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Agent-based simulation of non-urgent egress from mass events in open public spaces

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Abstract

Public mass events require thorough planning on allocating resources such as paramedics, police officers, urban cleaning teams, and their equipment (ambulances, patrol cars, garbage collection trucks, and other urban cleaning vehicles). Testing different scenarios of event venue layout and crowd behavior at the end of an event might be useful to plan the event and said resource allocation.

Our main objective is to model the non-urgent egress of participants at the end of an event, with possible applications for event management. That is when some resources are released (police and paramedics) and others are requested (urban cleaning teams).

Using the agent-based GAMA platform, we implemented a spatially explicit simulation model upon an extension of the Social Force Model that considers group behavior, and a novel implementation of the "social retention" phenomenon, to simulate non-urgent egress from public space mass gathering events. Focus groups with architecture, geography, and urban ergonomics experts were conducted for face validation and improvement of the model.

We present the outcome of a series of simulations of a scenario mimicking a real-life music event that took place in a square in downtown Lisbon, Portugal. Cell phone data captured during the event was used to calibrate the model. We analyzed model performance when the number of pedestrian agents increases, to assess the feasibility of using our approach in participatory discussions with stakeholders responsible for resources management.

On average, the egress evolution obtained in the simulations fit well with the evolution of cell phone counts captured during the event. The behavior of groups of agents evidenced real-life phenomena, such as the persistence of group cohesion and repulsion interactions (both with architectural obstacles and other agents).

Model performance degradation with the increasing number of agents may hamper the usage of this model/platform for participatory meetings, due to the incurred delay in obtaining results. To mitigate this problem, we plan to explore parallelization strategies for agent-based simulation, such as using GPUs.

Keywords: Agent-based modeling, Pedestrians simulation, Non-urgent egress, Social force model, Group behavior, Social retention

1. Introduction

Many events attracting a large number of participants take place in urban open public spaces such as squares or plazas. Examples include political rallies, protests, celebrations, music festivals, fireworks, or video mapping shows. Choosing an adequate public space for each event requires knowing the expected

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number of visitors, acoustic conditions, spatial context, and accessibility. It is also necessary to undertake risk analysis based on the carrying capacity and egress time from the public space hosting the event. The safety of urban public space events depends on a wide set of factors, such as the scope of the event, the profile of the expected visitors, and the geometry of the space. For instance, a protest of senior citizens over the degradation of their pensions would have different risk factors when compared to a concert for younger crowds. A rally for a tolerance-preaching political party would not be as risky as an extremist radical party with infiltrated agitators that sometimes lead to clashes with the police and even looting. In case of public order-disrupting situations, such as natural disasters, explosions, looting, or terrorist attacks, the geometry of the public space must allow for quick and efficient evacuation, to avoid or keep injuries and possible casualties to a minimum.

Fortunately, the vast majority of mass events in open public urban spaces are peaceful, therefore not requiring emergency evacuation. Nevertheless, the success of these "normal" events requires adequate planning to allow dealing with potential health incidents requiring immediate action (e.g. excessive sun exposure, digestive or heart disorders), guarantee public safety during the event and, after it, ensure that the venue is kept clean for later use by the city's inhabitants and visitors. That requires the scheduling of resources such as paramedics, police officers, urban cleaning teams, and their equipment (ambulances, patrol cars, garbage collection trucks, and other urban cleaning vehicles).

In this context, a simulation model can be an effective planning tool for stakeholders to explore the complex system of event maneuvering by allowing the testing of multiple scenarios without requiring empirical observation. Simulation models can also be applied in the participatory description of complex systems, such as the Companion Modeling approach [44], which allows the co-creation of conceptual models by stakeholders with possibly different views.

While event emergency evacuations have deserved extensive attention in the literature regarding modeling and simulation [20], the most common non-urgent situations have not received it. In this work, we consider the non-urgent outflow of the public space in which an event took place, after its end, when some resources are released (police and paramedics) and others are requested (urban cleaning teams). Simulation scenarios facilitate participatory discussions on various scenarios, regarding the allocation and de-allocation of those resources. That scheduling is highly dependent on the number of event participants, the flow capacity of the exit points, and the groups' routing dynamics.

The model should describe several microscopic phenomena of the different participating agents for realistic and meaningful results. One such phenomenon is that these events are usually attended by social groups of pedestrians who walk together (e.g., friends, work colleagues, families). The interactions within each group and among members of different groups impact the crowd behavior dynamics [29], which could also affect the efficiency of event egress, measured by egress rate (exiting people count per time unit). Although this is an important aspect of pedestrian dynamics, it has been often neglected in pedestrian flow models [8].

We have not yet found in the ABM literature a further social phenomenon present in these events: the visitor's inertia to leave the public space where the event has occurred, due to socialization within groups and/or the usual availability of food trucks. We coined this phenomenon as "social retention" and added it to our group behavior model. For calibrating and validating the macroscopic behavior of non-urgent egress with this improved simulation model, we compared simulation results with the "ground truth" provided by cell phone counts from a local telecom operator, as described ahead.

Our main objective is to propose an agent-based model (ABM) to simulate non-urgent egress dynamics of pedestrians from mass events in public open spaces, to be used in stakeholder participation and event planning. The model incorporates an existing validated Social Force Model (SFM) with group behavior, proposed in [29], and encompasses a novel representation of the social retention phenomenon. OpenStreetMap (OSM) geographical data, and the GAMA platform, a modeling and simulation development environment, are used to develop this model. Face validation and model feature collecting were assessed in several focus groups with distinct types of experts. Simulations of a real-life scenario were compared to event data using cell phone count data to perform macroscopic calibration and validation. A performance analysis is developed to assess the feasibility of this model for participatory planning among stakeholders.

This paper is organized as follows: in section 2 we recap the SFM and its extension to support group dynamics behavior and review some of the most relevant related works; in section 3 we present our agent-based model, covering the simulation platform, the description of how the geographical location was mapped in the simulation environment, how agents behavior was modeled and some additional model assumptions; on section 4 we describe our approach on model validation and calibration, presenting focus group results, the real-life scenario replicated in simulation, and the obtained simulation results and discuss them on section 5; finally, on section 6, we provide some conclusions and outline the future work.

2. Related work

2.1. The Social Force Model

The classic SFM, presented by Helbing and Molnár [15], is a microscopic mathematical model that represents pedestrian dynamics and interactions, based on the concept of *social forces*, presented by Lewin [24] as psychological forces from the environment and other pedestrians, which collectively act upon the decision-making of the movement of pedestrians, resulting in complex emergent patterns of pedestrian behavior.

In this model, there are three main terms regarding the assessment of the driving force of the actual velocity of a pedestrian: (i) the force towards the desired walking speed and the directions towards the destination, (ii) the repulsive forces from other pedestrians and obstacles (e.g., borders, walls, monuments), to avoid and keep distance from them, and (iii) the attractive forces from other possible sources (e.g., a shopping window on the way to a destination). The SFM has been widely used in pedestrian behavior models and simulations, with some modifications (e.g., the attractive forces often neglected) and improvements to consider additional phenomena such as panic behavior [14].

While the classic SFM does not implement group behavior, some relevant proposals based on SFM exist for modeling social group behavior in pedestrian dynamics. Moussaïd et al. [29] presented extensions to the classic SFM for representing inter-group and intra-group interactions of repulsion and attraction. Those authors extended the classic SFM with the following components: (i) intra-group interactions based on gaze, (ii) the attraction of group members to the group's centroid (or center of mass), responsible for group cohesion, and (iii) the repulsion interactions between group members to avoid collisions.

In [16], the authors present a more advanced extension to the previously referred group SFM by adding the following components: (i) the repulsion forces between groups and (ii) subgroup coordination forces.

2.2. Pedestrian flow movement

As mentioned earlier, most egress simulation studies consider emergency evacuations in closed spaces, such as cinemas, theaters, office or shopping mall buildings, stadiums, and public transportation stations.

We found a few applied in outdoor (open) spaces such as in our study [11, 35, 39, 27, 22, 32, 30], whose characteristics are summarized in Table 1. We can observe they do not address normal (non-urgent) situations or implement group dynamics behavior except for [30]. None addresses the inter-person in-situ socialization observable in normal, non-urgent scenarios when events finish, that we dubbed social retention.

In our case, we focus on normal (non-urgent) egress scenarios where event participants (pedestrians) flow out of the open public space when the event is over. Many pedestrian flow and crowd movement models were developed using diverse approaches, e.g., cellular automata, SFM, activity choice models, velocity-based models, behavioral models, network models, continuum models, and hybrid models [10]. As for the application in urban scenarios, examples can be more focused such as for simulating regional traffic flows of pedestrians to support the understanding of transport structure and functions [21] and for simulating the interactions of pedestrians and bicyclists [26], or more generic such as in [7] and [42], where models were designed and implemented to accommodate the particularities of spatial relationships and interactions between humans in space (space syntax).

