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Studying the Impact of Trained Staff on Evacuation Scenarios by Agent-Based Simulation

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Abstract. Human evacuation experiments can trigger distress, be unethical and present high costs. As a solution, computer simulations can predict the effectiveness of new emergency management procedures. This paper applies multi-agent simulation to measure the influence of staff members with diverse training levels on evacuation time. A previously developed and validated model was extended with explicit mechanisms to simulate staff members helping people to egress. The majority of parameter settings have been based on empirical data acquired in earlier studies. Therefore, simulation results are expected to be realistic. Results show that staff are more effective in complex environments, especially when trained. Not only specialised security professionals but, especially, regular workers of shopping facilities and offices play a significant role in evacuation processes when adequately trained. These results can inform policy makers and crowd managers on new emergency management procedures.

Keywords: Crowd Management, Evacuation, Agent-based model, Staff.

1 Introduction

Crowd incidents show the importance of well trained staff being present during evacuations. From past incidents it becomes clear that staff members need to communicate to the crowd what is happening as well as manage the directions and density of the crowd. The 1968 crowd crush disaster in Buenos Aires[1] was mainly due to the absence of clear exit signage and stewards to guide the public to the correct exit. It was unclear for people where the entry and exit points were. People moved towards exit gates that were closed, leading to 74 fatalities and 150 injured. In 1999, 54 people died, and 150 people injured in a crowd crush in a station in Minsk, Belarus[2]. More than 1000 people rushed inside the station tunnel to find cover from a thunderstorm. There was not enough staff present to manage the people entering the station. They had no information

[1] https://www.cbsnews.com/news/major-soccer-stadium-disasters/
[2] http://news.bbc.co.uk/1/hi/world/europe/356828.stm

on what was happening further down the tunnel, where people had been trampled. Two policemen that tried to manage the crowd died. The 2003 tragedy in the Station Nightclub in Rhode Island, USA, is also partly due to untrained staff[3]. Bar staff or managers should have stopped the band playing during the fireworks. Most people taking the familiar route to the entrance, this resulted in people getting stuck in the entrance. 100 people died in the fire.

As illustrated by these scenarios, staff members play a critical role in successfully evacuating a crowd during incidents. Moreover, in addition to regular security personnel and crowd managers, also other staff members such as bartenders, hostesses and food sellers may be crucial. In different environments, the same person can show different behaviours during a fire [1]. For example, when a fire in one's own house appears, the person most likely evacuates immediately or tries to stop the fire. When this person is in a shop or other public building, the person will expect the management of this building to be responsible for evacuation and initiating it [2]. Another explanation is that these non-security staff members know the environment, and most likely know what to do [3]. Be it security personnel or other staff, the fact is that staff members are not always well trained for evacuation and crowd management. This is partly because of responsibility, but also because of the excessive costs and practical difficulties associated with evacuation training.

In [4, 5] the authors analyse the regular staff behaviour (workers of stores) in five unannounced evacuations of Marks and Spencer retail stores. The client`s store started to evacuate on average 30.3 seconds after the alarm and the call to evacuate had been activated. The most notable of this case are the standard deviations ranging from 1 to 100 seconds among the population to start to evacuate. Results showed that regular staff behaviour is crucial to start the evacuation and inappropriate staff response could even induce long evacuation delays. A further study inspected the pre-movement times across 4 of the same stores [3]. It found a mean pre-movement time range from 25 to 37 seconds with standard deviations ranging from 13 to 19 seconds. Still, that time range is considerably less than the recognition times quoted in the British fire safety norm BSI DD240. The paper concludes that training staff should not be underestimated. Different incidents are reviewed and compared in [5]. In one of the cases, a fire in Japan took only 10 minutes to cover an entire floor, which indicates the importance of a fast evacuation. According to [6], the staff have a flagrant influence on the dynamics of an evacuation in many cases, as they have the power to calm down the population. Similarly, Vries et al. [7] suggest that the words said, attitude, and behaviour of employees transmit a sense of safety to a crowd.

