Understanding the Role of Emotions in Group Dynamics in Emergency Situations

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Abstract. Decision making under stressful circumstances, e.g., during evacuation, often involves strong emotions and emotional contagion from others. In this paper the role of emotions in social decision making in large technically assisted crowds is investigated. For this a formal, computational model is proposed, which integrates existing neurological and cognitive theories of affective decision making. Based on this model several variants of a large scale crowd evacuation scenario were simulated. By analysis of the simulation results it was established that (1) human agents supported by personal assistant devices are recognised as leaders in groups emerging in evacuation; (2) spread of emotions in a crowd increases the resistance of agent groups to opinion changes; (3) spread of emotions in a group increases its cohesiveness; (4) emotional influences in and between groups are, however, attenuated by personal assistant devices, when their number is large.

Keywords: Crowd evacuation · Cognitive modelling · Ambient intelligence · Multi-agent simulation

1 Introduction

Decision making under stressful circumstances, e.g., during evacuation, often involves strong emotions and emotional contagion from others [1, 6]. More generally, it is widely recognised in cognitive and neurological literature that emotions influence human decision making [2, 9, 12]. However, quantifying this influence is a challenging task. Previously, human decision making has been considered as entirely rational and has been modelled using economic utility-based theories [19, 20]. Purely rational decision making models were disapproved by many empirical studies (see e.g., [20]). However, devising a better alternative addressing the limitations of these models by combining cognitive (rational) and affective (emotional) aspects still remains a big challenge.

To address this challenge several computational models were proposed [10, 27, 29], which use variants of the OCC model developed by Ortony, Clore and Collins [23] as a basis. The OCC model postulates that emotions are valenced reactions to events, agents, and objects, where valuations are based on similarities between achieved states and goal states. Thus, emotions in this model have a cognitive origin. In contrast to

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these approaches, we employ a neurological fundament, on which a model of social decision making is built. This model exploits some of the principles underlying the OCC model but embeds them in a neurological context. By taking a neurological perspective and incorporating cognitive and affective elements in one integrated model, a more realistic and deeper understanding of the internal processing underlying human decision making in social situations can been achieved. This gives a richer type of model than models purely at the cognitive level, or diffusion (contagion) models at the social level abstracting from internal processing, for example, as addressed in [17]. More specifically, options in decision making involving sequences of actions are modelled using the neurological theory of simulated behaviour (and perception) chains proposed by Hesslow [16]. Moreover, the emergence of emotional states in these behavioural chains is modelled using emotion generation principles described by Damasio [7–9]. Evaluation of sensory consequences of actions in behavioural chains, also uses elements borrowed from the OCC model. Different types of emotions can be distinguished and their roles in the decision making clarified. Two types of emotions – hope and fear – are particularly relevant in the context of crowd evacuation. The emergence and dynamics of these two emotions are addressed in the model presented in the paper.

Evaluation of decision options and the emotions involved in it usually have a strong impact from the human's earlier experiences. In the proposed model for social decision making, this form of adaptivity to past experiences is also incorporated based on neurological principles. In such a way elements from neurological, affective and cognitive theories were integrated in the adaptive agent model proposed.

Usually decision making occurs in a social context (e.g., a group of people). People influence others and are influenced by others. In many studies on emotional decision making the social context is either ignored [27, 29] or comprises a small group of individuals [17]. In this paper we investigate social decision making in large crowds of people. The effects of emotional decision making on a large scale (a crowd) may differ significantly from the ones on a small scale (an individual or a small group).

Due to the ubiquitous use of personal communication devices (e.g., mobile phones), which often play a prominent role in emergency situations, also such devices need to be included in the model as information sources. Both researchers and authorities envision an important contribution of such and more intelligent assistant devices to monitoring and control of large mass events [13]. Thus, in the model some of the human agents are equipped with technical devices called personal assistants, able to receive information relevant for decision options from other devices.

In the literature [1, 26, 28, 30] it is indicated that people often form spontaneous groups during evacuation. On the one hand, dynamic formation of groups is recognised as a prerequisite for efficient evacuation [1, 30]. On the other hand, large uncontrolled groups may cause clogging of paths and increase panic [1, 26]. In this paper, *a group* is defined by a set of human agents, supporting the same decision option and located closely to each other in the physical space. To investigate the role of emotions in the formation and dynamics of groups, 5 hypotheses were formulated, which are discussed in the following.

In [24] the possession of knowledge is identified as a strong power basis in social groups, especially when they are situated in environments with scarce and uncertain information. In line with this argument, the following hypothesis is formulated:

Hypothesis 1: Human agents equipped with personal assistants, who obtain up-to-date information about the environment, are recognised as leaders in groups emerging in evacuation.

The next hypothesis is a known observation from the social psychology literature confirmed by empirical studies (see e.g., [22]):

Hypothesis 2: Emotions increase the consistency of social decision making and the robustness of a group against external perturbations (e.g., receipt of inconsistent information from strangers).

The third hypothesis follows from the second one.

Hypothesis 3: Emotions arising in social decision making increase the group cohesiveness.

Hypothesis 4: The higher the penetration rate of personal assistants, the less the influence of emotions on the group dynamics.

The last hypothesis is related to *the large group effect* known for social emergency systems [1]:

Hypothesis 5: Evacuation with larger groups proceeds more slowly (less efficiently) than with smaller groups.

The hypotheses were tested by agent-based simulation based on the proposed emotional decision making model in the context of a large scale crowd evacuation scenario. To validate the hypotheses the two-sample t-test was applied [32]. By analysis of the simulation results all the hypotheses were confirmed.

The paper is organised as follows. A case study is introduced in Sect. 2. The general modelling principles on which the proposed model is based are described in Sect. 3. A detailed formalisation of the proposed model for the evacuation scenario is provided in Sect. 4. The simulation and verification results for the hypotheses are presented in Sect. 5. Finally, Sect. 6 concludes the paper.