Very few studies specifically focused on normal event egress modeling have been conducted. Haghani et al. [13] presented econometric models obtained from collected stated-choice data in interviews with exiting passengers from a railway station in Melbourne, asking what exit decision they would have made in certain hypothetical scenarios at that station. These models assess and quantify the priority of distance, crowding, exit visibility, the proximity of the exits to their destination, the impact of decisions of other pedestrians, and spatial distribution of exits in exit choice for egress. The authors found that (1) for normal egress, the proximity of the exits to the destinations of pedestrians is a dominant factor; (2) avoiding crowded exits is a much higher priority in emergency egress than in normal egress and (3) crowd directional flows do not significantly impact normal egress decisions.

Shi et al. [36] assess the applicability of a pedestrian simulation model to reproduce the effect of exit design on egress flow under normal and emergency conditions. The authors verified the use of SFM with the Viswalk tool to simulate these effects by implementing and calibrating the model with empirical data from controlled experiments. They concluded this model could provide reasonable estimates for crowd escape under normal situations, but it was less capable of describing emergency scenarios.

2.3. Group behavior in pedestrian simulation

Some pedestrian behavior and crowd evacuation models incorporate group dynamics. Most of these models focus on the leader-following or herding effect of emergency evacuation, and not on groups derived from social ties in non-urgent egress. These studies also do not apply simulations in large-scale real environments.

Qiu et al. [31] presented an ABM based on Reynold's Boids algorithm [33] to simulate group behavior in pedestrian flow, assessing the influence of group size, intra-group structure, and inter-group relationships. Although not directly applied to egress scenarios, the authors concluded that the factors in the study are important in crowd evacuation.

Lemercier et al [23] proposed an RVO2-based ABM to assess the influence of the perceptions of pedestrians on their attitudes in a crowd movement. RVO2 is a collision avoidance model proposed in [41]. By combining leader-follower behavior, grouping, or no grouping, the authors concluded that a more realistic simulation of crowd behavior can be obtained.

Ma et al. [28] proposed an extension of the classic SFM to simulate leader-follower behavior in crowd evacuation, incorporating the visibility range of the area. The authors concluded that the impact of leadership on evacuation time depends on the range of visibility of the area and crowd size.

Li et al. [25] also presented an extension to the classic SFM by Helbing and Mòlnar for crowd evacuation, incorporating social groups and leader-follower behavior. Based on the results, the authors concluded group behavior causes more efficiency in egress than the classic SFM model.

Turgut et al. [40] presented an extended SFM model with two types of group behavior: leader-centered and group-centered behavior. Through the analysis of simulations in evacuation scenarios, the authors concluded that in (i) small groups, evacuation time is lower in leader-centered than in group-centered behavior (ii) the increase of leaders reduced evacuation time, and (iii) with multiple exits, group-centered behavior resulted in less evacuation time and better exit choice balancing than leader-centered behavior.

Bulumulla et al. [5] propose a generic approach of integrating diffusion modeling into an agent-based simulation framework that incorporates a social, a cognitive, and a physical model and applies it in a large-scale evacuation case study involving more than 35,000 agents. Results revealed that adding the social level can significantly affect evacuation outcomes.

Based on Table 1 we conclude that there is a gap regarding the simulation of non-urgent mass events egress in urban public open spaces (e.g., squares, plazas) and the inclusion of social/group interactions among agents, reinforcing the novelty of this study.

3. Agent-based model

This section introduces our proposed ABM using the Overview, Design concepts, and Details (ODD) protocol, a standardized format for providing a consistent, logical, transparent, and verifiable account of the structure and dynamics of ABMs [12]. Many examples based on ODD can be found online at the CoMSES Model Library, a digital repository that enforces reproducibility, and reuse of ABMs [18], as well as in top-tier journals [7, 22]. The full ODD of our model can be found in Appendix A and the source code for our GAMA implementation can be found in GitHub.

Table 1: Egress simulation studies summary
OUT (Outdoor), URG (Urgency), GRP (Groups Behaviour), SRT (Social Retention)

Study	Motivation	OUT	URG	GRP	SRT
[30]	Continuum dynamics-based simulation of emergency evacuation in outdoor environments	Yes	Yes	No	No
[32]	Simulator comparison for flood evacuation simulation in outdoor built environments.	Yes	Yes	No	No
[22]	Dynamic-data-driven ABM simulation of hurricane evacuation behavior	Yes	Yes	No	No
[27]	ABM Simulation of evacuation on outdoor public places, based on the Shanghai Stampede	Yes	Yes	No	No
[39]	Individual cognitive evacuation behavior ABM for simulation of pedestrian route selection	Yes	Yes	No	No
[35]	Multi-agent continuous simulation of large-scale evacuation scenarios at music festivals	Yes	Yes	No	No
[11]	ABM simulation of earthquake evacuation in outdoor spaces	Yes	Yes	Yes	No
[28]	SFM model of simulate leadership on crowd evacuation in rooms with limited visibility range	No	Yes	Yes	No
[25]	Crowd evacuation SFM model, incorporating social groups and leader-follower behavior	NA	Yes	Yes	No
[40]	Crowd evacuation SFM model with leader-centered and group-centered behavior	No	Yes	Yes	No
[5]	Framework of social, cognitive and physical ABM pedestrian modeling, applied in large-scale evacuation	NA	Yes	Yes	No

3.1. Purpose and patterns

The purpose of the model is to simulate non-urgent egress of visitors from mass gathering events happening in real-life urban public open spaces (e.g., squares, plazas), evaluating the impact of different built environments, obstacle layouts, hypothetical exit-choosing behaviors of the visitors, social retention and crowd density scenarios and number of individuals in a social group in the egress patterns, the main emergent phenomenon obtained from the model. It should aid decision-makers in choosing the appropriate public spaces for a specific event and deploy/release public utility teams (e.g., cleaning, emergency, and security) just in time. For example, stakeholders could use the model to test different scenarios in candidate public open spaces to host specific events to find the most appropriate given the expected event characteristics, and then test how pedestrians would use the space after the event. For resource allocation, given the known layout and predicted crowd characteristics of the event, decision-makers can simulate egress patterns, deciding when (e.g., when the people count reaches a certain threshold) and where (e.g., choose the exit with more security staff deployed) these public resources will be allocated.

Patterns we believe our model must be able to reproduce are as follows:

- **Pattern 1: Relation between built environment layout and egress times.** The layout of the obstacles and exits, total space geometry, the total available exit width, and the shape of the open space should affect egress rates. E.g., a closed environment with a single small exit should lead to larger egress times than the same environment, but with more, wider exits.

- **Pattern 2: Relation between exit choosing behavior and egress times.** Chaotic exit choosing should lead to higher egress times, as a greater number of collisions between erratic pedestrians should overall reduce the egress rates. Whereas, orderly behavior should minimize collisions, smoothing the flow of pedestrians toward the available exits.

- **Pattern 3: Relation between crowd density and egress times.** It is expected a significantly denser crowd egress from a built environment with less efficiency due to the increasingly expected collisions between pedestrians and bottlenecks at exits.

- **Pattern 4: Pedestrian collision avoidance** Pedestrians avoid bumping into other pedestrians and other obstacles, maintaining a certain distance between them and altering their routes to avoid them. This pattern is based on the Social Force Model by Helbing and Molnár [15]

- **Pattern 5: Group cohesion.** Members of a social group maintain spatial cohesion, i.e., maintain a certain proximity to each other. This pattern is based on group behavior studies [29, 16]
- **Pattern 6: Social retention.** Groups wait a random time at the event premises, after its end, to partake in intra and inter-group socialization, and nearby amenity usage (e.g., bars, kiosks, restrooms, clubs). This pattern is based on our observation of public open space mass events.

Patterns 1,2 and 3 are based on evacuation principles described in the *Society of Fire Protection Engineers (SFPE) Handbook* [17], which we believe can be observed in non-urgent egress as well.

3.2. Basic principles

The model is set over the concept of pedestrians attending mass gathering events in urban open spaces, and leaving the venue after the end of the event, without urgency. To the best of our knowledge, this particular setup has not yet been addressed in the literature. Some existing studies on ABM consider egress flow dynamics similar to those described in our model, but at a much smaller scale (usually room-wide) and in different contexts [43].

