers and destinations over time cannot rely on static schedules and routes like traditional systems do. In this work we are investigating the use of agent-based crowd simulation to evaluate how different passenger guidance systems affect agent navigation in a public transport hub. We study the effects of different digital signage placement strategies in terms of crowding and walking times and also analyse how the introduction of mobile phone guidance systems affects these metrics. Our results show that crowd simulation is a cost and time-efficient tool for the evaluation of guidance systems in public transport spaces that can also support the design of bus schedules and bay assignments.

### **1 INTRODUCTION**

Research of public transport systems based on autonomous mobility is increasingly important to city planners and decision makers in densely populated urban areas. A prevailing vision is to replace conventional buses and trains with driver-less autonomous vehicles (AV). Such vehicles would employ various strategies, ranging from centralised control to swarm-intelligence and platooning, to dynamically adapt to quantitative and spatial travel demand. However, creating a dynamic transport network implies that reliance on static routes and schedules may no longer be possible. As a result, passengers of autonomous public transport would rely entirely on guidance systems in order to find the the correct time and place to catch a vehicle to their desired destination and not on previous habits or knowledge. When adapting novel dynamic transport technologies, planners are therefore faced with the challenge of designing guidance systems that provide passengers with the necessary information to pick the correct time and place for catching their ride.

Two main types of guidance systems are currently used at bus interchanges by passengers: i) signage, e.g., placed on the ceiling or in form of information boards, and ii) applications on personal mobile devices. Following basic ergonomic principles, these types rank differently in terms of comprehension because of their visual features (e.g., shape and size) and cognitive features (e.g., familiarity, complexity). These features influence the time spent by a passenger on deliberation and the delay of putting a plan into action, which consequently impacts the passengers' flow within the public transport hub.

In order to understand the mechanisms of passenger flow in a public transport hub, we present a simulation-based technology that combines existing models for crowd motion and human behaviour with domain specific information. This allows evaluating the influence of various kinds of guidance systems on path finding and crowd behaviour in near-future public transport interchanges.

The contributions of this work are two-fold. First, we present an agent-based decision model for the movement of passengers in transit hubs. Second, we evaluate the effects of two different guidance systems on crowd behaviour in separate and combined use in a virtual scenario based on a real-life bus interchange.

The remainder of this paper is organised as follows: In Section 2, we give an overview of related work in the field of crowd simulation for guidance systems. We present our system design and models in Section 3. Section 4 discusses the simulation experiments and results. Section 5 concludes this article.

## **2 BACKGROUND AND RELATED WORK**

In the past, crowd behaviour research with regards to public transport has mostly emphasised crowd motion in constrained environments like train platforms and in emergency situations. For example, Lei et al. (2012) focus on the evacuation of a large transit terminal subway station. Using an agent-based model, they study the effect of occupant density, exit widths and automatic fare gates. Unfortunately, they do not consider the effects of signage visibility.

Studies that incorporate signage visibility include the article by Zhang et al. (2017), where the authors describe the optimisation of placement and count of signs to support the evacuation of pedestrians from public spaces. Similarly, Chu et al. (2015) conduct a large-scale simulation study using their tool SAFEgress, an agent-based egress simulation tool. They study the effect of signage, geometry, groups and crowds on emergent evacuation patterns. Evacuation of crowds is rather similar to guidance of passengers to their transport as both involve guided movement of crowds to certain destinations. Langner and Kray (2014) have studied the impact of dynamic signage on mass evacuation. Their agent-based simulation model is cell-based and assumes that a cell of 0.5 sqm can only accommodate one agent. In a case-study using a football stadium, they find that dynamic signage has a positive effect on the evacuation process.

Outside the context of mass evacuation, Mikusz et al. (2016) outline a simulation method to find the reach a network of signs has on its intended audience. The authors emphasise the importance of analysing signs from a viewer-centric perspective. This refers to evaluating how much of the information is absorbed by the viewer as opposed to measure raw view counts of the sign by passing viewers. While the work focuses on signage in a university campus it is also applicable analysing digital signage in public transport hubs and makes a case to further investigate detailed guidance information designs for digital signage.

Bauer et al. (2007) have studied methods for crowd control in public transport stations. They utilise a macroscopic model to study the effects of temporary access restrictions as well as arriving and departing trains. An alternative approach to studying the effect of signage visibility is proposed by Motamedi et al. (2017). The authors propose a signage visibility analysis system based on virtual reality technology which they validated in case studies in subway stations in Japan. Both the macroscopic model and the virtual reality system are promising methods to validate agent-based crowd simulation tools and increase the fidelity of the simulation.