2 Case Study

In the simulation study we focussed on evacuation of a train station. To ensure that the simulation setting is a true representative of reality, a real CAD design of an existing Austrian main railway station was incorporated to generate the space along with observed population statistics.

The station in the simulation model had 3 exits with different flow capacities. Exit E13 has largest capacity equal to a width of 7 cells followed by Exit E15 consisting of width equal to 5 cells. Exit SC1 has least width equal to 2 cells. The station was populated randomly with 1000 agents representing humans, from which a number of agents depending of the simulation trial (1 %, 5 % or 10 %) were equipped with personal assistants (see Fig. 1). In Fig. 1, three different colours representing agents heading towards three exits respectively (blue towards Exit E15, green towards Exit E13 and yellow towards Exit SC1) are shown. Out of a total population of 1000 agents, 1 % (with red labels) are equipped with personal assistants.

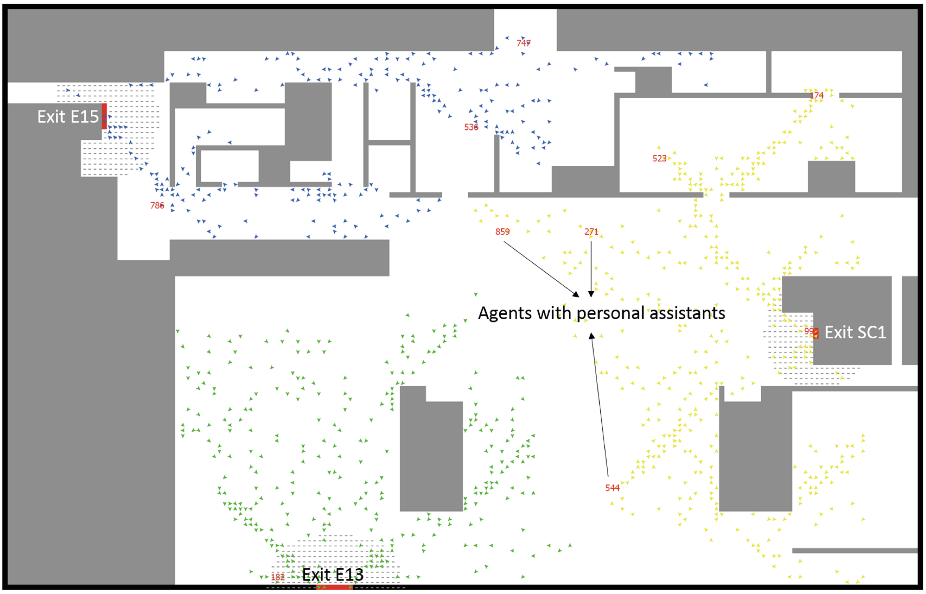

Fig. 1. A train station represented in the simulation environment with coloured dots representing agents heading towards three exits (Color figure online)

All personal assistants constantly received information about the degree of clogging of each exit from a global ‘evacuation control unit’. This information was assumed to be measured by a technology mounted on each exit. Furthermore, it is assumed that the global control unit provides reliable, up-to-date information to all personal assistants without any noise.

Each personal assistant had a location map used to transform the coordinates of an exit to the desired orientation to move. Thus, agents with personal assistants had direct access to information essential for successful evacuation, which they could propagate further by interaction with other agents.

Agents can interact with each other *non-verbally* by spreading emotions and intentions to choose particular exits, and *verbally* by communicating information about the states of the exits. The agents without devices were free to decide whether or not to follow agents with personal assistants or to rely on their own beliefs and exit choices. It is important to stress that the grouping effect is not encoded in our model explicitly, but emerges as a result of complex decision making by agents.

To verify the hypotheses formulated in the introduction, three variants of the scenario were introduced, which were simulated:

Variant 1: Agents generate and exchange both information and emotions during the social decision making.

Variant 2: Agents generate both emotions and information, but exchange only information.
Variant 3: Agents generate and exchange only information.
The simulation of all variants of the scenario is based on a social decision making model described in Sect. 4, which relies on a neurological fundament described in Sect. 3.

3 Theoretical Basis

Considering options and evaluating them is viewed as a central process in human decision making. An option is a sequence of actions to achieve a goal, as in planning. To model considering such sequences, from the neurological literature the *simulation hypothesis* proposed by Hesslow [16] was adopted. Based on this hypothesis, chains of behaviour can be simulated as follows: some situation elicits activation of s1 in the sensory cortex that leads to preparation for action r1. Then, associations are used such that r1 will generate s2, which is the most connected sensory consequence of the action for which r1 was generated. This sensory state serves as a stimulus for a new response, and so on. In such a way long chains of simulated responses and perceptions representing plans of action can be formed. These chains are simulated by an agent internally as follows:

> 'An anticipation mechanism will enable an organism to simulate the behavioural chain by performing covert responses and the perceptual activity elicited by the anticipation mechanism. Even if no overt movements and no sensory consequences occur, a large part of what goes on inside the organism will resemble the events arising during actual interaction with the environment.' [16]

As reported in [16], behavioural experiments have demonstrated a number of striking similarities between simulated and actual behaviour.

Hesslow argues in [16] that the simulated sensory states elicit emotions, which can guide future behaviour either by reinforcing or punishing simulated actions. However, specific mechanisms for emotion elicitation are not provided. This gap can be filled by combining the simulation hypothesis with a second source of knowledge from the neurological area: Damasio's emotion generation principles based on *(as-if) body loops*, and the principle of *somatic marking* [2, 8]. These principles were adopted to model evaluation of options.

Damasio [7–9] argues that sensory or other representation states of a person often induce emotions felt within this person, according to a *body loop* described by the following causal chain:

sensory state → preparation for the induced bodily response → induced bodily response → sensing the bodily response → sensory representation of the bodily response → induced feeling

As a variation, an *as if body loop* uses a direct causal relation as a shortcut in the causal chain: preparation for the induced bodily response → sensory representation of the induced bodily response. The body loop (or 'as if body loop') is extended to a recursive body loop (or recursive 'as if body loop') by assuming that the preparation of the bodily response is also affected by the state of feeling the emotion as an additional causal relation: feeling → preparation for the bodily response. Thus, agent emotions are modelled based on reciprocal causation relations between emotion felt and body states. Following these emotion generation principles, an 'as if body' loop can be incorporated in a simulated behavioural chain as shown in Fig. 2 (left). Note that based on the sensory states different types of emotions may be generated.