The model tries to approximate reality by setting a continuous space, a fine-grained time scale, and the microscopic representation of all individual pedestrians. At the agent level, the interactions between the crowd members follow the established Social Force Model (SFM) first presented by Helbing and Molnár [15], extended with social group behavior in [29]. SFM considers repulsive and attractive forces that dictate the speed of pedestrians to avoid obstacles and other pedestrians on their way to the desired destination. The social group extension adds group cohesion forces, as pedestrians from a group want to be close to each other [29]. In contrast to evacuation scenarios, where the choice of exit depends on several factors such as panic levels, distance to the exit, etc., in non-emergency scenarios, exit depends on the will of the pedestrians. Some may go to a restaurant or bar, others may walk to a nearby landmark, and others may choose transportation to return home. This behavior is difficult to predict due to many factors, so the choice of exit is based on a randomized weighted assignment. The weight is the relative attractiveness of each exit. For example, an exit leading to more popular amenities, public transportation, or parking would be more attractive and therefore receive a higher weight. The assignment is made by group, as it is assumed that all group members will exit together. Instead of leaving the venue immediately after the event, event attendees may stay, socialize, and use local amenities. We call this phenomenon "social retention".

3.3. Simulation platform

The proposed model is implemented with version 1.8.1 of the GAMA platform. It is an Eclipse-based Integrated Development Environment (IDE) for spatially explicit, agent-based, and agent-oriented modeling and simulation [38]. We chose this platform for the following reasons: (i) it is designed to develop and run complex, large-scale models, with wide support for integrating and visualizing geographic information systems (GIS) data, having a wide library of geographic operations, (ii) the used modeling language (GAML) is accessible for programmers and non-programmers, (iii) it provides a headless mode, allowing to run simulations in dedicated servers without the overhead of a user interface and (iv) a responsive support team. These characteristics allow for fast development and exploration of new models.

3.4. Model environment

The environment is composed of the buildings and other obstacles (e.g., bodies of water) that delimit the open space, the permanent or semi-permanent physical structures that might act as obstacles inside the open space (e.g., monuments, kiosks, parking lot entrances), the spawning polygon (i.e., the area where the pedestrians are placed) and the exit geometries, which are modeled as polygons that demarcate the passage to the exiting streets bordering the open space polygon. Each exit is assigned an attractivity percentage so that their sum is 100%. This allows stakeholders to test scenarios with different proportions of exit preferences to identify those that create bottlenecks.

We use QGIS 3.16 LTS to manually model the exit geometries, open space limit polygons, and obstacles not represented in OSM, and to download and process OSM building geometry data to model the built environment of the public open spaces.

3.5. *Agents modeling*

This subsection gives an overview of agent behavior. Its detailed presentation is included in the formalization of the ODD protocol in Appendix A.

The represented active agents are (i) the pedestrians exiting the urban public space and (ii) groups of the former, tracking their members to implement group behavior social forces. The model agent (an observer agent) orchestrates the concurrent processing of the pedestrian agents made available in the used version of the GAMA platform to mimic their autonomy. This agent is also responsible for calculating the result statistics.

The pedestrian agents, organized into social groups, walk toward the chosen exit using a simplified (due to performance concerns for massive simulations) implementation of the extended SFM for social group behavior presented in [29], based on the model of Helbing and Molnár [15]. For each simulation cycle, each pedestrian agent evaluates the repulsive social forces exerted on it by other pedestrians and obstacles, and the attractive forces exerted on group members, representing group cohesion. Group agents store references to their members to improve the efficiency of calculating in-group cohesion for visualization. Building geometries are static agents, as they have no behavior, and serve as obstacles in the SFM submodel.

3.5.1. *Social retention*

In normal scenarios of public space events, when there is no mandatory or urgency-driven evacuation of the space, we can observe that many participants remain at the location, mainly to socialize within their social groups or with other groups, or use local amenities (e.g. food trucks, bars, restrooms, kiosks, public furniture). As aforementioned, we refer to this phenomenon as *social retention*. In emergencies (e.g., natural or manmade disasters), and events where the participants are forced to leave the venue right after the end of the event (e.g., private festivals, sports exhibitions), as opposed to the previous event type, pedestrians begin moving toward the exits, almost all at the same time, or in an orderly fashion, promoted by event staff.

Reifying the phenomenon of social retention increases the realism of pedestrian behavior during non-emergency exits in open public space events. To simulate a socialization period at the end of an event, agents remain stationary until their group's social retention time has elapsed, and then move toward their selected exit. The retention time is randomly assigned to groups with a distribution specific to the type of event, ranging from 0 to the maximum expected social retention time (i.e., the expected delay for the last group to decide to leave the room), which we define as the "exit time". This value must be determined based on observation and study of the type and location of the event taking place.

3.5.2. *Pedestrian agents*

The pedestrian agents represent the pedestrians who attend a public open space mass event and are organized in social groups, as normally expected in this type of event. These groups consist of pedestrians who attend the event together and have social ties, such as friends, family, coworkers, and couples [29], staying together during and after the event. Usually, groups leave the event as they arrive, except if group members have different destinations, or groups change through socialization. In this model, we consider groups do not change, and all group members choose the same exit. In future work, social group mutation may be implemented.

During simulation initialization, pedestrians are assigned to groups and randomly placed at a location within a short distance of their group center. This distance is determined according to the maximum group size and the expected crowd density so that group members have just enough space to fit within a circumference. Each group is then assigned (i) an exit according to a weighted random algorithm, where the weights are the relative attractiveness of the exits, and (ii) a randomly assigned social retention time. When the event ends, group members proceed to their assigned exit after their social retention time has elapsed.

At each cycle, the pedestrian agents follow the following steps:

1. If the simulation time has not exceeded the social retention time of the pedestrian's group, the pedestrian's speed is reduced to 0. The following behaviors still apply, as pedestrians must be able to move to make way for other pedestrians who want to egress.

2. If an obstacle is close enough and stands between the pedestrian agent and its intended exit, the desired velocity of the pedestrian points to a direction perpendicular to the direction of the pedestrian towards the nearest point of an obstacle, to move around it until the path is clear. If not, the desired velocity points to its chosen exit (the group's chosen exit). For open spaces without maze-like paths that require wayfinding, this approach works well with low computational effort, improving simulation performance.
3. For each of the other members in its group it calculates the repulsive force exerted (to avoid collisions among group members) and the attraction force to the group's centroid (to keep group cohesion), using the equations proposed in [29], accumulating them in the total sum of forces;
4. For each neighbor pedestrian within a defined distance from the agent, which is not part of its group, it calculates the repulsive force using the classic SFM motion equation [15], adding them to the total sum of forces.
5. The pedestrian agent calculates its final velocity from the obtained sums of forces and desired walking velocity.
6. The agent displaces according to the previously calculated velocity if there are no obstacles or limits ahead.
7. If the agent reaches its chosen exit geometry, it is removed from the simulation. Else, returns to step 1 in the next iteration.

3.5.3. Group agents

As aforementioned, the group agents are auxiliary agents that keep track of group members and calculate group centroid for the pedestrians to calculate group cohesion social forces.

The number of groups is calculated from the total number of pedestrians and the average group size. During simulation initialization, the location for the center of each group is randomly created inside the polygon defining the area for agents' placement according to a two-dimensional uniform distribution. The pedestrians are then placed at a set distance to the centroid of their respective groups. At the creation of a group, its social retention time ($T_{retention}$) is randomly assigned with the defined random distribution, from 0 to the specified egress period (T_{egress}). At each cycle, a group agent behaves as follows:

1. The group agent checks if a group member has left the simulation. If that happens, it is removed from the group's list of members.
2. The agent calculates the group's centroid based on the current position of all its current members.
3. If there are no members left, the group agent is removed from the simulation.

4. Model validation and calibration

4.1. Validation

For the face validation and evolution of the model, a series of focus groups with architects, geography and tourism researchers, and ergonomics/behavioral psychology experts were performed. The obtained feedback was used to implement and improve the model. An overview of the focus group results is explained in this section.

In these focus groups, the model and its purpose were explained. Then they were shown animations of the simulations in two scales: the entire square (macroscopic focus), and focusing on single groups (microscopic focus).

The first focus group was conducted with architecture doctoral students. In this focus group, the social retention time was not yet implemented (all the pedestrians' agents traversed toward the exits of the venue at the same time). The exit choice was also random but weighted by exit width (wider exits were more likely to be chosen by groups). The inner obstacles were omitted in this version. In the presented simulations, the group size was homogeneous (4 elements), and the walking speed was set to 1.34 m/s, as proposed in [4]. The participants suggested the following points:

- Exit choice would depend on the time of day, exit visibility, public transportation/parking lot access, shop/amenity access, and knowledge of urban fabric;
- Pedestrians do not leave the venue simultaneously in normal scenarios, as some may remain at the premises engaging in social activities or amenity usage. This is the concept of social retention that was later incorporated into the model;
- Group sizes and speeds should follow statistical distributions for more realism, instead of fixed values, as presented.