As human evacuation experiments can trigger distress, be unethical and present high costs, computer simulations can be a solution to determine the effectiveness of new emergency management procedures. Few evacuation models consider social aspects in evacuations and almost none include staff members instructing evacuees. The ASCRIBE model [8] represents crowd members as agents that possess a number of static personality characteristics (openness and expressiveness) as well as dynamic mental states (beliefs, intentions and emotions). The ESCAPES model [9] also features

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3 https://en.wikipedia.org/wiki/The_Station_nightclub_fire

mechanisms to represent the mental states of agents, as well as their interactions. In contrast to ASCRIBE, the authors in [22] do study the role of security personnel. Their agents are modelled by giving them a low 'FearFactor' and a high 'calming effect' on other agents. A similar, but slightly different system for crowd simulation is MACES [10]. Within MACES, agents have different stress levels, where high levels of stress may result in more difficulty to orient oneself quickly. Different agent roles are explored, such as trained leaders, untrained leaders and untrained non-leaders. The authors conclude that communication is a key factor to a success evacuation.

In this research, we build upon the results discussed in these papers by studying the effect of *communication skills* of security personnel on evacuation time. The presence of calm authorities in the environment has a contagious effect on the population, and it is well known that not running reduces the evacuation time due to fewer falls and less congestion at the exits [11, 12]. As perceived in the situations described above, we observe relevant aspects shared by incidents that are 1) Every minute is important to a successful evacuation; 2) The staff influences the decision to start to evacuate; 3) Even with most people evacuating voluntarily in a brief period of time, part of them still remain in the environment, delaying the decision to evacuate. Those people should be the target to an efficient evacuation.

Indeed, the current paper is part of a larger project that aims to develop a simulation-based system to train staff members in how to act in stressful circumstances [13]. The emphasis is on adequate communicative skills, e.g., how to quickly convince passers-by that (and how) they have to evacuate from a burning building without making them more stressed. Our expectation is that having more and better trained personnel generally results in more efficient evacuation procedures. However, the extent to which this will be the case and the precise circumstances in which trained staff members are beneficial are hard to predict without actually testing this in real scenarios. As a solution, *agent-based simulation* is used in this research to better understand the impact of trained staff on evacuation scenarios.

The main research question is what is the effect of the level of training of staff members on the evacuation time in environments that differ in complexity? To answer this question, we chose an existing crowd simulation model[4] [14–16] and extended it by explicitly incorporating the role of staff members with different levels of training. By systematically varying the model's parameters and running simulations, the impact of staff training on evacuation time can be determined. The remainder of this paper is structured as follows. Section 2 describes the used model while Section 3 presents results of the simulations. Section 4 concludes the paper with a discussion.

2 Model Description

The evacuation dynamics were modelled using an agent-based model with the beliefs-desires-intentions paradigm [17] and a temporal-causal network modelling approach approach [18]. Fig. 8 of Appendix shows a representation of the internal decision

[4] Source code available to download in: (removed due to blind review)

process of an individual, his (or her) actions and the external factors that influence his beliefs, desires and intentions. Each node has a value between 0 and 1 and represents a characteristic, action or external stimulus. The oriented arrows indicate how one or several nodes influence other nodes at each simulation step. Each arrow has a weight that regulates its contribution in a node input. Some nodes have fixed values e.g.: 'Gender' is 0 or 1, indicating the gender of the agent. Others have formulas which combine the input signals to generate a new node output transmitted to following nodes. Details of connection weights and node formulas are described in our previous work [14]. The model was validated against a complex benchmark named Exodus[5].

The results are close to expected by the benchmark, see [19] for more details. The actions of the agents are described in Table 1 of Appendix. The internal states can be divided in beliefs, intents and intermediate states among beliefs, intentions and actions. The familiarity node represents the agent's beliefs about the environment. It is binary, either the agent knows the environment or not. If it is familiar with the environment, then it always takes the nearest exit. If it is not familiar, it will trace a route to the main exit after it decides to evacuate. In the midway of its position and the main exit, it can be convinced by a staff agent to follow him to the nearest exit. The intention to evacuate depends on the *belief of danger*, which is directly linked to observations from the external world. The *fear belief* is a combination between external stimuli and feedback loops of *desire to evacuate* and *desire to walk randomly*. These last two states compete with each other. They inversely drive the two intention states. Other cultural factors like nationality, compliance, age and gender impacts on several internal nodes and they define the individual personality of each agent. Observation states link external events with the internal model and they are part of the personality. The weights of the links connecting these states give more importance to external events when they are set close to 1 or less importance when set close to 0. All these factors are considered because of their importance in the incident scenarios. Parameters like speed range of males, females, children and elders; nationality, compliance and fall rate are set according to technical specifications, see [14] for more details. The external stimuli of each agent are described in Table 2 of Appendix.