In the *OCC model* [23] a number of cognitive structures for different types of emotions are described. By evaluating sensory consequences of actions s1, s2, …, sn from Fig. 2 using cognitive structures from the OCC model, different types of emotions can be distinguished. More specifically, the emergence of hope and fear in agent decision making in an emergency scenario will be considered in Sect. 4. The OCC model has been extensively used for representing emotions in diverse ambience intelligence frameworks. For example, in [33], using the OCC model emotions are generated that influence decision making of and negotiation between agents in a group. No neurological or psychological validity of the model is asserted in this work. Moreover, the knowledge about emotional influences on social processes in ambient intelligence environments is still rather limited. To the best of our knowledge, influence of emotions on such aspects as group cohesiveness and robustness of social decision making in an ambient intelligence setting has not been studied before.

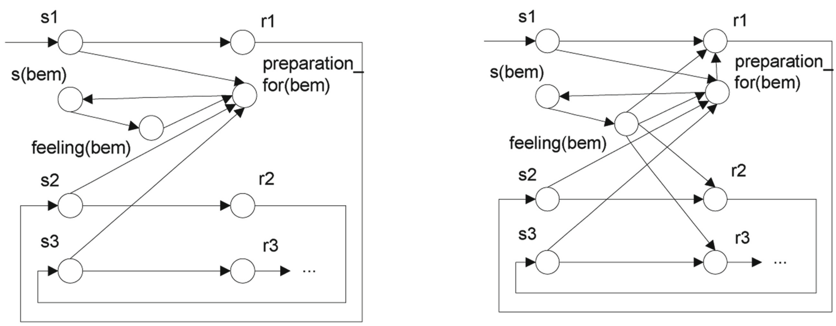

Fig. 2. Simulation of a behavioural chain extended with an 'as if body' loop with emotional state bem (left) and with emotional influences on preparation states (right)

Hesslow argues in [16] that emotions may reinforce or punish simulated actions, which may transfer to overt actions, or serve as discriminative stimuli. Again, specific mechanisms are not provided. To fill this gap the Damasio's *Somatic Marker Hypothesis* was adopted. This hypothesis provides a central role in decision making to emotions felt. Within a given context, each represented decision option induces (via an emotional response) a feeling which is used to mark the option. For example, a strongly negative somatic marker linked to a particular option occurs as a strongly negative feeling for that option. Similarly, a positive somatic marker occurs as a positive feeling for that option. Damasio describes the use of somatic markers in the following way:

> 'the somatic marker (..) forces attention on the negative outcome to which a given action may lead, and functions as an automated alarm signal which says: beware of danger ahead if you choose the option which leads to this outcome. The signal may lead you to reject, *immediately*,

> the negative course of action and thus make you choose among other alternatives. (…) When a positive somatic marker is juxtaposed instead, it becomes a beacon of incentive.' [9, pp. 173–174]

To realise the somatic marker hypothesis in behavioural chains, emotional influences on the preparation state for an action are defined as shown in Fig. 2 (right). Through these connections emotions influence the agent's readiness to choose the option. From a neurological perspective, the impact of a sensory state to an action preparation state via the connection between them in a behavioural chain will depend on how the consequences of the action are felt emotionally.

As neurons involved in these states and in the associated 'as if body' loop will often be activated simultaneously, such a connection from the sensory state to the preparation to action state may be strengthened based on a general *Hebbian learning* principle [14, 15] that was adopted as well. It describes how connections between neurons that are activated simultaneously are strengthened, similar to what has been proposed for the emergence of mirror neurons; e.g., [18, 25]. Roughly spoken this principle states that connections between neurons that are activated simultaneously are strengthened. From a Hebbian perspective, strengthening of connections as mentioned in case of positive valuation may be reasonable, as due to feedback cycles in the model structure, neurons involved will be activated simultaneously.

Thus, by these processes an agent differentiates options to act based on the strength of the connection between the sensory state of an option and the corresponding preparation to an action state, influenced by its emotions. The option with the highest activation of preparation is chosen to be performed by the agent.

As also used as an inspiration in [17], in a social context, the idea of somatic marking can be combined with recent neurological findings on the *mirroring function* of certain neurons (e.g., [18, 25]). Mirror neurons are neurons which, in the context of the neural circuits in which they are embedded, show both a function to prepare for certain actions or bodily changes and a function to mirror similar states of other persons. They are active not only when a person intends to perform a specific action or body change, but also when the person observes somebody else intending or performing this action or body change. This includes expressing emotions in body states, such as facial expressions. The mirroring function relates to decision making in two different ways. In the first place *mirroring of emotions* indicates how emotions felt in different individuals about a certain considered decision option mutually affect each other, and, assuming a context of somatic marking, in this way affect how by individuals decision options are valuated in relation to how they feel about them. A second way in which a mirroring function relates to decision making is by applying it to the *mirroring of intentions or action tendencies* of individuals (i.e., preparation states for an action) for the respective decision options. This may work when by verbal and/or nonverbal behaviour individuals show in how far they tend to choose for a certain option. In the computational model introduced below in Sect. 4 both of these (emotion and preparation) mirroring effects are incorporated.

4 Modelling Emotional Decision Making

First, in Sect. 4.1 a modelling language is described used for formalisation of the model. Then, the formal model is provided in Sect. 4.2.

4.1 The Modelling Language

To specify dynamic properties of a system, the order-sorted predicate logic-based language called LEADSTO is used [4]. This language satisfies essential demands for dynamic modelling of agent systems in natural domains. In particular, it allows the possibility of both discrete and continuous modelling of a system at different aggregation levels. Furthermore, it has numerical expressivity for modelling systems with explicitly defined quantitative relations presented by difference or differential equations. Moreover, for specifying qualitative aspects of a system, LEADSTO is able to express logical relationships between parts of a system.