The second focus group was conducted with geography and tourism researchers. In the presented version of the model, internal barriers were implemented as suggested by the first focus group. The other conditions remained the same as in the first focus group. The participants produced the following comments:

- Model visualization should be improved. Examples included using an aerial view picture of the environment as background and changing pedestrians from triangles to more realistic ellipsoid shapes;
- Exit attractivity should be parameterized with a relative weight for each exit, instead of random choice weighted by width;
- Age distribution should be included, where social forces and/or walking speed change with it (e.g., older people are naturally slower than younger people);
- Include the time of day and weather, as event dynamics might vary with these variables.

The final focus group was conducted with ergonomics and behavioral psychology researchers. In this focus group, the attractiveness of the exits and the social retention time were implemented, as well as the suggested visualization features. The participants did not find any significant flaws in the model, thus completing the face validation phase of this model version.

4.2. Calibration

For a macroscopic calibration of the model, we ran simulations mimicking the end of the *Monumental Tour*, a mass event that took place in the Lisbon City Hall square on October 29$^{\text{th}}$, 2022, under the sponsorship of the French National Commission for UNESCO, combining electronic music, heritage (Lisbon City Hall), and digital art (video mapping). This event was chosen for model calibration because (i) the area surrounding the square has a low population density (few residents), thus reducing the number of false positives in cell phone counts that did not participate in the event, and (ii) because by the time the event ended the majority of nearby amenities were closed, leading to less external influence.

The model environment is a two-dimensional digital twin of the built environment of this square, modeled with OSM elements and obstacle structures that are not present in OSM data. Figure 1a shows the aerial view of the modeled open public space, and Figure 1b shows a snapshot of its simulated digital twin, with pedestrian agents in the space simulating proximity to a stage in front of the City Hall building (to the right), as occurred during the event.

The *LxDataLab initiative* provides datasets to solve different problems in the city of Lisbon. One of the provided datasets is the estimated count of detected cell phones in each cell of 200X200m of a grid spanning the entire city of Lisbon, in intervals of 5 minutes, provided and processed by one of the main mobile phone network operators in Portugal.

To reproduce this scenario in the simulation, we consider the previous dataset as a surrogate for people who were at the event, since one of the mobile network cells covers most of the Lisbon City Hall square. The initial pedestrian count in the simulations was then based on the number of cell phones detected in the grid cell at the end of the event, removing possible irrelevant counts. The count evolution patterns from the cell phone data are compared to the simulation count evolution from the end of the event, from 29$^{\text{th}}$ October 23:30 to 30$^{\text{th}}$ October 03:00, when the counts stabilize to a minimum. Figure 2 shows a graph with the previously mentioned data.

(a) Aerial view of the real twin (Google Maps) (b) Digital twin on GAMA with 1 595 pedestrian agents

Figure 1: Simulation environment (Lisbon City Hall square)

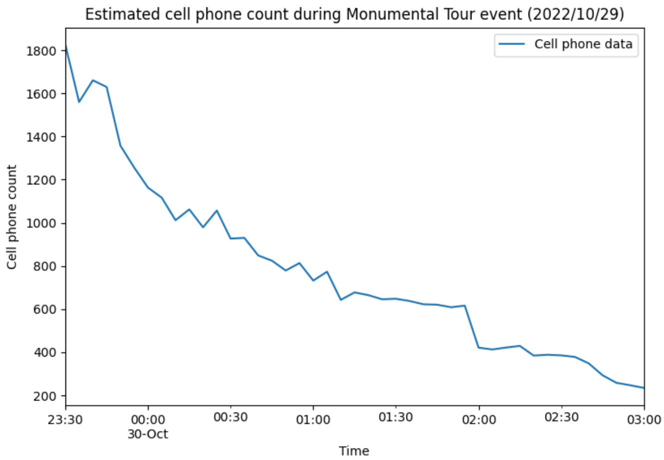


Figure 2: Monumental Tour ending cell phone data

Regarding the captures at the Lisbon City Hall square after the end of the Monumental Tour event, we can observe a peak of 1 825 counts in the grid cell that best captures this public open space. We can also observe a minimum of approximately 230 counts, which can be observed through multiple days (counts do not go much lower than this value through the dataset), representing possible residents, accommodation clients/workers, or staff outside the event, all which can be detected alongside the pedestrians attending the event, but must not be considered for simulation. Thus, we assumed 230 as a constant number of counts who did not partake in the event and considered a total of 1 595 ($1\,825 - 230 = 1\,595$) pedestrians at the venue for simulation, at the end of the event. To normalize the simulation results to the cell phone counts obtained during the event, the 230 counts are added to every simulated count at every time point obtained from the simulations.

Due to the lack of studies on the distribution of group size in public events, we used the distribution observed at the 2016 Kumbh Mela, a large religious mass gathering in India, where the observed group sizes ranged from 2 to 5 members, with groups larger than 5 members splitting into subgroups [37]. According to the authors, group speed tends to decrease with group size. The distribution of group sizes and corresponding speeds is shown in Table 2, calculated by averaging the observed values in this study. Individuals (i.e., pedestrians without groups) are not considered in this scenario, as in crowds, up to 70% of people move in groups [29]. More research is needed on the size of groups at different types of events.

Table 2: Group statistics

Group size	Frequency	Average walking speed [m/s]
2	61.39%	1.080
3	21.49%	0.990
4	11.35%	0.976
5	5.77%	0.935

The pedestrians' groups spawn with uniform distribution inside a well-defined polygon (which can be observed in Figure 1b). The chosen group center spawn distance was 2 meters, which seemed adequate for the scenario's maximum group size and crowd density.

The egress period is set as 3.5 hours, matching the time observed in the estimated pedestrian counts of the event from the peak counts to when the counts stabilize at the minimum. The social retention distribution was chosen to make the probability of a group having 0 retention time higher than having the maximum possible value (egress period time), as we can observe in the cell phone count data, the count decreases faster at the start of the egress period than at the end, suggesting the egress rate decreases over time. For this, we needed to transform a random uniform distribution variable of social retention into this type of distribution. For that, we chose the following equation, which transforms the random uniform distribution variable into the desired distribution variable:

$$T_{retention} = \frac{T_{random}^2}{T_{egress}} \tag{1}$$

where $T_{retention}$ is the random social retention time, T_{egress} is the egress period time, and T_{random} is a random value from 0 to T_{egress} with uniform distribution.

The defined step for each simulation cycle was 0.1 seconds. Simulations ended after the egress period elapsed in simulated time (3.5h). Exits have equal weights, meaning they all have the same probability of being chosen by a group. The parameters of the SFM sub-model defined for these simulations and set values are depicted in Table 3. The parameters for the classic SFM were set based on the simulations made in the original study [15]. The parameters for the group SFM component were chosen based on multiple simulations, until group behavior provided more realism, through discussion followed by group consensus among the authors. This approach was required due to the lack of empirical studies for high-density group behavior in mass events. Further calibration of these parameters should be done in future work.

As an output of each simulation, the model provides (i) graphical snapshots of the positioning of agents throughout time, and (ii) a set of CSV files with the outcome variables (remaining pedestrians), where each line corresponds to 300 simulated seconds (5 minutes).

5. Results and discussion

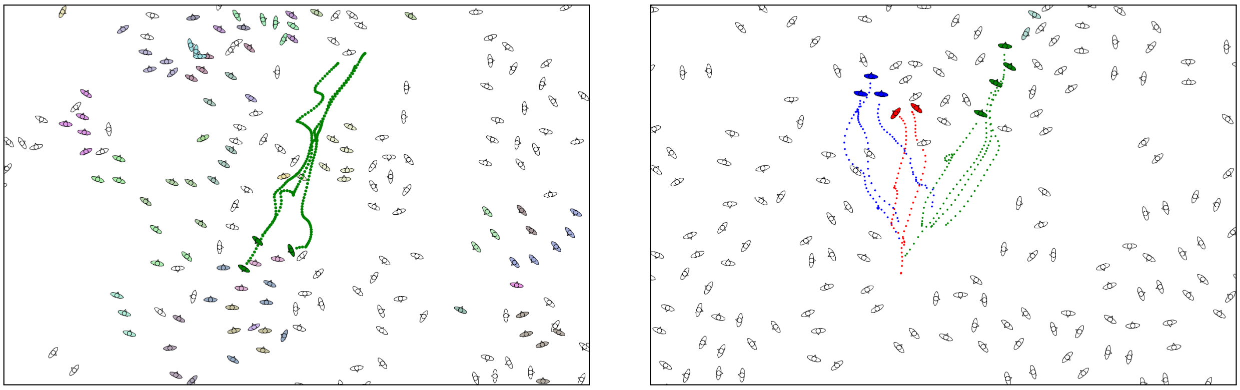
5.1. Data analysis

In Figure 3a we can observe a close-up snapshot (extract) of the simulation of the Monumental Tour in the Lisbon City Hall square, showing the paths of 3 members of a single group throughout several simulation cycles, as highlighted with dotted lines (one dot per cycle). These paths show an avoidance pattern to other pedestrians/groups, as we can observe accentuated velocity changes (value and direction) and a following cohesion pattern, showing the model's ability to describe these behaviors. The remaining pedestrian agents in the snapshot represent other moving groups (highlighted in light colors), and static pedestrians (in white), i.e., those who are socializing before leaving this public space.