An agent can observe the instructions of one or more staff members several times, as described at the end of this section. It always has the option to either accept the staff suggestion or not. Together with other nodes, the *obs_staff_instr* node is directly linked to the *action_movetoexit* node. The *action_movetoexit* is a combination of the speed of the passenger and his target: one of the exits. The value of the intention to evacuate influences the speed of moving to the exit. The familiarity, observation of staff instructions, and the public announcement influences the choice of exit [20]. The *obs_staff_instr* is either 0 or 1. If the agent observes a staff agent, then it has a chance of accepting the staff instruction, activating the *obs_staff_instr* node. As described in Section 1, staff members influence the decision of customers or visitors on delaying their evacuation or not. In [3] and [4], the authors refer to regular workers of stores and how their posture is reflected in the clients' attitudes during emergency scenarios. In terms of modelling, we consider two staff types: Authorities specialised in security ($Staff_{sec}$), which

[5] http://fseg.gre.ac.uk/exodus/index.html

have at least some training on how to manage incidents. In the most cases, they are in lower quantity, not sufficient to cover all areas. On the other hand, store, service and office workers ($Staff_{wor}$) are present in most parts of an environment but, in general, do not are regularly training to deal with incidents. Both walk randomly and have the same effect on the agents (people), which is to convince them to evacuate. The only differences between them are the quantity and ability to convince people to evacuate. We consider $Staff_{sec}$ agents with initial training skills of between 0.5 and a maximum of 1, while $Staff_{wor}$ training skills range from 0 to a maximum of 0.5. The relation among normal agents (clients, audience, passengers, etc.) and staff agents is modelled into the connection between *staff_instr* and *obs_staff_instr* nodes. It considers the quantity of staff agents in the observable distance of a regular agent and the ability of a staff agent to convince regular agents to evacuate. If a regular agent is convinced, then it keeps the desire to evacuate until the end of the simulation.

3 Experiments

3.1 Methodology

With the use of a validated evacuation model that includes social elements, our experiments aim to determine the effect of the number and type of staff members on the evacuation process and time.

Measurements: The average evacuation time and the assembly area rate will be measured as indications of the effect of the staff members. The average evacuation time refers to the average egress time of the agents since the incident has started until the last agent has egressed. The assembly area rate is the measurement of agents that reach one of the zones close to the exits. This measurement is a complement measurement to avoid distortions injected by the limited egress capacity of the exit doors.

Environment: In order to isolate the social effect of staff on the population, we selected two variations of neutral scenarios already used in our previous works [14–16]. The first is a square room without walls. The second environment adds two barriers separating the room in 3 parts, occulting the incident of people placed on 2 of the 3 areas of the room. Both rooms are $400m^2$ and have one main exit that everybody knows and one secondary exit that only the agents familiar with the environment know. The doors are 4 metres wide. The incident is randomly placed around the centre of the room, between the walls and the assembly areas and has a fixed size of $8m^2$ (2% of the room size). Fig. 1 shows the two environments.

Variables: The density varies in 2 and 4 people per square metres. Both staff and people are randomly distributed. The $Staff_{wor}$ skills in managing incidents varies in steps of 25% from 0% to 50%, while, $Staff_{sec}$ varies in steps of 25% from 50% to 100%. These values come from an existing paper on the use of serious games for training [21]. The incident is identified as a red square of fixed size randomly placed on the middle of the room and between the assembly areas.

All other parameters remain fixed: (a) contagion model, public announcement, fire alarm, helping and falling behaviours are enabled, (b) the percentage of males and females is 50%, percentage of children and elderly is 15%, percentage of people alone is

50%, while the other half of the population is divided in groups of 2, 3 and 4 people and divided in 33%, 33% and 34% respectively of the people who are in groups, (c) the cultural distributions are divided evenly. For more details about these social parameters, see Section 1.3 of [14].