Confirmation that agent-based crowd simulation is a valid approach for the simulation of passengers in public transport hubs is provided by Tang and Hu (2017). They argue that cellular automata are insufficient due to the difficulty of adding rules and "purposive goals" for the agents. They employ an agent-based model to study the movement of pedestrians in large transit stations in China (Beijing and Xuzhou) and conclude that their agent-based crowd simulation can provide valuable insights. Interestingly, they note that in extreme situations such as emergency evacuations, the lack of irrational decisions in agent-based models limits the applicability of the approach. Similarly, the study of Peng and Ruihua (2010) shows that agent-based crowd simulation is feasible approach to study the movement of pedestrians in public transport spaces. Their approach is similar to the one presented in this paper: they use a 3-tier architecture comprised of an event tier, a navigation tier, and a agent dynamics tier. Not only can our agent model described in the next section be mapped to these tiers, but also are the models used for each tier (Events, A\*, Social Force) similar, supporting the design decisions made for our simulation model.

### 3 SYSTEM DESIGN

In the following we describe the models used to emulate information perception and behaviour of crowds as well as the public transport hub setting to which agents are being deployed.

The simulation system is implemented in CrowdTools, a crowd simulation framework developed by the Parallel and Distributed Computing Centre (PDCC) at NTU Singapore Cai et al. (2010). CrowdTools offers sophisticated frameworks for modelling human decision making and emotions Luo et al. (2009) aiding the plausible simulation of individuals, crowds and emergent behaviour. Additionally CrowdTools and its library of models are highly customisable, which goes as far as allowing to exchange the underlying simulation engine between the built-in engine, MASON (Luke et al. 2005) and Repast Symphony (North et al. 2013).

#### 3.1 Agent Behaviour

A pedestrian agent in the simulated system starts out with a destination in mind for which it will attempt to find a departure location for vehicles that are serving it. For many agents this constitutes a change of vehicles during multi-leg itineraries, thereby emphasising the importance of quickly accessible and digestible information. For the sake of simplicity and without loss of generality we will focus on a single leg of the trip. Multi-leg itineraries can be constructed as a sequence of single legs where the same rules and conditions apply for each leg. Quick decision making is relevant here as well, when itineraries that are planned ahead of time need to be updated due to ongoing changes in traffic. The Agent behaviour is composed of three models to combine spatial path finding, quick reasoning about currently available information as well as collision avoidance for nearby pedestrians. Using this methodology we are able to recreate emergent behaviour commonly observed in crowds, which is an essential input for evaluating interchange and information designs. For spatial navigation the agent employs an A-Star algorithm that calculates the shortest path from one point to another and around obstacles and highly crowded areas. The search graph used by A-Star is based on a grid with cell resolution of one square metre, which is projected onto the simulation area. CrowdTools offers a variant of the A-Star with added smoothed random noise, which we chose to approximate a slight human error component in path finding. The algorithm is then further customised to penalise heavily crowded areas and encourage agents to try and evade large gatherings where possible. Every 60 seconds the search graph weights are updated by adding in the count of agents that passed over the cell in that duration. This proved to be very effective in reducing unnaturally large crowds that may appear as an artefact of collision detection. While navigating through the interchange, agent collision detection is performed by a social force algorithm (Helbing and Molnar 1995). This allows the agent to evade non-static obstacles such as other agents in an ad-hoc manner. Finally, to emulate rapid decision making agents use the Recognition-Primed Decision (RPD) model.

##### 3.1.1 Recognition-Primed Decision

Recognition-Primed Decision (RPD) recreates rapid decision making based on the agent's familiarity with the current situation. It is derived from the Recognition-Primed Decision model of human decision making by Gary Klein (Klein 1997). RPD is motivated by the insight that people frequently make decisions based on estimation and guesswork rather than purely rational processes. In terms of the simulation framework, RPD is defined as a tuple of input and output  $\langle W, A \rangle$ . The input  $W$  denotes the working memory, also known as internal state, of an agent. The output  $A$  is the set of actions the agents can perform. The goal of RPD is to find the appropriate action for an agent to execute when applied to its internal state. RPD is fundamentally organised as a state machine where the states are referred to as *experiences*. Each experience contains a directed acyclic graph of stages, which constitutes a state machine of its own. The first stage of an experience stage graph is called entry stage. Each stage is associated with a set of cues which can be perceived by agents. If an agent perceives a cue it can be considered an active cue.

Unlike classic state machines, transitions between experiences are not statically defined. When transitioning from one experience to another, the next one is chosen according to the highest familiarity

value of its entry stage. To quantify familiarity for an agent, for each experience the weights of all active cues of its entry stage are summed up. The experience with the entry stage that is most familiar to the agent is chosen. Once the agent enters a new experience it will traverse its stage graph. As indicated by the directedness of the graph, stages have to be traversed in a fixed sequence while branching off is allowed. Once an end of the state graph is reached, the experience is considered complete and a transition to another experience will occur.

Stages check against an agent’s working memory to determine whether a violation or success occurred. If a stage is violated, the experience it belongs to is considered violated as well and a state transition to another experience initiated. If a state is completed, then the agent enters the next stage in the graph. Secondly, stages provide actions that agents will perform as long as they are in the stage.