Figure 3b shows another snapshot, where we can see three colored groups (of 2, 3, and 4 members, respectively) passing through static "socializing" pedestrians, also showing group cohesion and pedestrian maneuvering.

Table 3: SFM Model parameters and their assigned values for the simulations

Parameter	Description	Value
V0	Desired walking speed of a pedestrian	Group speed [m/s]
A_ped	The pedestrian repulsion strength parameter of the classic SFM	2.1
D_ped	The pedestrian range of repulsive forces parameter of the classic SFM	0.3 [m]
A_obs	The obstacle repulsion strength parameter of the classic SFM	10
D_obs	The obstacle range of repulsive forces parameter of the classic SFM	0.2 [m]
ped_influence_radius	The range within which a pedestrian exerts social forces	1 [m]
obs_influence_radius	The range within which an obstacle exerts social forces	5 [m]
Tr	The relaxation parameter of the classic SFM	0.5 [s]
shoulder_length	The shoulder width of the pedestrians	0.45 [m]
B_group_attr	The intra-group attraction strength parameter of the extended group SFM	10
B_group_rep	The intra-group repulsion strength parameter of the extended group SFM	1
group_rep_threshold	The range within which group members exert repulsive forces	0.65 [m]
group_attr_threshold	Distance from group center from which attractive forces occur (N=group size)	(N-1)/2



(a) Snapshot 1

(b) Snapshot 2

Figure 3: Simulation close-ups

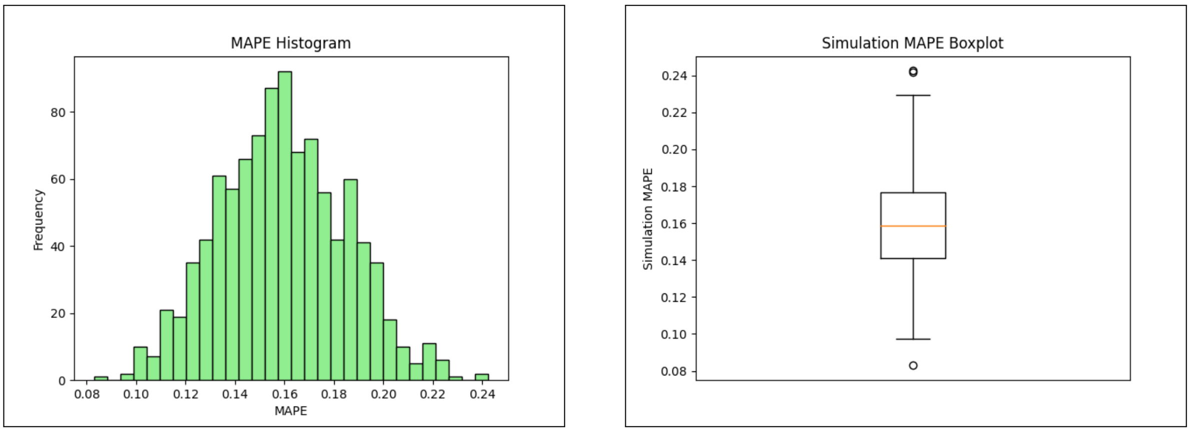
To account for the variability in simulation results due to model stochasticity, 1 000 simulations were run for the given scenario. For each simulation, we calculate the Mean Absolute Percentage Error (MAPE), supported by the Mean Absolute Error (MAE) of its obtained visitor count curve, using as ground truth the estimated cell phone data from LxDataLab to evaluate the model simulation accuracy.

The mobile network operator claims that the spatial accuracy of the detections is due to the triangulation of data from multiple cell towers. Since several cell towers cover the City Hall Square according to OpenCellID, an open database of cell towers, we expect the counting accuracy to be acceptable as a baseline.

Then, we analyzed the variability of the errors with a box plot. The mean of the simulation MAPEs is approximately $\overline{X_{MAPE}} = 0.16$, with a standard deviation of $s = 0.025$, which indicates a good fit with the cell phone data, accounting for the noise the data may have. The mean of the MAEs is approximately $\overline{X_{MAE}} = 127.76$, with a standard deviation of $s = 18.87$. Both errors have low relative variability, meaning the stochasticity of the model appears to not excessively affect simulation results.

Figure 4a shows the histogram of MAPE in the 1 000 simulations. We can observe a bell-shaped curve in the data with low apparent skewness, visually resembling a normal distribution. In Figure 4b, the box plot of MAPE in the 1000 simulations confirms distribution symmetry and the presence of minimal outliers.

To ascertain the normality of Mean Absolute Percentage Error (MAPE), a Kolmogorov-Smirnov (K-S) distribution adherence test was conducted. The test statistic yielded $D = 0.23$, with a two-tailed significance of $p = 0.2$. Consequently, there is no basis to reject the null hypothesis ($p > 0.2$), signifying statistical significance in accepting the normality of MAPE. This strengthens the confidence in the reliability of the simulation results and their adherence to the "ground truth" data.



(a) Histogram (30 bins)

(b) Box Plot

Figure 4: Mean Absolute Percentage Error (MAPE) in the 1000 simulations

Figure 5 depicts the obtained results in a graph, containing the 1 000 simulations (in grey), and the real cell phone count data (in blue). We can observe that most of the time the simulation lines sit below the ground truth line, meaning the model tends to underestimate people counts. This inaccuracy may derive from the social retention distribution, which could make the groups wait longer, the noise of the cell phone count data, and the nature of the event, as being an open space public event, there is less control over the pedestrian flows. We can see some spikes in the data, which could be derived from detection estimation errors, new people arriving at the City Hall square or using the open space to reach other destinations, making the cell phone count decrease slower than the simulated results, where the arrival of new people at the venue during the egress period is not considered.

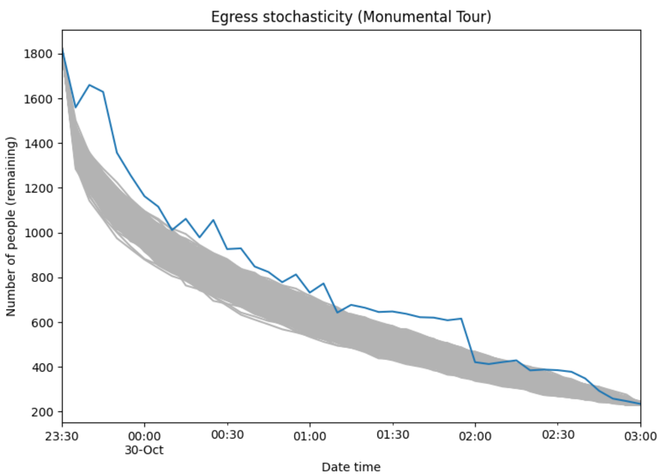


Figure 5: Simulation results VS cell phone data

Overall, the model showed a good fit with the cell phone data, given the obtained parameters, and a relatively low variability due to stochasticity, showing the plausibility of the model and selected parameters, and its possible utility in event management. The calibration of the model parameters could be further improved to obtain lower errors. A more comprehensive analysis of these events should be performed to understand new factors and dynamics to be described in the model.

5.2. Simulation performance

All simulations were deployed and run on an Ubuntu 20-04 (Linux) VM created on top of OpenStack, an open-source cloud computing platform used by INCD to provide computing and storage services to the Portuguese scientific community. The VM has 8 virtual CPUs and 128 GB of RAM, allowing it to run several parallel simulations with adequate memory allocated to each.