Quantity of simulations: For each experiment, the minimum number of repetitions is defined by the equation $n \geq [(100 \cdot Z \cdot s)/(r \cdot \bar{x})]^2 = 63.70$. This number is rounded up to 65 in order to guarantee that the error in each outcome result is within 5% of the maximum error with 95% of confidence. Z = confidence interval of 95%→1.96; s = standard deviation = 63.55; r = max. error of 5%; $\bar{x}$ = avg. evacuation time of 100 samples = 312.11. The results represent the average of these runs [22].

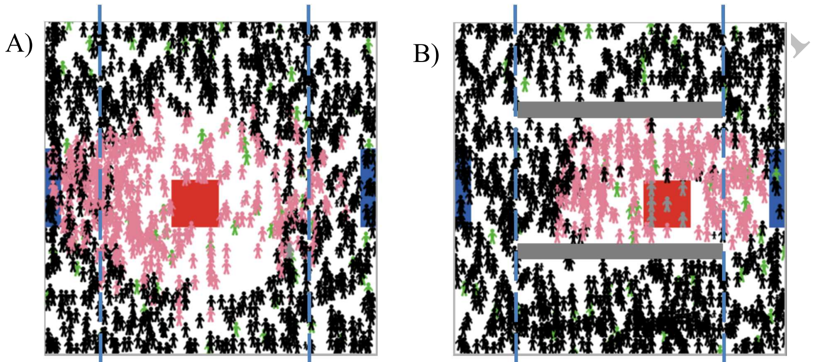

Fig. 1. Layout of rooms. Fig. 1A without walls and Fig. 1B with 2 walls in grey. The assembly areas are between the dashed lines and the exit doors in blue. The incident is in red; agents in pink are evacuating; in black are those still not aware; grey are casualties and staff is green.

3.2 Experiment A – Effect of Staff$_{wor}$ in a Square room without walls

The experimental design to determine the effect of Staff$_{wor}$ in a neutral scenario varies the following parameters: Crowd Density = 2, 4; Number of staff$_{wor}$ = 0, 8, 16, 32, 64 and staff$_{sec}$ = 0; Skills ability of staff$_{wor}$ = 0%, 25%, 50%.

The graphs A and B of Fig. 2 show the influence of Staff$_{wor}$ on evacuation time in an open room. While, there is no influence of Staff$_{wor}$ on the time to reach the assembly area, the final evacuation time is significantly reduced (more than 1 minute) when #staff$_{wor}$ ≥ 32. The reason for a low influence of Staff$_{wor}$ on reaching the assembly areas is that in an open space it is easy and fast for regular agents to see the incident and affect others with their fear. As many regular agents are observing the incident, the social influence is big and the impact of Staff$_{wor}$ is only a small added factor.

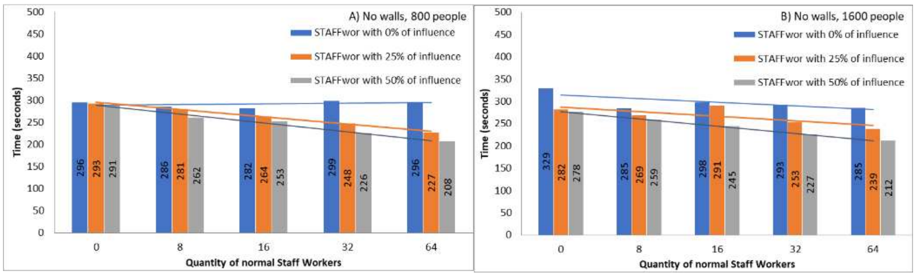

Fig. 2. Average evacuation time of agents and trend lines. No Walls room with $\text{Staff}_{\text{wor}}$