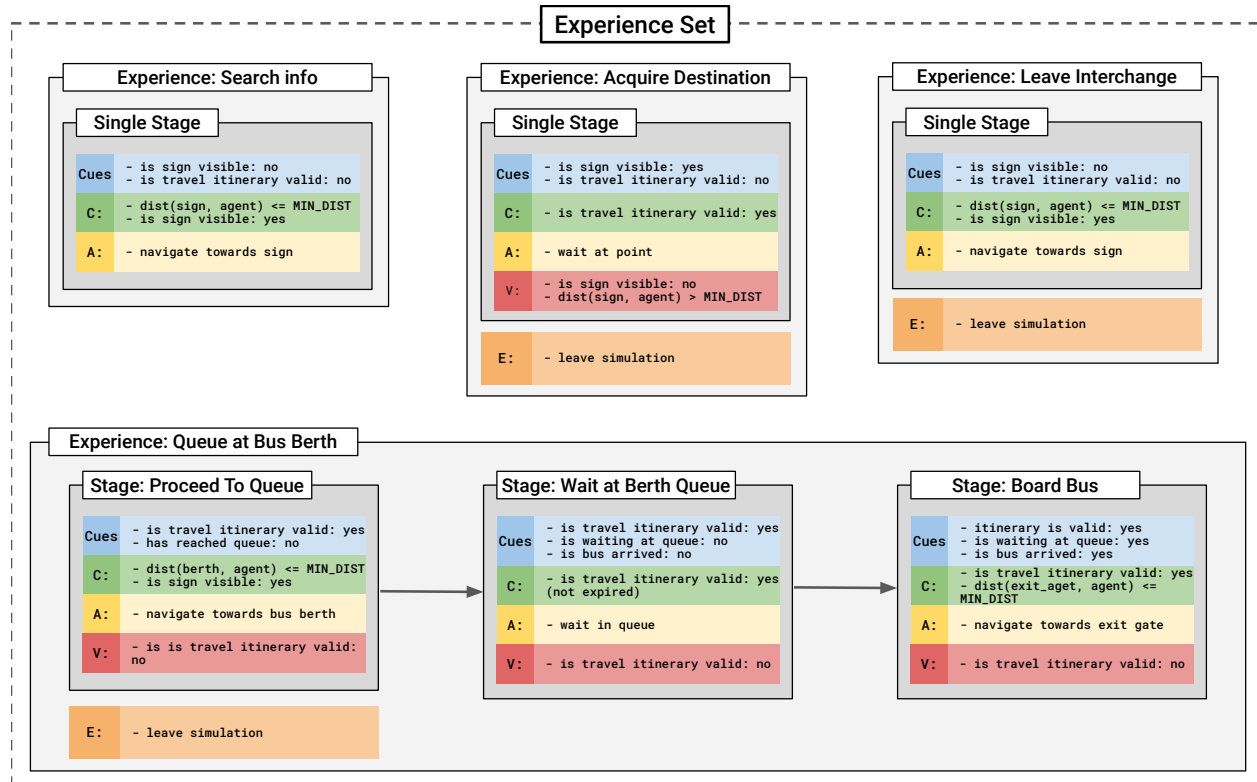


Figure 1: Agent behaviour as RPD state machine.

Figure 1 shows the RPD state machine for the agents in our bus interchange simulation. The terms C and V denote the conditions for a stage to be completed or violated, respectively.

Experiences allow to trigger events on successful exit, which are defined by the term E. Both agent population and available experiences distinguish between arrival and transit. Arriving agents do not possess a follow-up destination to visit, which will prompt them to enter *Leave Interchange*. This experience guides an agent to conclude the current journey and depart the interchange on foot. The exit for each agent is chosen randomly to emulate pedestrian choices to visit the adjacent mall for running errands or leaving directly to the street.

If an agent has a destination but no a valid itinerary, the *Search Info* experience is entered next. The agent will attempt to find a digital sign in the transport hub from which they can retrieve their departure time and location. Once a sign is within a certain range and readable for the agent they can enter the *Acquire Destination* experience, which mainly consists of perusing a nearby digital sign to find out the desired itinerary. Once an agent has a valid itinerary it may enter the *Queue at Bus Berth* experience, with

its sequence of three stages: stage one will prompt the agent to navigate to the queuing area of their target berth. Stages two and three correspond to waiting in the queue and boarding the bus, respectively. This compartmentalisation reflects the three different actions taken during the encompassing experience as well as the strict order in which to perform them. If an agent misses their bus, the itinerary expires and becomes invalid. As a consequence, the stage and experience are violated and a new experience that matches the current cues perceived by the agent best is selected.