Dynamics in LEADSTO is represented as evolution of states over time. A state is characterized by a set of properties that do or do not hold at a certain point in time. To specify state properties for system components, ontologies are used which are defined by a number of sorts, sorted constants, variables, functions and predicates (i.e., a signature). For every system component A a number of ontologies can be distinguished: the ontologies IntOnt(A), InOnt(A), OutOnt(A), and ExtOnt(A) are used to express respectively internal, input, output and external state properties of the component A. Input ontologies contain elements for describing perceptions of an agent from the external world, whereas output ontologies describe actions and communications of agents. For a given ontology Ont, the propositional language signature consisting of all state ground atoms based on Ont is denoted by APROP(Ont). State properties are specified based on such ontology by propositions that can be made (using conjunction, negation, disjunction, implication) from the ground atoms. Then, a *state* S is an indication of which atomic state properties are true and which are false: S: APROP (Ont) $\rightarrow$ {true, false}.

LEADSTO enables modeling of direct temporal dependencies between two state properties in successive states, also called *dynamic properties*. A specification of dynamic properties in LEADSTO is executable and can be depicted graphically. The format is defined as follows. Let $\alpha 1$ and $\alpha 2$ be state properties of the form 'conjunction of atoms or negations of atoms', and e, f, g, h non-negative real numbers. In the LEADSTO language the notation $\alpha 1 \twoheadrightarrow_{e,\, f,\, g,\, h} \alpha 2$ means: if state property $\alpha 1$ holds for a certain time interval with duration g, then after some delay (between e and f) state property $\alpha 2$ will hold for a certain time interval of length h (Fig. 3). When $e = f = 0$ and $g = h = 1$, called standard time parameters, we shall write $\alpha 1 \twoheadrightarrow \alpha 2$. To indicate the type of a state property in a LEADSTO property we shall use prefixes input(c), internal(c) and output(c), where c is the name of a component. Consider an example dynamic property:

input(A)|observation_result(fire) $\twoheadrightarrow$ output(A)| performed(runs_away_from_fire)

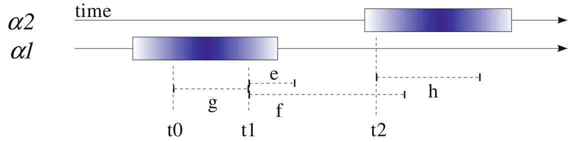

Fig. 3. Timing relationships for LEADSTO expressions.

Informally, this example expresses that if agent A observes fire during some time unit, then after that A will run away from the fire during the following time unit.

In addition, LEADSTO allows expressing mathematical operations, e.g., has_value (x, v) $\twoheadrightarrow_{e, f, g, h}$ has_value(x, v*0.25).

Next, a *trace* or *trajectory* γ over a state ontology Ont is a time-indexed sequence of states over Ont (where the time frame is formalised by the real numbers). A LEADSTO expression $\alpha 1 \twoheadrightarrow_{e, f, g, h} \alpha 2$, holds for a trace γ if:

$$\forall t1\, [\forall t[t1 - g \leq t < t1 \Rightarrow \alpha 1 \text{ holds in } \gamma \text{ at time } t] \\ \Rightarrow \exists d[e \leq d \leq f \,\&\, \forall t' \,[t1 + d \leq t' < t1 + d + h \Rightarrow \alpha 2 \text{ holds in } \gamma \text{ at time } t']$$

To specify the fact that a certain event (i.e., a state property) holds at every state (time point) within a certain time interval a predicate holds_during_interval(event, t1, t2) is introduced. Here event is some state property, t1 is the beginning of the interval and t2 is the end of the interval.

An important use of the LEADSTO language is as a specification language for simulation models. As indicated above, on the one hand LEADSTO expressions can be considered as logical expressions with a declarative, temporal semantics, showing what it means that they hold in a given trace. More details on the semantics of the LEADSTO language can be found in [4].

4.2 The Computational Model

Depending on a situational context an agent determines a set of applicable options to satisfy its goal. In the case study the goal of each agent is to get outside of the train station in the fast possible way. This is achieved by an agent by moving towards the exit that provides for fastest evacuation as it perceived by the agent. Evacuation options are represented internally in agents by one-step simulated behavioural chains, based on the neurological theory by Hesslow [16] (see Fig. 4). Note that if more than one exit is known to the agent, then in each option representation the preparation state corresponding to the option's exit is generated. Computationally, alternative options considered by an agent are being generated and evaluated in parallel.

According to the Somatic Marker Hypothesis [8], each represented decision option induces (via an emotional response) a feeling(s) which is used to mark the option. For example, a strongly positive somatic marker linked to a particular option occurs as a strongly positive feeling for that option. The decision options from our study evoke two types of emotions - fear and hope, which are often considered in the emergency context. To realise the somatic marker hypothesis in behavioural chains, emotional influences on the preparation state for an action are defined as shown in Fig. 4. Through these connections emotions influence the agent's readiness to choose the option.

In Fig. 4 the burning station situation elicits activation of the state srs(evacuation_required) in the agent's sensory cortex that leads to preparation for action preparation_for(move_to(E)). Here E is one of the exits of the station. Furthermore, this preparation state is affected by the sensory representations of the perceived preparation of the neighbouring agents for the action and of the emotions felt towards the option.