To test how execution time varies with the number of pedestrian agents, we measured the real-life time (in milliseconds) of the first cycle (after the initial model loading time) of isolated simulations (i.e., each simulation was running without other simultaneous simulations) with the same general scenario, but with different agent population sizes and maintaining a fixed group size of 4 and walking speed of 1.34 m/s [4]. In each simulation, the agent population size was set with a value ranging from 1 000 to 20 000 agents in increments of 1 000 (except between 15 000 and 20 000). With polynomial regression, using the *Trendline* feature from Microsoft Excel for curve-fitting analysis, we obtained the following approximated equation for the relationship between cycle time (T_{cycle}) and agent number (N_{agents}) in this scenario:

$$T_{cycle} = 0.000262N_{agents}^2 - 0.132912N_{agents} - 445.153406 \tag{2}$$

Other types of regressions were tested. Only polynomial and power regressions produced curves with a great fit (R-squared close to 1). We chose the polynomial regression with the least degrees (2) to better represent the data, as its R-squared ($R^2 = 0.999652$) was higher than the obtained power regression function ($R^2 = 0,998956$). The fitted power equation has a power of approximately 2.121193, suggesting a more-than-quadratic evolution. Figure 6 depicts a graph with the measurements collected from these simulations, and the estimated equation fitted for the data. We can observe a very close fitting with the available data points, suggesting an accelerated, non-linear positive evolution of the execution time in a single cycle with the number of agents.

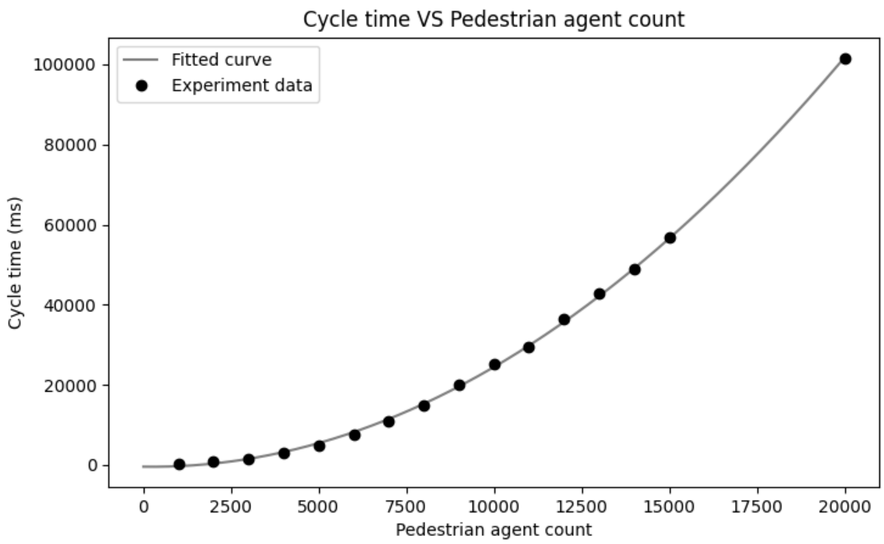


Figure 6: Relation between pedestrian agent count and simulation cycle time

The total execution time of a simulation may have an ever faster evolution with agent count, due to the possibility that a simulation with a massive number of agents needs considerably more cycles (e.g., due to pedestrian bottlenecks at exits) and that each cycle takes more time to complete, as suggested by the approximated curve, generating a compounding effect. For massive-scale simulations, the execution time would be impractically long for stakeholder participation.

The simulation speed is also shown to be affected by group size distribution and the execution time of simulations increased with the decrease in group size, despite egress times being similar. The rationale is that for a constant number of event participants, if we reduce group size, the number of groups is higher, causing an increase in group agents' computing time.

The available GAMA feature for parallel SFM computing for each agent was tried but did not increase performance significantly.

5.3. Validity threats

Models are, by definition, abstractions, and therefore do not convey all the details of reality. In our ABM we considered some simplifying assumptions that may be viewed as potential internal validity threats. We address each one separately.

The accuracy of used cell phone data may be flawed. Since we do not have access to raw cell phone tower data, we cannot control the accuracy of estimations. The used grid cells do not overlap perfectly with the simulated public open space, meaning that the obtained counts do not precisely represent the number of persons in the exact square limits. As such, counts should be considered as reference values, and not absolute values, so the results should only be considered by relative count patterns.

The possible spatial inaccuracy regarding cell phone count estimation can threaten the validity of models calibrated with it. To mitigate this issue, we can use and join other techniques to count people in public open space mass events, such as different types of sensors installed in strategic points in the area of the event (e.g., infrared sensors at exits/entrances to count people inflow and outflow, sensors to detect devices using short-range wireless communication technologies such as Wi-Fi and Bluetooth [9]) and video/image monitoring of open space events with computer vision head counting [6].

Our empirical evidence is that the distribution of group size can vary widely and also depend on the event type. For instance, an event targeted at families is likely to have an average group size smaller than an event for youngsters, like a hard-rock concert. More empirical studies are needed on the distribution of group sizes at different types of mass events in open public spaces.

Obtaining realistic weights for exits' attractivity may not be feasible, since that depends on multiple factors such as surrounding geographic distribution of demography, access to public transportation (and its timetable), exit visibility, knowledge of the surrounding space, subjective perception of corresponding crowding, to name a few. Probably the only mitigation action for this handicap will be defining extreme scenarios for each exit in the participatory discussions with stakeholders responsible for resource management.

The parameters for the group SFM component were calibrated iteratively based on the authors' perceptions of realistic groups' behavior. Again, more empirical studies on that behavior in mass events are sought.

Finally, pedestrian flow beyond the exits is not considered, being assumed as non-restricting to egress flow. Any constraints to the flow of pedestrians beyond the exits would influence the egress rates.

6. Conclusions and future work

The research presented in this paper is a continuation of our previous work [3], analyzing the egress time for multiple scenarios of crowd density in the urban public open space using a derived model for egress flow rates in exits, from the *Society of Fire Protection Engineers (SFPE) Handbook* [17], and [1]., where the initial version of the simulation model is introduced, without the implementation of group behavior.

In this paper, we present an ABM to simulate the non-emergency evacuation of pedestrians from mass events, taking into account the group behavior proposed in SFM, extended with the modeling of the social retention phenomenon.

Our ABM model was described using the ODD protocol to allow model transferability to other scenarios. Using the GAMA platform, we simulated the exit of 1595 pedestrians from the City Hall Square in Lisbon, mimicking the Monumental Tour event that occurred in this public open space. The model was face-validated and improved through a series of focus groups with experts, and calibrated with mobile phone data collected during the event, showing a good fit with real data.

Performance analysis of our model showed that simulation time grows non-linearly with the number of agents, making it infeasible for real-time stakeholder participation beyond a certain limit.

Since we aim to develop digital twinning models for extreme crowding situations, we need to generate simulations with a higher pedestrian density. However, the current setup is not efficient enough to obtain simulation results in a reasonable time. To mitigate this problem, we plan to improve algorithm efficiency by (i) exploring agent downscaling [2] or (ii) using GPU-enhanced ABM tools such as *FLAME GPU 2* [34]. The latter allows non-specialists in GPU programming to develop parallelized models, to increase concurrency in agent calculations.

A recent example of using the parallelized computing capabilities of GPUs to advance simulations at the scale of a real city, with high spatial and temporal resolution, is reported in [19]. Migrating our model to a GPU simulation platform poses several challenges due to the effort of (i) rewriting our model in a different language (currently coded in GAMA's GAML) with new parallelization and synchronization constructs, and (ii) implementing GIS primitives (readily available in GAMA).

To improve the realism of the ABM model and thus mitigate threats to its face validity (i.e., the perceived realism or plausibility of the model and its outputs), we plan to consider the more advanced group SFM algorithm presented in [16]. Further studies of non-emergency crowd evacuation conditions should be conducted to enable calibration of model parameters and to identify additional macroscopic and microscopic behaviors to be modeled in the agents. Other demographic variables, such as age distribution, will be included in future model iterations.

Another issue that deserves future work is the analysis of the influence of group size on the social retention phenomenon, as larger groups may lead to increased socialization among group members and with members of other groups.