### 3.2 Environment and Signage Visibility

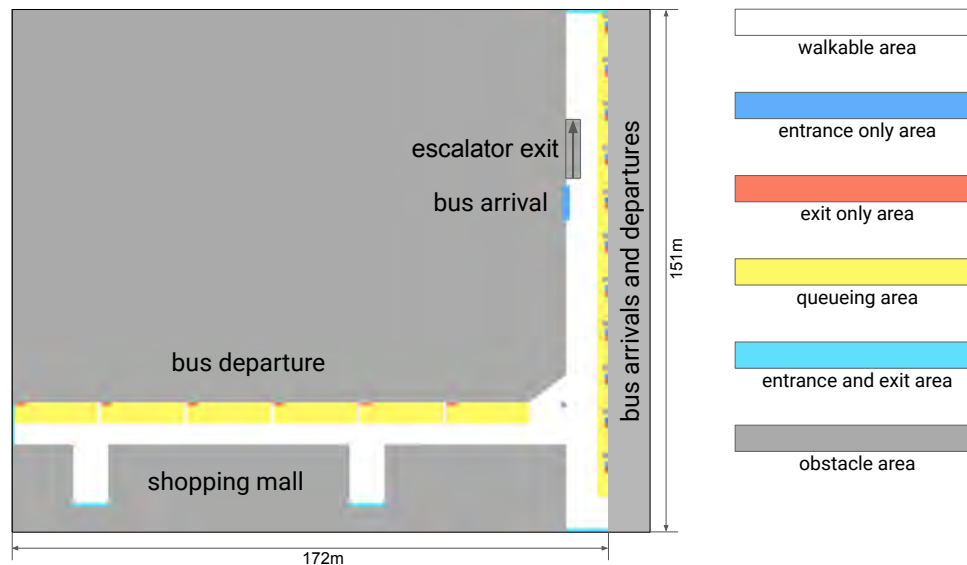


Figure 2: Overview of the Boon Lay bus interchange.

For our study area we selected the Boon Lay Bus Interchange as it is one of the larger interchanges and a regional transport hub in Western Singapore. Its size of 172 by 151 meters and number of bus berths make a fair amount of navigation necessary to move from one incoming bus to the next departure. In figure 2 the layout and accessibility are shown. The interchange has exits and entrances towards the street as well as a shopping mall this is also connected to a train station. The interior of the interchange is divided into two bus berth areas. The left section acts as a terminus and contains one single entrance for arriving buses to drop off passengers. For buses starting their routes, there are six large berths with ample queuing space per berth for departing passengers. The far right side contains twelve smaller berths with separate entrances and exits for each of them.

Despite the increasing number of innovations brought about by research into future public transport systems, self-updating information boards placed at well visible locations remain critical in providing passengers with scheduled departures, arrivals and updates thereof. Readability and comprehensibility of the information from a given point in space is not only subject to distance and unobstructed line of sight. Fonts, colour schemes, shapes and icons can support the perception of information. Therefore, to emulate the visibility of publicly accessible signage, we overlay the scenario area with an individual heat map for each sign. The cells of the heat map contain a value proportional to the visibility and legibility of the information on the sign. This value results in part from the angle between the cell and the direction the sign is facing as well as the absolute distance. Additional factors could include obstruction through architectural features or difference in height, if the sign is visible from various heights or storeys in the

building. Combining the visibility matrix cell value at an agent’s location with individual agent parameters such as their approximate eye sight or attention level determines whether an agent is able to retrieve the information displayed on the sign.

Let  $c_i$  be the cell in which agent  $i$  resides,  $v_i$  the sight capability parameter of the agent,  $c_s$  the cell in which the nearest sign is placed. The agent is able to read the sign if:

$$los(c_i, c_s) \cdot (1 - pen(\|c_i - c_s\|, \gamma(c_i, c_s))) \geq v_i \quad (1)$$

with  $\|c_i - c_s\|$  being the distance between the agent and the sign,  $\gamma(c_i, c_s)$  the angle between sign  $s$  and the cell  $c_i$ . The penalty function  $pen()$  incorporates the two parameters yielding a value between 0 and 1, 0 indicating no readability and 1 indicating perfect readability. A straightforward choice for a penalty function is to simply linearly reduce readability with increasing distance and angle. The line of sight factor  $los(c_i, c_s)$  between agent and sign resolves to 0 if the view of the sign from the agent’s position is obstructed and to 1 otherwise.

## 4 EXPERIMENTS AND RESULTS

We examine the effects of multiple digital signage placement configurations. We also explore how the pedestrian path-finding changes when a second source of information, personal mobile devices, is introduced. Therefore we will experiment with varying rates of adoption of either technology. To generate plausible pedestrian traffic, the population is split into 30% arriving and 70% transiting agents. For the remainder of this paper we are focusing on the behaviour of the latter agents, while the former will provide us with background traffic for increased realism. As a metric for assessing the quality of an interchange configuration we measure the time a pedestrian actively spends from entering the public transport hub until boarding a bus to leave it again. The term ‘active’ includes only time spent walking to signs or berths and perusing signage. Time spent waiting in the queue for the departing bus is ignored. If a pedestrian misses their bus and has to return to a signage to find the next berth from which to depart, this time is added to the active count. Our simulation uses a range of parameters that require real-life information. These have to be set on a case-by-case basis, specific to the mode of dynamic transport, to calibrate the model accurately. Table 1 shows the most influential parameters.