Nevertheless, the $\text{Staff}_{\text{wor}}$ still play a role, guiding other agents to the nearest exit, reducing the bottleneck of the main exit door and influencing the final evacuation time. As shown in Fig. 2, the more $\text{Staff}_{\text{wor}}$, the better the results. Furthermore, when there is almost no one in the room, but only a few regular agents, the $\text{Staff}_{\text{wor}}$ speed up the evacuation of those last agents, convincing them to escape. That is not the case in simulations without the intervention of $\text{Staff}_{\text{wor}}$. Those few regular agents take more time to evacuate because they do not have many more agents to share information (fear) with and, in most cases, the only possibility of evacuating is when they observe the incident by themselves. This behaviour matches with what is summarized in item 3) of Section 1. Another important pattern is the regularity in the evacuation time injected by $\text{Staff}_{\text{wor}}$. In all cases and subsequent experiments, increasing the number of staff and their skills leads to a lower standard deviation (σ), for the average evacuation times. To cite an example, in the experiment of Fig. 2, from $\#\text{Staff}_{\text{wor}} = 0$ to $\#\text{Staff}_{\text{wor}} = 64$, σ is respectively 42, 38, 30, 22 and 17. Hence, staff promotes order, and predictability on results, even with variations on agents and incident positions.

3.3 Experiment B – Effect of $\text{Staff}_{\text{sec}}$ in a Square room without walls

The experimental design to determine the effect of $\text{Staff}_{\text{sec}}$ in a neutral scenario varies the following parameters: Crowd Density = 2, 4; Number of $\text{staff}_{\text{wor}} = 0$ and $\text{staff}_{\text{sec}} = 0$, 2, 4, 8, 16; Skills ability of $\text{staff}_{\text{sec}}$ = 50%, 75%, 100%. The results in Fig. 3 reflect the same behaviours of Section 3.2 with less intensity, mostly because of the number of $\text{Staff}_{\text{sec}}$. Apparently, the number of $\text{Staff}_{\text{sec}}$ is insufficient to deal with the quantity of agents. The effect of the $\text{Staff}_{\text{sec}}$ is surrounded by the amount of social influence among the regular agents.

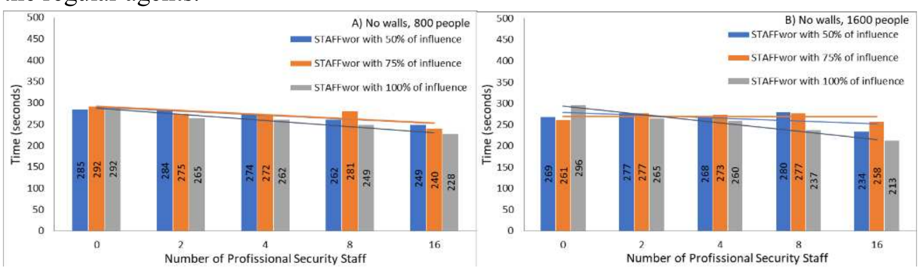

Fig. 3. Average evacuation time of agents and trend lines. No Walls room with $\text{Staff}_{\text{sec}}$

3.4 Experiment C – Effect of Staff$_{wor}$ in a Square room with division walls

Experiment C follows the design of Experiment A. It measures the effect of Staff$_{wor}$ in a neutral scenario with barriers dividing the environment in 3 parts. The walls make the environment more complex, the social influence among the regular agents reduces. In this scenario, 2/3 of them cannot easily see the incident and get in contact with others beyond the wall. Assembly area rates and evacuation times increase comparing to the results with and without Staff$_{wor}$. Increasing the quantity of Staff$_{wor}$ results in a reduction of the evacuation time and assembly area time. Moreover, the effects are clear when skills are set to 50%. Comparing Fig. 4A with Fig. 4B and Fig. 5A with Fig. 5B, the number of staff per people also has a significant impact on reducing the evacuation and assembly area times. That fact indicates again that the quantity of staff influences the results, which also occurred in Experiment B (Section 3.3). According to Fig. 4, 32 or more Staff$_{wor}$ reduce the final evacuation time by more than a minute, which is a significant achievement for managing incidents, as cited in item 1) of Section 1.