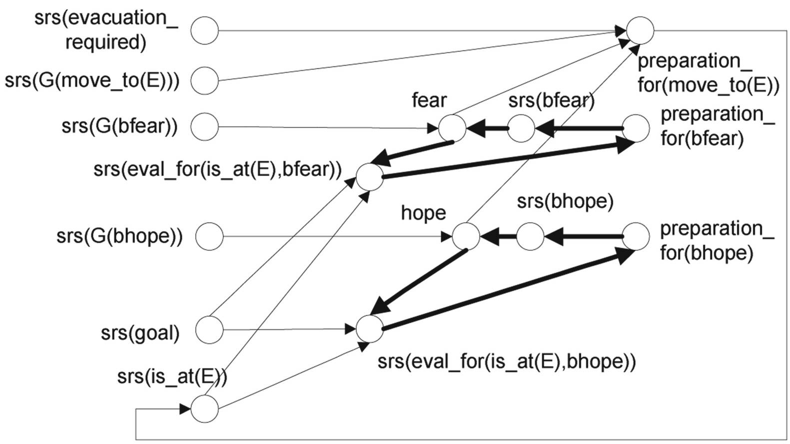

Fig. 4. The emotional decision making model for the option to move to exit E.

Formally:

srs(evacuation_required, V1) & srs(fear, V2) & srs(hope, V5) & srs(G(move_to(E)), V3) & preparation_for(move_to(E), V4)
$\twoheadrightarrow$ preparation_for(move_to(E), V4 + γ(h(V1, V2, V3, V5) – V4)Δt),

where G(move_to(E) is the aggregated preparation of the neighbouring agents to action move_to(E), h(V1, V2, V3, V5) is a combination function:

$$h(V1, V2, V3, V5) = \beta\,(1 - (1 - V1)V2(1 - V3)(1 - V5)) + (1 - \beta)\, V1\, V3\, V5(1 - V2)$$

Here β is a parameter that reflects the agent's predisposition to think positively ($\beta > 0.5$) or negatively ($\beta < 0.5$). Parameter γ reflects the agent's rate of change of its state.

The option with the highest activation of preparation is chosen to be performed by the agent.

Then, associations are used such that preparation_for(move_to(E)) will generate srs (is_at(E)), which is the most connected sensory consequence of the action move_to(E). The strength of the link between a preparation for an action and a sensory representation of the effect of the action (see Fig. 4) is used to represent the confidence value of the agent's belief that the action leads to the effect. This is modelled by the following formal property:

preparation_for(move_to(E), V) & connection_between_strength(preparation_for(move_to(E)), srs (is_at(E)), ω) ↠ srs(is_at(E), ωV)

The simulated sensory states elicit emotions, which guide agent behaviour either by reinforcing or punishing simulated actions. By evaluating sensory consequences of actions in simulated behavioural chains using cognitive structures from the OCC model [23], different types of emotions can be distinguished. As a simulated behavioural chain is a kind of a behavioural projection, cognitive structures of prospect-based emotions (e.g., fear, hope, satisfaction, disappointment) from [23] are particularly relevant for the evaluation process. In our study two types of emotions - fear and hope – are distinguished. According to [23], the intensity of fear induced by an event depends on the degree to which the event is undesirable and on the likelihood of the event. The intensity of hope induced by an event depends on the degree to which the event is desirable and on the likelihood of the event. Thus, both emotions are generated based on the evaluation of a distance between the effect states for the action from an option and the agent's goal state.

In particular, the evaluation function for hope in the evacuation scenario is specified as

$$eval(g,\ is\_at(E)) = \omega,$$

where ω is the confidence value for the belief about the accessibility of exit E, which is an aggregate of the agent's estimation of the distance to the exit and the degree of clogging of the exit. Although it is assumed that the distances to the exits are known to the agents, the information about the degree of clogging of the exits is known only to technology-equipped agents.

Emotions emerge and develop in dynamics of reciprocal relations between cognitive and body states of a human [7, 8]. These relations, omitted in the OCC model, are modelled from a neurological perspective using Damasio's principles of 'as-if body' loops and somatic marking described in Sect. 3. The 'as-if body' loops for hope and fear emotions are depicted in Fig. 4 by thick solid arrows. These loops are formalised by the properties provided below.

The evaluation properties for fear and for hope of the effect of action move_to(E) compared with the goal state goal is specified formally as:

srs(goal, V1) & srs(is_at(E), V2) & srs(fear, V3) &
connection_between_strength(preparation_for(move_to(E)), srs(is_at(E)), V4) &
srs(eval_for(is_at(E), bfear), V5)
↠ srs(eval_for(is_at(E), bfear), V5 + γ(h(V4*f(goal, is_at(E)), V3) – V5) Δt),

where f(goal,is_at(E)) = |V1-V6|, V6 = eval(goal, is_at(E), and
h(V1, V2) = β (1-(1-V1)(1-V2)) + (1-β) V1 V2.

srs(goal, V1) & srs(is_at(E), V2) & srs(hope, V3) &
connection_between_strength(preparation_for(move_to(E)), srs(is_at(E)), V4) &
srs(eval_for(is_at(E), bhope), V5)
↠ srs(eval_for(is_at(E), bhope), V5 + γ(h(V4* f(goal, is_at(E)), V3) – V5) Δt),

where f(goal, is_at(E)) = 1-|V1-V6|, and V6 = eval(goal, is_at(E)).

The evaluation of the effects of the action for a particular emotional response to an option determines the intensity of the emotional response:

srs(eval_for(is_at(E), bhope), V1) ↠ preparation_for(bhope, V1)

srs(eval_for(is_at(E), bfear), V1) ↠ preparation_for(bfear, V1)

The agent perceives its own emotional response and creates the sensory representation state for it:

preparation_for(bhope, V) ↠ srs(bhope, V)

preparation_for(bfear, V) ↠ srs(bfear, V)

Finally the dynamics of the emotional states are formalised as follows:

srs(bhope, V1) & srs(G(bhope), V2) & srs(hope, V3) ↠ srs(hope, V3 + γ(h(V1, V2) – V3) Δt)),

where h(V1,V2) is a combination function defined above.

srs(bfear, V1) & srs(G(bfear), V2) & srs(fear, V3) ↠ srs(fear, V3 + γ(h(V1, V2) – V3) Δt)),

The social influence on the individual decision making is modelled based on the mirroring function [18] of preparation neurons in humans. It is assumed that the preparation states of an agent for the actions and for emotional responses for the options are body states that can be observed with a certain intensity or strength by other agents from the neighbourhood. Furthermore, it is assumed that an agent is able to observe preparation states of other agents in its neighbourhood specified by radius r. Note that the agent's neighbourhood changes while the agent moves.