### 4.1 Sign Distribution Scenarios

In a first set of experiments, we compare digital signage placement variations to demonstrate the effects on crowd movement and path-finding. Figure 3 shows a visibility heat map for each of the four simulation runs. A red value indicates good visibility of a sign, a dark blue value represents a location where there is no sign visibility. In total, we investigate four different signage densities, ranging from low to very high:

Table 1: Simulation parameters and values used in the experiments.

Parameter	Value
simulation duration	4 hours
avg. agent IAT at entrances	4.5s
avg. bus IAT	{120s, 240s}
average number of alighting passengers	11
agent sensor range	20m
preferred (max) velocity	mobile phone users: 0.9 (1.3) m/s, others: 1.23 (2.0) m/s
signage perusing duration	10 seconds

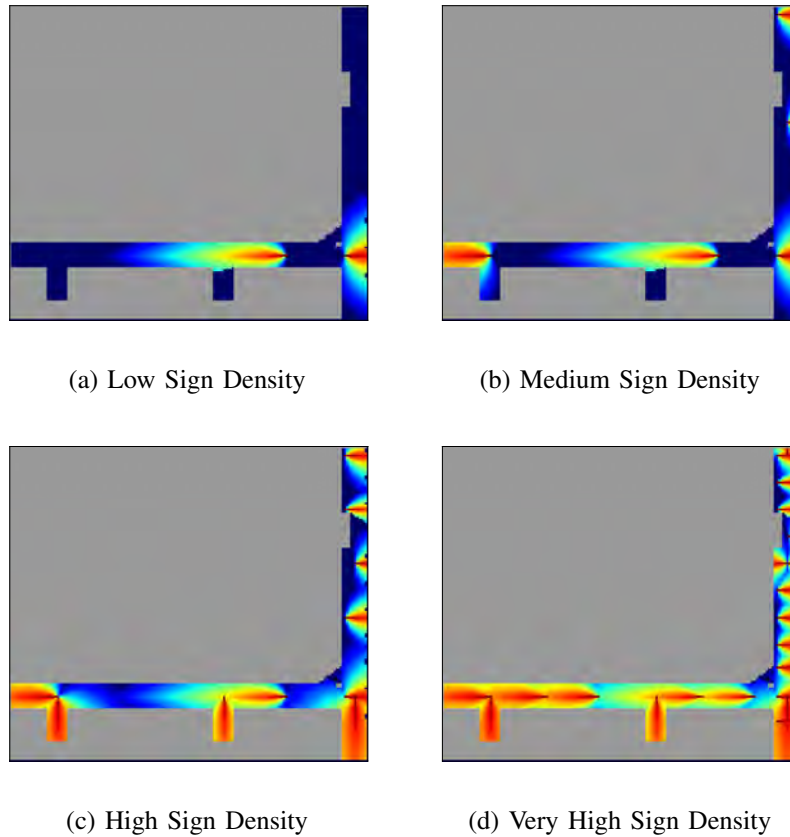


Figure 3: Overview of signage visibility in the evaluated simulation scenarios.

- **Scenario 1 - Low Signage Density** In this scenario (Figure 3a) there are only two signs placed in the transport hub. This sparse placement would most likely be infeasible for a real-world deployment, however, can serve as a lower bound for our experiments.
- **Scenario 2 - Medium Signage Density** Three more signs are added at entrances and exists of the transit hub. The signs are spaced out over the east-west and north-south corridor. This increases the coverage of entrances while also reducing the distance passengers have to backtrack should they miss a bus and require updated information on future departures. The layout is shown in Figure 3b).
- **Scenario 3 - High Signage Density** In the third scenario, five more signs were added, bringing the total sign count to 10. As can be seen in Figure 3c), all entries are equipped with digital signage as well as numerous bus stops.
- **Scenario 4 - Very High Signage Density** In this scenario, the entire east-west corridor is covered as well as every single bus berth entry in the north-south corridor, as shown in Figure 3d). In this scenario, a sign is visible from almost every location in the transit hub. While such a dense signage placement might be infeasible in a real-world scenario, this scenario can serve as an upper bound.