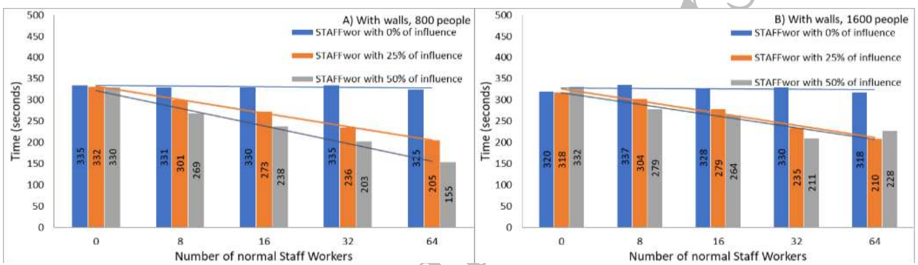

Fig. 4. Average evacuation time of agents and trend lines. No Walls room with Staff$_{wor}$.

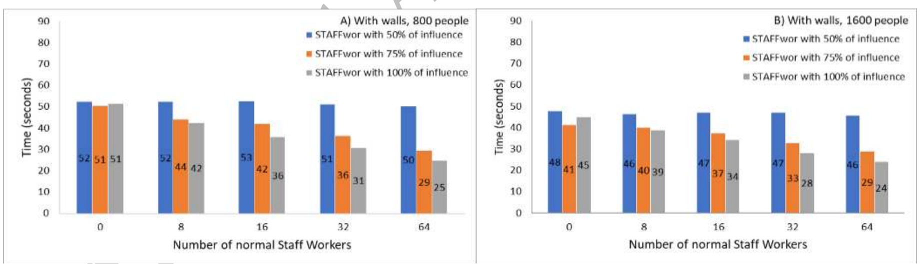

Fig. 5. Average assembly area time of agents. No Walls room with Staff$_{wor}$.

3.5 Experiment D – Effect of Staff$_{sec}$ in a Square room with division walls

Experiment D follows the design of Experiment B. It measures the effect of Staff$_{sec}$ in a neutral scenario. Similar to Experiment B, Fig. 6 and Fig. 7 show a clear influence of Staff$_{sec}$ in reducing the average evacuation time. The same effect is observed to egress time when comparing the results to the room without walls in the same conditions, despite the lower effect when compared with Experiment C. Again, the quantity of Staff$_{sec}$ is a dominant factor to limit the influence of Staff$_{sec}$.

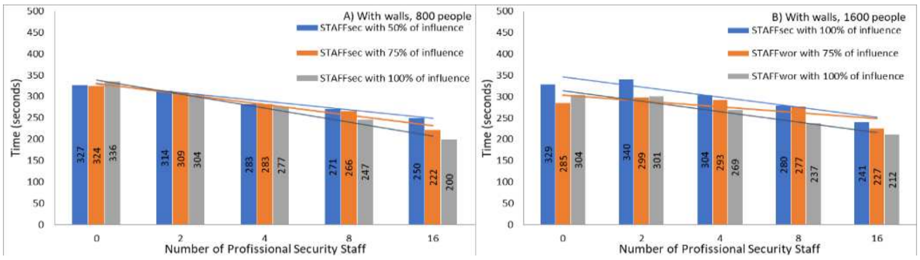

Fig. 6. Average evacuation time of agents and trend lines. No Walls room with Staff_{sec}

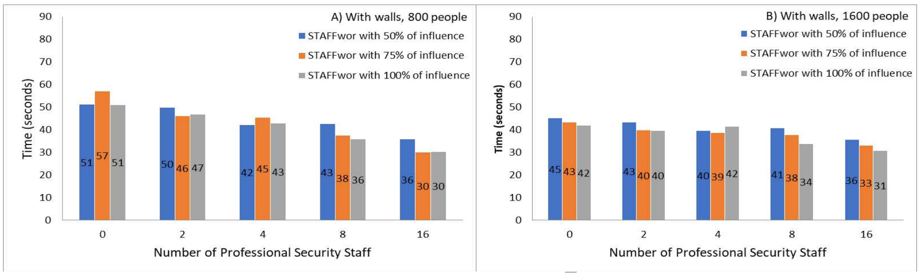

Fig. 7. Average assembly area time of agents. No Walls room with Staff_{sec}

4 Discussion

In this paper, multi-agent based simulation was applied to study the effect of different training levels of staff members on the evacuation time in environments that differ in complexity. To this end, a previously developed (and validated) crowd simulation model was taken as point of departure [14–16], and was extended with explicit mechanisms to simulate staff members that guide passers-by to the nearest exit. By manipulating a parameter for 'skills', we could simulate a range of different types of staff members, varying from 'regular' staff members that have not received much training to well-trained security personnel or staff members.