The *contagion strength* of the interaction from agent A_2 to agent A_1 for a preparation state p is defined as follows:

$$\gamma_{pA_2A_1} = \varepsilon_{pA_2} \cdot \mathrm{trust}(A_1, A_2) \cdot \alpha_{pA_2A_1} \cdot \delta_{pA_1}$$

Here ε_{pA2} is the personal characteristic expressiveness of the sender (agent A_2) for p, δ_{pA1} is the personal characteristic openness of the receiver (agent A_1) for p.

Trust is an attitude of an agent towards an information source that determines the extent to which information received by the agent from the source influences agent's belief(s). The trust to a source builds up over time based on the agent's experience with the source. In particular, when the agent has a positive (negative) experience with the source, the agent's trust to the source increases (decreases). Currently experiences are restricted to information experiences only. An information experience with a source is evaluated by comparing the information provided by the source with the agent's beliefs about the content of the information provided. The experience is evaluated as positive (negative), when the information provided by the source is confirmed by (disagree with) the agent's beliefs. The following property describes the update of trust of agent A_i to agent A_j based on information communicated by A_j to A_i about the degree of clogging of exit E:

trust(A_i, A_j, V1) & communicated_from_to(A_j, A_i, clogging(E, V2)) & belief(A_i, clogging(E, V3)) $\twoheadrightarrow$ trust(A_i, A_j, V1 + γ_{tr}*(V3/(1 + e^{α}) – V1)),

here α = –ω1*(1–|V2–V3|), parameter ω1 determines the steepness of change of the trust state.

An agent A_i perceives the joint attitude of the crowd towards each option by aggregating the input from all agents in its neighbourhood $\aleph$:

(a) the aggregated neighbourhood's preparation to each action p is expressed by the following dynamic property:

$\wedge_{Aj\in\aleph}$ internal(A_j)|preparation_for(p, V_j) $\twoheadrightarrow$ internal(A_i)|srs(G(p), $\Sigma_{j\neq i}\, \gamma_{pAjAi}\, V_j / \Sigma_{j\neq i}\, \gamma_{pAjAi}\varepsilon_{pAj}$)

(b) the aggregated neighbourhood's preparation to the emotional responses (hope and fear) for each option:

$\wedge_{Aj\in\aleph}$internal(A_j)|preparation_for(bhope,V_j)$\twoheadrightarrow$internal(A_i)|srs(G(bhope),$\Sigma_{j\neq I}\, \gamma_{beAjAi}\, V_j/\Sigma_{j\neq i}\, \gamma_{beAjAi}\varepsilon_{beAj}$)

$\wedge_{Aj\in\aleph}$internal(A_j)|preparation_for(bhope,V_j)$\twoheadrightarrow$internal(A_i)|srs(G(bhope),$\Sigma_{j\neq I}\, \gamma_{beAjAi}\, V_j/\Sigma_{j\neq i}\, \gamma_{beAjAi}\varepsilon_{beAj}$)

The Hebbian learning principle for links connecting the sensory representation of options with preparation states for subsequent actions in the simulation of a behavioural chain is formalised as follows (cf. [14, 15]):

connection_between_strength(srs(evacuation_required), preparation_for(move_to(E)), V1) & srs (srs(evacuation_required), V2) & preparation_for(move_to(E), V3) $\twoheadrightarrow$ connection_between_strength(srs(evacuation_required), preparation_for(move_to(E)), V1 + (η V2 V3 (1 – V1) – ξV1)Δt),

where η is a learning rate and ξ is an extinction rate.

5 Simulation Results

The model was implemented in the Netlogo simulation tool [31] by cellular automata. In this tool the environment is represented by a set of connected cells, where moveable agents (turtles) reside. Cells can be walkable (open space and exits) and not-walkable (concrete, partitions, walls). Each cell of the environment is accessible from all the exits.

The three variants of the model described in Sect. 2 were implemented as 3 simulation conditions:

Condition 1: Agents generate and exchange both information and emotions during the social decision making.
Condition 2: Agents generate both emotions and information, but exchange only information.
Condition 3: Agents generate and exchange only information.

Since the model contains stochastic elements, 50 trials were performed for each simulation setting with 1000 heterogeneous agents with the parameters drawn from the ranges of uniformly distributed values as indicated in Table 1 below to represent a diversity of agent types that may occur in real emergency situations. It is assumed that the agents have average to high expressiveness and openness. The agents do not have a strong predisposition to think positively or negatively (β) in the simulation. The agents have an average to high rate of change of their states (γ). The agents have an average learning rate (η) and a low extinction rate (ξ), as often assumed in neurological models. It is assumed that humans trust technology in the same manner as to human strangers. A human agent has a low initial trust value to all other agents; it increases (decreases) slowly ($\omega 1 = 9$) its trust to an agent after a positive (negative) experience with the agent.

Table 1. Ranges and values of the agent parameters used in the simulation.

ε for all states from all agents	δ for all states from all agents	β	γ	η	ξ	Δt	r	$\omega 1$	Initial trust to all agents
[0.7, 1]	[0.7, 1]	[0.55, 0.7]	[0.7, 1]	0.6	0.1	1	10	9	[0.1, 0.3]

In the following simulation results and testing of the hypotheses formulated in Sect. 1 are discussed. To test the hypotheses, the simulation traces generated for each condition were analysed using the TTL Checker Tool [5].