First, we show how the crowd simulation model can evaluate how the signage placement influences crowding. To this end, we visualise agent movement as heat maps, shown in Figure 4. For these heat maps we exclude passenger queues at the bus berths and focus only on active agents to emphasise hot-spots of agent movement. The figures focus on the north-south corridor as it exhibits notably more traffic and higher density than the rest of the interchange. The low signage density scenario requires agents starting in the north-south corridor to walk towards the signboard located at the intersection of the two corridors. Once

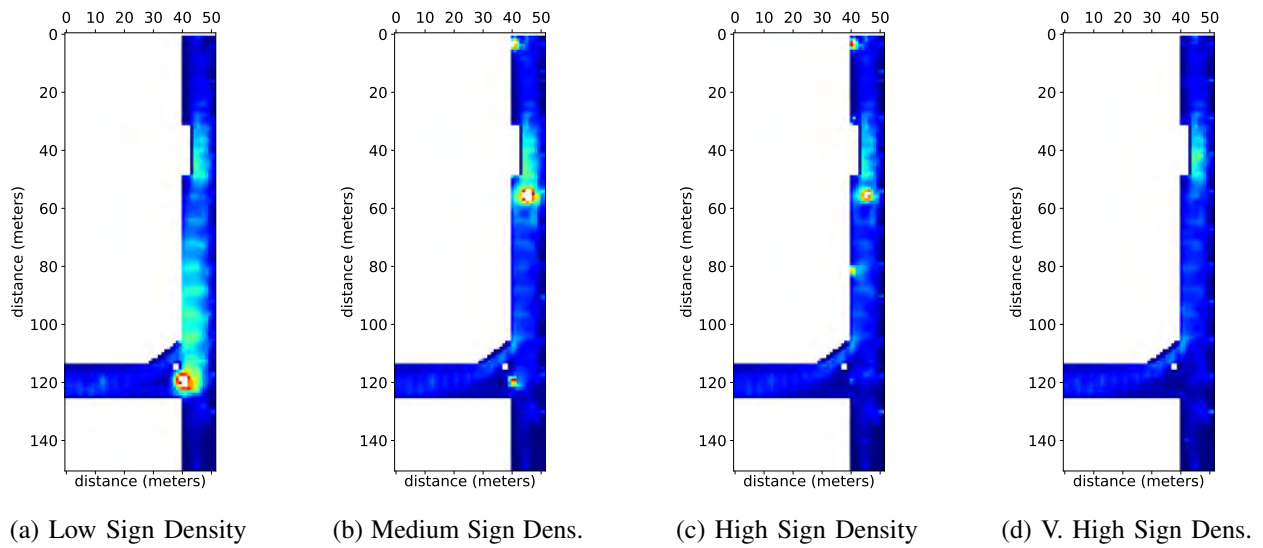


Figure 4: Cumulative heat maps of crowd densities in different signage placement scenarios.

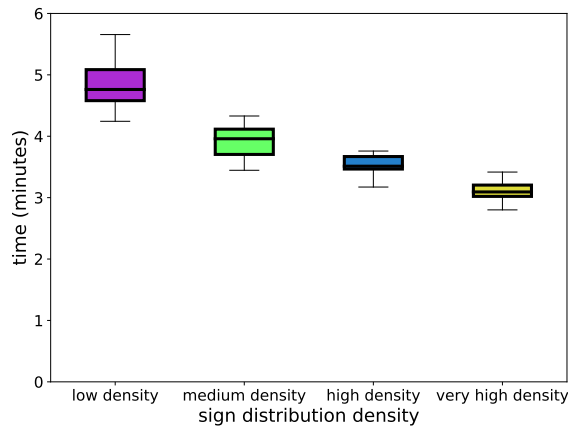


Figure 5: Time needed for a passenger to find the correct bus berth.

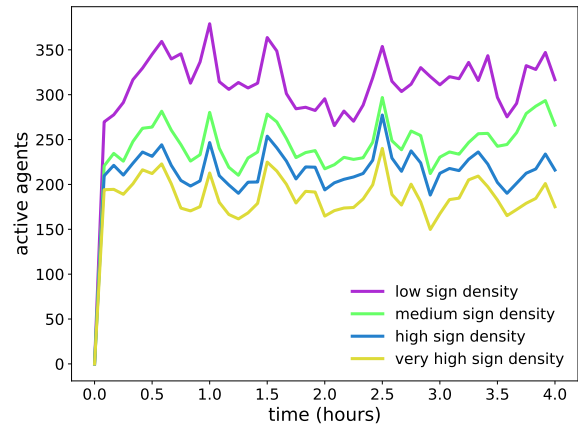


Figure 6: Active agents in the simulation scenario.

they learn which bus berth to go, they might even have to turn around and walk back against the stream of people trying to reach the signboard. The heat map in Figure 4a shows that the north-south corridor exhibits significant crowding, with some agents even temporarily stuck next to the signboard. In Figure 4b, we observe that the two extra signs in the north-south corridor (see medium density scenario in Figure 3b) help alleviate this problem and reduced crowding in the southern part of the corridor. However, we noticed a new hot-spot of agent crowding caused by one particular sign that was placed near the narrow corridor next to the escalator. Agents reading the sign blocked the corridor for passengers trying to pass the narrow corridor. Adding additional signs (Figure 4c) reduced the crowding at this location. We observed no critical hot-spot in the highest sign density scenario (Figure 4d). We conclude that our agent-based model captured the expected crowding situation of the low sign density scenario, and additionally identified a hot-spot that we did not foresee.