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Appendix A. Model ODD protocol

Appendix A.1. Purpose and patterns

The purpose of the model is to simulate non-urgent egress of visitors from mass gathering events happening in real-life urban public open spaces (e.g., squares, plazas), evaluating the impact of different built environments, obstacle layouts, hypothetical exit-choosing behaviors of the visitors, social retention and crowd density scenarios and number of individuals in a social group in the egress patterns, the main emergent phenomenon obtained from the model. The model should aid decision-makers in choosing the appropriate public spaces for a specific event and deploy/release public utility teams (e.g., cleaning, emergency, and security) just in time. The patterns we believe our model must be able to reproduce are the following:

- **Pattern 1: Relation between built environment layout and egress times.** The layout of the obstacles and exits, total space geometry, the total available exit width, and the shape of the open space should affect egress rates. E.g., a closed environment with a single small exit should lead to larger egress times than the same environment, but with more, wider exits.
- **Pattern 2: Relation between exit choosing behavior and egress times.** Chaotic exit choosing should lead to higher egress times, as a greater number of collisions between erratic pedestrians should overall reduce the egress rates. Whereas, orderly behavior should minimize collisions, smoothing the flow of pedestrians toward the available exits.
- **Pattern 3: Relation between crowd density and egress times.** It is expected a significantly denser crowd egress from a built environment with less efficiency due to the increasingly expected collisions between pedestrians and bottlenecks at exits.
- **Pattern 4: Pedestrian collision avoidance** Pedestrians avoid bumping into other pedestrians and other obstacles, maintaining a certain distance between them and altering their routes to avoid them. This pattern is based on the Social Force Model by Helbing et al. [15]
- **Pattern 5: Group cohesion.** Members of a social group maintain spatial cohesion, i.e., maintain a certain proximity to each other. This pattern is based on group behavior studies [29, 16]
- **Pattern 6: Social retention.** Groups wait a random time at the event premises, after its end, to partake in intra and inter-group socialization, and nearby amenity usage (e.g., bars, kiosks, restrooms, clubs). This pattern is based on our observation of public open space mass events.

Patterns 1,2 and 3 are based on evacuation principles described in the *Society of Fire Protection Engineers (SFPE) Handbook* [17], which we believe can be observed in non-urgent egress as well.

Appendix A.2. Entities, state variables, and scales

Appendix A.2.1. Entities

4 entity types are partaking in this model: (i) the Model entity, (ii) environment entities, (iii) pedestrian agents, and (iv) group agents.

The Model entity only serves as an orchestrator of the domain entities, controlling the behavior of most agents as if the agents were autonomous. The use of this entity was chosen to test the parallelization features of the GAMA Platform.

The environment entities are composed of the GIS polygonal representations of the buildings that surround and delimit the open space, as well as the buildings inside the space (e.g., statues, monuments), the usable area of each public open space, which is modeled as a polygon enclosed by the surrounding buildings or borders with bodies of water (e.g., river boundaries, coast), where pedestrians will randomly spawn, and the exit geometries (or targets), which are modeled as polygons that cover the entrances to the exiting streets, bordering the open space polygons.

The pedestrian agents represent the visitors of the event, who egress from it. The group agents represent the social groups in which the pedestrians are organized (e.g., families, friends, work colleagues).

These were the chosen entities, as the model is intended to assess the impact of the interactions between these entities on egress patterns.

Appendix A.3. State variables

The environment entities are static and passive and serve as limits or targets for the pedestrian agents. Thus, the only state variables of these entities are their geometry configurations. In Table A.4, the state variables of the remaining entities are presented.

Table A.4: Model state variables

Entity	Variable	Description	Possible Values	Units
Pedestrian	speedX	The X-axis component of the instantaneous speed	-	m/s
	speedY	The Y-axis component of the instantaneous speed	-	m/s
	heading	The instantaneous angle of direction	-	degrees
	exit_target	The exit the pedestrian wants to reach	Environment entity (exit)	-
	location	The spatial location of the agent	Location point	-
Group	id	The identification of the group	-	-
	members	The list of members of the group	List of pedestrians	-
	centroid	The center of mass of the group	Location point	-
	social_time	The time a group takes to socialize	-	s

Appendix A.4. Scale

This ABM represents both space and time. The space is two-dimensional and finite and is represented on a continuous scale. The dimensions of the environment depend on the represented open space. The elementary unit of time represented in the model is 0.1 seconds, which is the value of the time step in a simulation cycle. The scales were chosen in a compromise between realism (the more continuous space and time are, the more realistic the model is) and simulation execution time.

Appendix A.5. Process overview and scheduling

The whole process and schedule are fairly simple. At the start of a simulation, the model agent initializes the environment geometries, groups, and pedestrians. After the spawn, at each simulation time step, the agents behave as follows:

1. The group agents execute the group submodel (in an undefined order), calculating their centroids and managing group member activity.
2. In an undefined order, the pedestrian agents execute the egress submodel, in which they move toward their chosen exits.
3. At each simulation second (10 steps), the model updates the output files with the number of remaining pedestrians in the simulation.

A simulation ends when the number of active pedestrians reaches a defined percentage of the number of spawned pedestrians.

Appendix A.6. Design concepts

Appendix A.6.1. Basic principles

The model is set over the concept of pedestrians attending mass gathering events in urban open spaces, and leaving the venue after the end of the event, without urgency. It appears this particular system has not been yet addressed in the state of the art. Some studies and ABM have been developed addressing egress flow dynamics similar to the ones described in the model, but represent a much smaller scale (usually room-scale), and different contexts [43]. At the agent level, the interactions between the crowd members follow the established Social Force Model (SFM) first presented by Helbing et. al. [15], extended with social group behavior in [29]. The social force models represent repulsive and attractive forces that act upon the psychology of the pedestrians, dictating an actual velocity to be chosen by a pedestrian, to avoid obstacles/other pedestrians and reach the desired destination. The social group extension adds group cohesion forces, as pedestrians from a group want to be close to each other [29]. As opposed to scenarios of evacuation, where the chosen exit will depend on multiple factors, such as panic states, distance to exit, etc., the egress in non-urgent scenarios will depend on the will of the pedestrians. Some may go to nearby bars, others may want to enter public transportation to return to their homes. This behavior is hard to predict due to a multitude of factors, and as such, the exit choice is modeled as a random process, weighted by the relative attractivity of exits (e.g., an exit that leads to more popular amenities, public transportation, or parking lots could have more attractivity; a less popular street will have less attractivity than a more popular one). The choice is made as a group, as it is assumed all members of a group want to go to the same location. The event visitors, instead of exiting the venue right after the event, may remain there, socializing and using local amenities. We coin this phenomenon "social retention".

The model tries to approximate reality by setting a continuous space, a fine-grained time scale, and the microscopic representation of all individual pedestrians.

Appendix A.6.2. Emergence

The main emergent phenomenon obtained from the model is the egress pattern, which is represented by the number of remaining pedestrians in the venue at each time step. It emerges from the interaction between the pedestrian agents, due to social forces, their spatial displacement towards the chosen exit, and social retention waiting times. The model does not include imposed results.

Appendix A.6.3. Adaptation

The pedestrian agents adapt their desired velocity during each step according to the social forces acting upon them, which come from the other neighboring agents. They also adapt when they encounter obstacles in their desired paths, walking around and avoiding them.

Appendix A.6.4. Objectives

The adaptation of the agents does not have clear decision-making objectives. The agents move towards the chosen exit or around an obstacle in their path to the exit.

Appendix A.6.5. Learning

Learning is not implemented in this model.

Appendix A.6.6. Prediction

Prediction is not implemented in this model.

Appendix A.6.7. Sensing

Each pedestrian agent senses its neighboring pedestrians, obstacles, and its group center of mass, evaluating their distance and calculates the acting social forces.

Appendix A.6.8. Interaction

The main interaction between agents is through the calculation of the social forces they apply to each other.

Appendix A.6.9. Stochasticity

The stochasticity is applied in this model in the processes of (i) pedestrian and group spawning, (ii) exit choosing, and (iii) group social retention time. The pedestrians are randomly clustered around their group centers (within a certain distance from the group center), which are randomly picked locations inside the open space polygon with uniform random distribution, the exits are chosen with weighted random distribution, where the weight is the exit's attractivity.

Appendix A.6.10. Collectives

The collectives implemented in the model are the pedestrians' social groups. The social groups are modeled as entities, as they keep track of group members and the group centroid (calculated each cycle). The pedestrians will use the state variables of their group agents for the motion submodel.

Appendix A.6.11. Observation

The only observed variables during and after the model are the count of the current pedestrians in the model (the ones who did not egress at a given time step), and the number of pedestrians who left at each time step, which are calculated dynamically by counting the agents.

Appendix A.7. Initialization

The model is intended to simulate multiple environmental and behavioral scenarios. Each scenario is defined in an experiment, which in GAMA represents an execution of a model, being initialized with key values to represent the scenario. The environment is built from shapefiles containing relevant geometries. For a given open space, 3 files must be passed as parameters to parameters are *buildings_file, targets_file, and start_ area_file* which represent the shapefiles with the geometries of, respectively, the surrounding and internal buildings of the open space, the geometries representing the available exits and the area in which the pedestrians will spawn.