The simulations results showed several interesting findings. For instance, presence of staff has more effect in more complex environments. The average evacuation time and average assembly area time could be reduced mainly by increasing the number of staff placed at strategic locations in the environment, but also by using (a smaller number of) better trained staff members. Although these findings may not be extremely surprising by themselves, the added value of the current simulation model is that we are now able to explain in more detail why they occur and predict in which hypothetical circumstances they occur. Since the majority of parameter settings have been based on empirical data acquired in an earlier study, the resulting simulations are expected to be reasonably realistic. If the model is applied to real-life scenarios, it can provide rough indications of the added value of training staff member, thus serving as a decision support tool for investments in training staff.

Nevertheless, there is room for a more extensive validation of the simulation model. As soon as more empirical data about evacuation scenarios and the role of staff members becomes available, such a validation could be performed. Another interesting direction for future research is to conduct an experiment to explicitly test the impact of staff members who have worked with our training system [13] in the context of an evacuation experiment or drill in a controlled environment.

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Appendix

Table 1. Description of individual actions of each agent in a simulation.

Action	Description
Fall (enabled)	The agent falls and remains stopped for a certain amount of time. Falls are a consequence of speed, age and crowd congestion.
Die	If the agent is at the same place where the incident occurs, it dies.
Express belief of danger	The agent expresses its dangerous belief level to other agents.
Express fear	The agent shows its fear level to other agents around him.
Walk	Agent strolls randomly in the environment until it decides to evacuate.
Help	An agent can help other fallen agents. The decision depends on its own gender, age and that of the fallen person, and if the agent is part of a group.
Evacuate	Evacuation is directly related with the intention to evacuate which is influence by its fear level and belief of danger.

Table 2. Description of external stimuli of each agent.

Input	Description
Crowd congestion location	The number of agents and their speed depending on the number of agents within the same square metre:≤4 people (no speed reduction), 5 people 62.5%, 6 people 75%, 7 people 82.5%, 8 people 95% [23].
Fire location	If the agent observes the incident it changes its belief of dangerous.
Alarm	Is 'on' after three minutes of the simulation. Then all agents are aware that something unusual is happening. Some agents start to evacuate immediately, others take more time to be convinced about the danger.
Others belief dangerous	The beliefs of danger of all agents in the vision range.
Others fear	The fear sensations of all agents in the vision range.
Public announcement	Is 'on' one minute after the alarm is 'on'.
Staff instructions	Agent receives instructions from staff member in its observable range.

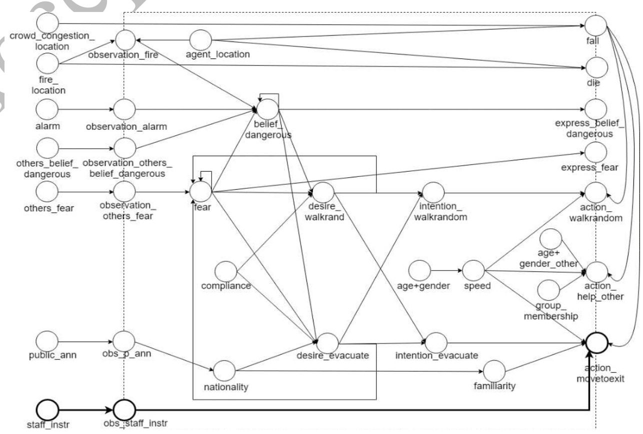

Fig. 8. Graphical conceptual representation of the internal model of a regular agent