We also analysed the time required by agents to complete their tasks, which is to reach their outbound connection. Figure 5 shows our results in the form of a boxplot over the averages of all 10 simulation



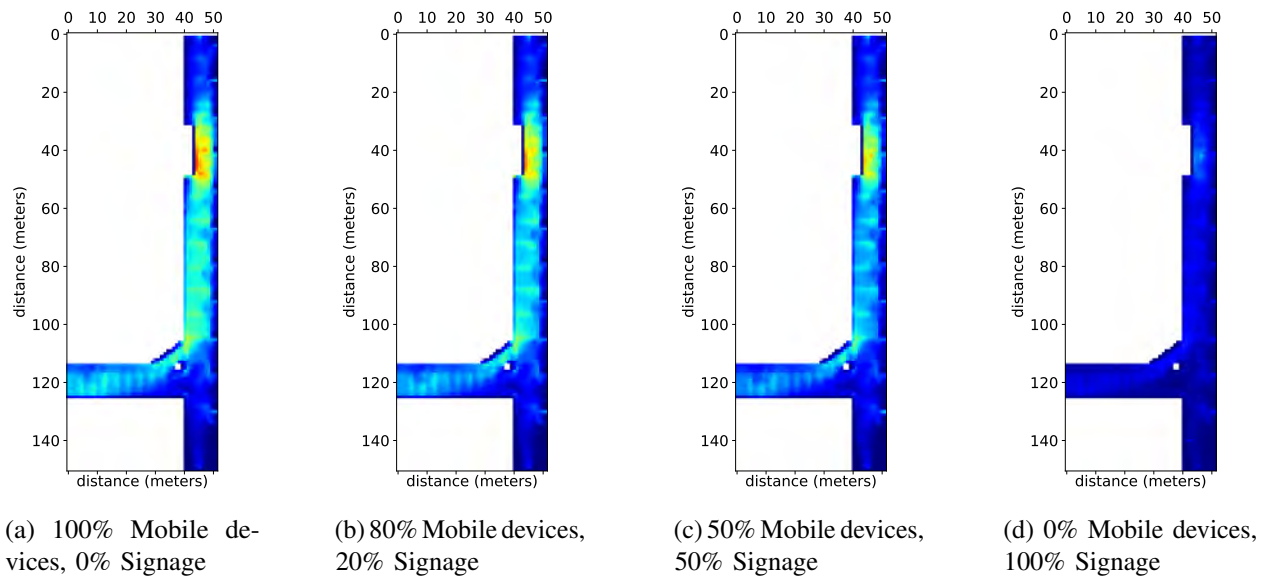


Figure 7: Cumulative heat maps of crowd density for varying rates of mobile device and signage users.

runs. For each scenario, a box is drawn from the first quartile to the third quartile, and the median is marked with a thick line; additional whiskers extend from the edges of the box towards the minimum and maximum of the data set, but no further than 1.5 times the interquartile range. We observe that increasing the sign density consistently achieves a reduction in active time required per agent, from around 5 minutes in the low density scenario down to 3 minutes in the very high density one. The main reason for that is that agents have to take fewer and shorter detours to a digital signboard to learn from which bus berth their bus is departing. Noteworthy here is that not every sign is equal and the impact of a sign on the crowd varies by its location. Signs placed in heavily frequented areas help to break up crowds quickly by disseminating information right where a large amount of pedestrians enter the interchange. Without signs there, crowds that congregate in these areas would have to move further to find a digital sign and thus add to the congestion in the corridors.

Figure 6 shows the number of agents simultaneously present in the transit hub. When agents require a longer time to finish their task, then naturally more agents populate the simulation scenario, which in turn increases crowding, which reduces walking speeds. This negative feedback loop causes a significantly higher number of agents to be present in the transit hub when sign density is low. Agent-based crowd simulation can help quantify this number and therefore support the design of transit hub layouts.

#### 4.2 Multiple Sources of Information Scenarios

In the second set of our experiments we introduce another option for digital guidance. Pedestrians now may use either digital signage or personal mobile devices. Assuming that mobile users keep checking their phone frequently their overall velocity will be lower compared to pedestrians who look at digital signage once and then proceed swiftly to their departure berths (Walsh et al. 2019). To emulate this we consider an average velocity of 1.23 metres per second for passengers without mobile devices (Rahman et al. 2012) and we extrapolate a walking speed for mobile phone users of 0.9 metres per second (Walsh et al. 2019). For the sake of simplicity, we assume that mobile phone users will not make use of the digital signs in the transit hub. The given maximum velocities in the table apply for evasion manoeuvres in the social force algorithm. The trade-off for faster movement of signage users is the necessary detour to a digital sign as well as 10 seconds required to peruse the sign for departure information.