The building geometries come from the OpenStreetMap (OSM) initiative, a volunteer-based mapping project to map the entire world, offering geographic data for free use. This data source was chosen due to its growing support, free-use data, and wide and detailed coverage of accurate geographical data across the world. The geometries of exit and start areas are created manually with the QGIS software, using as a reference the data from OSM. The exits must have a field called *id*, representing its identification number. The main model initialization parameters are the following:

- *nb_people* is an initialization parameter representing the number of pedestrians that will spawn in the simulation.
- *group_distribution_values* is a list containing the relative frequency a group size should be created (e.g., if a group size of 4 has 0.5, 50% of the total groups should have 4 elements). The sum of the values must be equal to 1.
- *exit_attractivity_values* is a list with the relative attractivity weights of every modeled exit (from 0 to 100), where the sum of the values must be equal to 100. The number of the position of the list element maps to the id of the exit (e.g., the first element of the list is the attractivity of the exit with id 1).
- *group_speed_values* is a list containing the group speeds for each group size.
- *egress_interval_period* represents the expected time for an event to be fully empty of visitors. This value should be determined by analyzing the type of event and its characteristics.

Based on the set values of *nb_people* and *group_distribution_values* at the start of the simulations, the number of groups is calculated. At the beginning of a simulation, for each obtained group, a group center location is randomly created to guarantee a uniform distribution across the environment area. The pedestrians who are members of a specific group are then spawned with two-dimensional random uniform distribution within a set distance to the center of their respective groups. The group members are then assigned to their group agents, having mutual access to each other. Then, all members of a group choose the same exit, randomly distributed by the weight of the chosen exit's attractivity. At last, the groups choose a random social retention time, based on random distributions, with values limited by the egress periods, both defined for the event type.

Appendix A.8. Input data

The model does not use input data to represent time-varying processes.

Appendix A.9. Submodels

The submodels in this model are implemented in the behavior of the pedestrian agents and group behavior. They consist of the (1) egress submodel and (2) group auxiliary submodel.

Appendix A.9.1. Egress submodel

This submodel describes the egress action of the pedestrians. They pursue the chosen exit for their group, moving through space until the desired exit is reached, avoiding strangers and obstacles, and maintaining group cohesion. The motion is implemented with adapted versions of the classic SFM by Helbing et. al [15], with an adaptation of the extension to adopt group behavior, presented by Moussaïd et al [29]. The implementations are based on the implementation found in the GitHub repository [1], adapted for the GAMA platform.

The parameters of this model are presented in Table A.5. The parameters for the classic SFM were set based on the simulations made in the original study [15]. The parameters for the group SFM component were chosen based on multiple simulations, until group behavior provided more realism, through discussion followed by group consensus among the authors. This *expert-panel* approach was required due to the lack of empirical studies for high-density group behavior. Further calibration of these parameters should be done in future work.

Table A.5: Egress submodel parameters

Parameter	Description	Unit
V0	Desired walking speed of a pedestrian	m/s
A_ped	The pedestrian repulsion strength parameter of the classic SFM	-
D_ped	The pedestrian range of repulsive forces parameter of the classic SFM	m
A_obs	The obstacle repulsion strength parameter of the classic SFM	-
D_obs	The obstacle range of repulsive forces parameter of the classic SFM	m
ped_influence_radius	The range within which a pedestrian exerts social forces	m
obs_influence_radius	The range within which an obstacle exerts social forces	m
Tr	The relaxation parameter of the classic SFM	s
shoulder_length	The shoulder width of the pedestrians	m
B_group_attr	The intra-group attraction strength parameter of the extended group SFM	-
B_group_rep	The intra-group repulsion strength parameter of the extended group SFM	-
group_rep_threshold	The range within which group members exert repulsive forces	m
group_attr_threshold	The distance from group center from which attractive forces occur	m

For each simulation cycle, the submodel for each pedestrian agent acts as follows:

1. If the simulation time has not passed the social retention time of the pedestrian's group, the pedestrian's speed is reduced to 0. The following behaviors still apply, as pedestrians must be able to move to make way for other pedestrians who want to egress.
2. The agent checks if there is an obstacle near enough, between the agent and its desired destination. If that happens, the heading becomes a perpendicular angle to the heading to the nearest point of the obstacle. The agent will then want to walk left or right of the obstacle. The agent goes to step 4.
3. The heading is calculated through the current instant speed components, using the *atan2* operation. If both speed components have a non-zero value, the heading is the angle toward the chosen exit.

$$heading = atan2(speedY, speedX) \tag{A.1}$$

Else, the heading is calculated through the direction vector between the pedestrian agent's location and the centroid of its desired destination using the *heading(from, to)* operation, where *from* is a location from where the heading points, and *to*, where the heading points to:

$$heading(from, to) = atan2(to.y - from.y, to.x - from.x) \tag{A.2}$$

In steps 2,3, and 4, all the forces acting upon the pedestrian will be calculated. The X and Y components of the forces are summed in variables *sum_forces_X* and *sum_forces_Y*, respectively.

[1] urlhttps://github.com/chraibi/SocialForceModel

4. The pedestrian agent obtains its group's centroid from the respective entity. Using the centroid, if the agent's distance to the centroid is more than the defined group attraction threshold, the pedestrian calculates the group cohesion force components using the following equations:

$$groupAttrForceX = B\_group\_attr \times cos(heading(self, centroid))\times \\ (1 - sin(heading(self, centroid) - heading))) \tag{A.3}$$

$$groupAttrForceY = B\_group\_attr \times sin(heading(self, centroid))\times \\ (1 - sin(heading(self, centroid) - heading))) \tag{A.4}$$

5. The pedestrian queries its neighbors, considering the influence radius, and for each one: If the neighbor pedestrian is a member of its group, and the distance between the agent and the neighbors is less than the group repulsion threshold, the group collision avoidance forces are calculated using the equation:

$$groupRepForceX = B\_group\_rep \times cos(heading(neighbor, self))\times \\ (1 - sin(heading(neighbor, self) - heading))) \tag{A.5}$$

$$groupRepForceY = B\_group\_rep \times sin(heading(neighbor, self))\times \\ (1 - sin(heading(neighbor, self) - heading))) \tag{A.6}$$

Else, if a neighbor pedestrian is not part of the agent's group, the repulsive forces from the classic SFM are calculated with the equations:

$$pedRepForceX = A\_ped \times e^{(shoulder\_length - distance(self, obstacle))/D\_ped}\times \\ cos(heading(neighbor, self)) \times (1 - sin(heading(neighbor, self) - heading))) \tag{A.7}$$

$$pedRepForceY = A\_ped \times e^{(shoulder\_length - distance(self, obstacle))/D\_ped}\times \\ sin(heading(neighbor, self)) \times (1 - sin(heading(neighbor, self) - heading))) \tag{A.8}$$

6. The repulsive force components from the neighboring obstacles within the obstacle influence radius are calculated, using the equations:

$$obsRepForceX = A\_obs \times e^{(shoulder\_length - distance(self, obstacle))/D\_ped}\times \\ cos(heading(obstacle, self)) \times (1 - sin(heading(obstacle, self) - heading))) \tag{A.9}$$

$$obsRepForceY = A\_obs \times e^{(shoulder\_length - distance(self, obstacle))/D\_ped}\times \\ sin(heading(obstacle, self)) \times (1 - sin(heading(obstacle, self) - heading))) \tag{A.10}$$

7. Having the total sums of the X and Y force components, the instantaneous speed components are calculated as follows:

$$speedX = speedX + step \times (sum\_forces\_x + (V0 \times cos(hd) - speedX)/Tr) \tag{A.11}$$

$$speedY = speedY + step \times (sum\_forces\_y + (V0 \times sin(hd) - speedY)/Tr) \tag{A.12}$$

8. Having the speed components, the pedestrian tries to move, obtaining its next location:

$$next\_location = (location.x + speedX \times step, location.y + speedY \times step) \tag{A.13}$$

If the next position is valid, the agent's position is set as that position. Otherwise, the agent does not move, and both speed components are set to 0. If the next position is inside the agent's desired exit, it is removed from the simulation, else, the submodel repeats for the agent.

Appendix A.9.2. Group submodel

This submodel consists in updating the group characteristics each cycle, according to the locations and behaviors of pedestrians. After the group and pedestrian initialization, at each cycle, a group agent behaves as follows:

1. The group agent checks if a group member has left the simulation. If that happens, it is removed from the group's list of members.
2. The agent calculates the group's centroid based on all its members' current positions.
3. If there are no members left, the group agent is removed from the simulation. Else, return to step 1.