To evaluate *Hypothesis 1* two evaluation metrics were introduced: *following index (fi),* which reflects the degree of following of technology-assisted agents by other agents, and *group size* (*gs*). As shown below, the metrics are defined per a technology-assisted agent L (i.e., fi_L, gs_L) and by taking the mean over all technology-assisted agents (i.e., fi, gs). The following index is defined as follows:

$$fi_L = 1/|N| \cdot \sum\nolimits_{A \in N} |F_{A,L}| / (t\_last - t\_first_A), \qquad fi = \sum\nolimits_{i \in LEAD} fi_i / |LEAD|,$$

where t_first_A is such that

∃o1:INFO at(communicated_from_to(L, A, inform, o1), t_first_A) & ∀t:TIME, o:INFO t < t_first_A & ¬at(communicated_from_to(L, A, inform, o), t);

N = {a | t_first_A is defined}; $F_{A,L}$ = {t | t ≥ t_first_A & ∃d1,d2: DECISION at(has_preference_for(A, d1), t) & at(has_preference_for(L, d2), t) & d1 = d2 & at(distance_between(A, L) < dist_threshold, t) },

t_last is the time point when L is evacuated, LEAD is the set of all technology-assisted agents.

The group size is defined as follows:

$$gs_L = \sum\nolimits_{t=1..t\_last} FT_{L,t} / t\_last, \qquad gs = \sum\nolimits_{i \in LEAD} gs_L / |LEAD|,$$

where $FT_{L,t}$ = {ag | t ≥ t_first_{ag} & ∃d1,d2: DECISION at(has_preference_for(ag, d1), t) & at (has_preference_for(L, d2), t) & d1 = d2 & at(distance_between(A, L) < dist_threshold, t) }.

The obtained results are summarised in Table 2. As one can see from the table, the emergence of groups with agents equipped with personal assistants as guiding leaders occurs in all conditions ($fi > 0$), thus, the hypothesis 1 is confirmed.

In *Condition 1* the most clogged exit throughout the simulation is Exit SC1, as it is the closest exit to most of the agents (Fig. 5a). As information about clogging of other exits spreads through the population of agents, the clogging of Exit SC1 decreases, but still remains higher than the clogging of other exits. Agents react to the change of clogging of the exits by changing their preferred exits (Fig. 5b). The amount of agents aiming at exit SC1 decreases throughout the simulation, whereas the numbers of agents choosing E15 and E13 fluctuate depending on the situation around these exits.

Table 2. The simulation results for 50 simulation trials for three simulation conditions. Standard deviation is provided in brackets.

Coefficient	Condition 1	Condition 2	Condition 3
fi	0.42 (0.15)	0.33 (0.11)	0.21 (0.11)
gs	27 (8.1)	15 (5.5)	11(3.2)
si_{exit1}	0.12 (0.03)	0.32 (0.04)	0.65 (0.07)
si_{exit2}	0.12 (0.04)	0.23 (0.05)	0.45 (0.08)
si_{exit3}	0.13 (0.04)	0.21 (0.07)	0.29 (0.07)
ci	1.5 (0.4)	1.9 (0.7)	7.1 (0.7)

Information about the exits received by the agents influences their emotional states (Fig. 6). The technology-assisted agents, who receive information about exits first, change their emotions more rapidly than the agents without such devices (cf. the dynamics of hope in Fig. 6a and b). Furthermore, information provided by the technology-assisted agents spreads rapidly and is readily accepted by other agents, as can be seen from the similarity of the dynamics of the emotions in Fig. 6a and b.

To verify *Hypothesis 2* a smoothness degree of the preparation for each action (i.e., move to exit E) averaged over all agents is determined in each simulation trial (*smoothness index* (si_E)):

$$si_E = \sum\nolimits_{t=1\ldots t\_last-1,\ a\in N} p_{t,E,a}/|N|,$$

$$\text{with } p_{t,E,a} = \begin{cases} |v_{t+1,E,a} - v_{t,E,a}|, & \text{when } |v_{t+1,E,a} - v_{t,E,a}| \geq \varepsilon \\ 0, & \text{when } |v_{t+1,E,a} - v_{t,E,a}| < \varepsilon \end{cases}$$

Here N is the set of all agents, $v_{t,E,a}$ is the value of preparation_for(move_to(E)) for agent a at time point t; ε is a threshold for distinguishing small changes from large changes; ε is taken 0.1 for the analysis.

Thus, the smoothness index depends on the rate of change of the agent's opinion based on incoming information. This index indicates the robustness of a group of agents to messages provided by agents outside the group, which support a decision

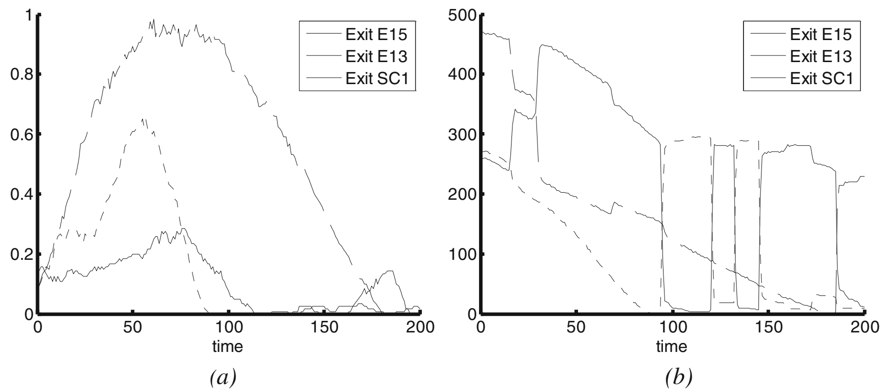

Fig. 5. (a) The change of the degree of clogging of each exit over time in *Condition 1*; (b) The change of numbers of agents heading to each exit in *Condition 1.*