5 References

1. Canter, D.V.: Fires and human behaviour. John Wiley & Sons (1980)
2. Proulx, G.: How to initiate evacuation movement in public buildings. Facilities. 17, 331–335 (1999)
3. Samochine, D., Boyce, K., Shields, T.: An Investigation Into Staff Behaviour In Unannounced Evacuations Of Retail Stores - Implications For Training And Fire Safety Engineering. Fire Safety Science. 8, 519–530 (2005). doi:10.3801/IAFSS.FSS.8-519
4. Shields, T.., Boyce, K..: A study of evacuation from large retail stores. Fire Safety Journal. 35, 25–49 (2000). doi:10.1016/S0379-7112(00)00013-8
5. Gwynne, S.M.V., Purser, D., Boswell, D.L.: Pre-Warning Staff Delay: A Forgotten Component in ASET/RSET Calculations. In: Peacock, R.D., Kuligowski, E.D., and Averill, J.D. (eds.) Pedestrian and Evacuation Dynamics. pp. 243–253. Springer US, Boston, MA (2011)
6. Smith, C.A., Ellsworth, P.C.: Patterns of cognitive appraisal in emotion. Journal of personality and social psychology. 48, 813 (1985)
7. de Vries, P.W., Galetzka, M., Gutteling, J.M.: Inzet communicatie bij crowd management en crowd control. Universiteit Twente-Faculteit Gedragswetenschappen (2013)
8. Bosse, T., Hoogendoorn, M., Klein, M.C.A., Treur, J., van der Wal, C.N., van Wissen, A.: Modelling collective decision making in groups and crowds: Integrating social contagion and interacting emotions, beliefs and intentions. Autonomous Agents and Multi-Agent Systems. 27, 52–84 (2013). doi:10.1007/s10458-012-9201-1
9. Tsai, J., Fridman, N., Bowring, E., Brown, M., Epstein, S., Kaminka, G., Marsella, S., Ogden, A., Rika, I., Sheel, A., Taylor, M.E., Wang, X., Zilka, A., Tambe, M.: ESCAPES - Evacuation Simulation with Children, Authorities, Parents, Emotions, and Social comparison. 8 (2011)
10. Pelechano, N., O'Brien, K., Silverman, B., Badler, N.: Crowd simulation incorporating agent psychological models, roles and communication. First International Workshop on Crowd Simulation. 21–30 (2005)
11. Helbing, D., Johansson, A.: Pedestrian, crowd and evacuation dynamics. In: Encyclopedia of complexity and systems science. pp. 6476–6495. Springer (2009)
12. Santos, G., Aguirre, B.E.: A critical review of emergency evacuation simulation models. (2004)
13. Bosse, T., Gerritsen, C., de Man, J.: An Intelligent System for Aggression De-Escalation Training. In: ECAI. pp. 1805–1811 (2016)
14. van der Wal, C.N., Formolo, D., Robinson, M.A., Minkov, M., Bosse, T.: Simulating crowd evacuation with socio-cultural, cognitive, and emotional elements. In: Transactions on Computational Collective Intelligence XXVII. pp. 139–177. Springer (2017)

15. Formolo, D., van der Wal, C.N.: An Adaptive Simulation Tool for Evacuation Scenarios. In: Portuguese Conference on Artificial Intelligence. pp. 766–777. Springer (2017)
16. van der Wal, C.N., Formolo, D., Bosse, T.: An agent-based evacuation model with social contagion mechanisms and cultural factors. In: International Conference on Industrial, Engineering and Other Applications of Applied Intelligent Systems. pp. 620–627. Springer (2017)
17. Rao, A.S., Georgeff, M.P., others: BDI agents: from theory to practice. In: ICMAS. pp. 312–319 (1995)
18. Treur, J.: Network-Oriented Modeling. Springer International Publishing, Cham (2016)
19. Formolo, D., van der Wal, C.N.: Simulating collective evacuations with social elements. In: Conference on Computational Collective Intelligence Technologies and Applications. pp. 160–171. Springer (2017)
20. Challenger, R., Clegg, C.W., Robinson, M.: Understanding crowd behaviours: Practical guidance and lessons identified. TSO (2010)
21. Bosse, T., Gerritsen, C., de Man, J.: Evaluation of a virtual training environment for aggression de-escalation. In: Proceedings of Game-On. pp. 48–58 (2015)
22. Kotrlik, J., Higgins, C.: Organizational research: Determining appropriate sample size in survey research appropriate sample size in survey research. Information technology, learning, and performance journal. 19, 43 (2001)
23. Still, G.K.: Introduction to crowd science. CRC Press (2014)