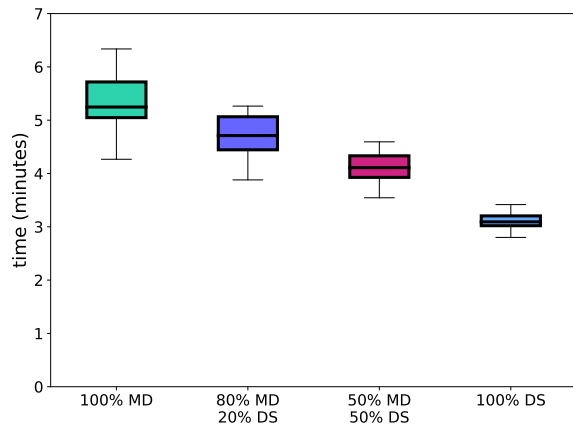


Figure 8: Time needed for a passenger to find the correct bus berth in the mobile device scenario.

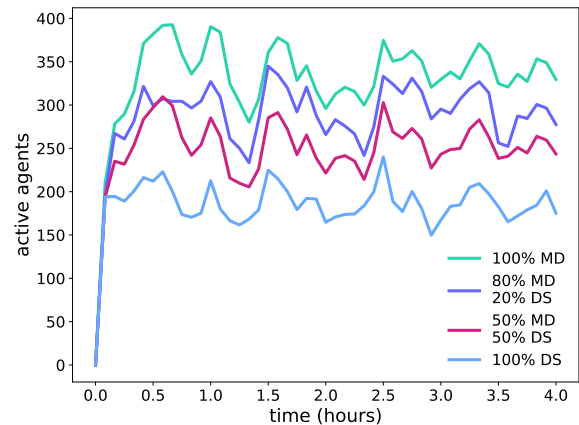


Figure 9: Active agents inside the mobile device simulation scenario.

Analysing the agent heat maps in Figure 7 we can observe the difference in crowding caused by both types of digital guidance systems. Mobile device users usually follow the shortest path to their bus berth, except when avoiding crowded areas, while digital signage users tend to congregate around signs before moving to their departure berths. The optimised paths of mobile users are more direct but also frequented more heavily because many agents' shortest paths are partially overlapping. Most notably this happens at the intersection between the two main corridors but also at the narrow corridor near the escalator exit where the lower walking speed of the agents caused crowding (Figure 4a). These effects decreased with more users referring to digital signage as their source of information (Figures 4b and Figure 4c). Please note that Figure 7d corresponds to Figure 4d, however normalised to the crowding in the mobile phone scenarios to allow for visual comparison.

The lower walking speeds and the resulting crowding causes passengers in the mobile phone scenarios to take considerably longer to reach their location. (Figure 8). We observe an average of over 5 minutes for the 100% mobile phone scenario, which is similar to the low signage density scenario in Section 4.1. Decreasing the number of mobile phone users lowered the average time required for each passenger to reach their berth accordingly. This is further supported by the results shown in Figure 9 where we compare the number of active agents over the simulation duration. The numbers of simultaneous agents exceeded the worst case of the signage distribution experiments, causing negative feedback in terms of crowding and thus time needed to finish their task. It appears that the penalties of detours and perusing delay are more than offset by a more even distribution of agents throughout the interchange. A key takeaway here is that information displays in public spaces can not only assume the function of information dissemination, but also have the additional capability of directing the flow of crowds.

## 5 CONCLUSION AND FUTURE WORK

In this work we presented an approach for the evaluation of guidance systems in future hubs for autonomous public transport. The simulation model focuses on agent-based crowd simulation and combines path finding, collision avoidance, and rapid decision making algorithms to approximate plausible agent behaviour. As a proof of concept, we have evaluated a scenario based on a real-world transit hub where buses are dynamically assigned bus berths and passengers do not know in advance to which bus berth they have to walk. Our experiments have shown that our approach is capable of capturing the influence of signage distribution on crowding and even identify locations where the placement of signs can have negative effects. We also analysed how an alternative guidance system based on personal mobile devices compares to a sign-based

one and found that it has severe effects on crowding, assuming that people looking at their devices exhibit a slower walking speed.

Future work is needed to gather information about pedestrian characteristics for an improved level of detail and calibration of the simulation model. It should be emphasised that the experiments in this work serve to illustrate the expressiveness of the model and deliver estimates of the effects observed. Accurate and substantiated predictions require closely calibrated models and parameters that are fine tuned on a case-by-case basis. There are ongoing studies looking into data collection via virtual reality experiments and real world observation.

Not only is simulation-based evaluation a promising avenue to explore, it can be further developed into simulation-based optimisation by automating exploration the of configurations and evaluation. This has significant potential to aid the research and design process by automating part of it and providing a valid pre-optimised foundation for infrastructure planners and designer to base their work on.

## ACKNOWLEDGEMENT

This work was financially supported by the Singapore National Research Foundation under its Campus for Research Excellence And Technological Enterprise (CREATE) programme.

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