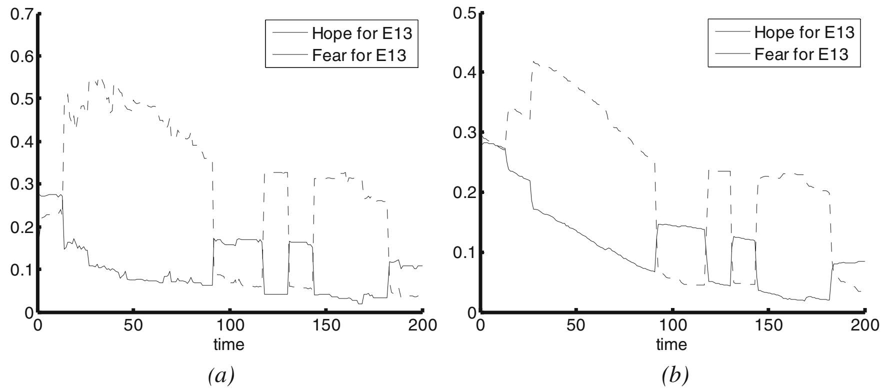

Fig. 6. The emotional response toward the option to follow exit E13 averaged over technology-assisted agents (a) and over the agents without devices (b).

option different from the one currently supported by the group. Note that a group is defined by a set of human agents, supporting the same decision option and located closely to each other in the physical space. In the evacuation scenario this occurs when the situation around an exit(s) changes. Then, the agents with personal assistants receive new information, based on which they may change their decisions. Further, these agents spread new information to other agents in their neighbourhood. If besides information also emotions are being spread (see Table 2, condition 1 and Fig. 7a), the population of agents change their decisions gradually. When emotions are generated, but are not being spread, the group becomes less robust to changes and reacts more abruptly to incoming messages (see Table 2, condition 2 and Fig. 7b).

In the situation when emotions are not generated, the agents in a group change their decisions frequently, rapidly and drastically (see Table 2, condition 2 and Fig. 7b). Such a form of behaviour is highly unrealistic for human beings.

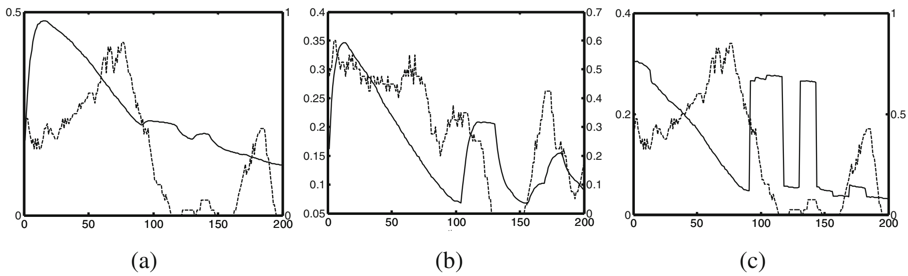

Fig. 7. The change of the preparation to move to exit E15 averaged over the whole population of agents (solid line; left vertical axis), and the change of the degree of clogging of exit E15 (dotted line; right vertical axis) in condition 1(a), condition 2(b) and condition 3(c); the horizontal line is time.

Thus, the outcomes of the simulation support *Hypothesis 2* that generation and spread of emotions increase the consistency of social decision making.

To verify *Hypothesis 3* the metrics called *change index* (ci), reflecting the frequency of group change by an agent, was introduced.

It is defined by:

$$\mathrm{ci}_L = 1/|N| \sum\nolimits_{A \in N} |S_{A,L}|, \qquad \mathrm{ci} = \sum\nolimits_{i \in LEAD} \mathrm{ci}_i / |LEAD|,$$

where LEAD is the set of all agents with personal assistants,

$S_{A,L}$ = {t | (t∈ $F_{A,L}$ & (t + 1) ∉ $F_{A,L}$) OR ((t + 1)∈ $F_{A,L}$ & t ∉ $F_{A,L}$) }, and
$F_{A,L}$ = {t | t ≥ t_first$_A$ & ∃d1,d2:DECISION at(has_preference_for(A, d1), t) & at(has_preference_for (L, d2), t) & d1 = d2 & at(distance_between(A, L) < dist_threshold, t)}, at(X,t) denotes that X holds at time point t, and

t_first$_A$ is such that ∃o1:INFO at(communicated_from_to(L, A, inform, o1), t_first$_A$) & ∀t:TIME, o: INFO t < t_first$_A$ & ¬at(communicated_from_to(L, A, inform, o), t), and

N = {a | t_first$_A$ is defined}.

The average change index in *Condition 3* was 4.7 and 3.7 times higher than in *Conditions 1* and *2* respectively (Table 2, ci row). Thus, when emotions are not generated, agents are significantly less attached to their group than in the case when emotions are generated and being spread. The two-sample t-test performed on the outcomes of *Condition 3* and *Condition 1* and on the outcomes of *Condition 3* and *Condition 2* confirms *Hypothesis 3* with 95 % confidence.

To test *Hypothesis 4*, *Conditions 1* and *2*, with and without spread of emotions correspondingly, with the penetration rates of personal assistant devices equal to 1, 5 and 10 % were simulated 50 times each. Then, for each simulation case the mean values of the coefficients si_{exit1}, si_{exit2}, si_{exit3}, ci, fi, describing the dynamics of emerging groups, were determined. After that, the differences between the corresponding coefficients for *Conditions 1* and *2* were calculated averaged over 50 simulations (Table 3), which can be seen as measures of similarity of the group dynamics between the conditions.

Table 3. The differences between the group dynamics coefficients for *Conditions 1* and *2* for different penetration rates averaged over 50 simulations

Penetration rate, %	1	5	10
$<si_{exit1}^{cond2} - si_{exit1}^{cond1}>$	0.35	0.2	0.05
$<si_{exit2}^{cond2} - si_{exit2}^{cond1}>$	0.25	0.11	0.03
$si_{exit3}^{cond2} - si_{exit3}^{cond1}>$	0.21	0.08	0.03
$<ci^{cond2} - ci^{cond1}>$	0.9	0.4	0.1
$<fi^{cond2} - fi^{cond1}>$	0.12	0.09	0.04

The results in Table 3 indicate that with an increase of the number of personal assistant devices, the differences between *Conditions 1* and *2* become smaller. This can be explained as follows: Personal assistant devices support the consistency of social decision making by providing uniform information to human agents. When the number of the personal assistant devices becomes high, most of the human agents will be situated within the reach of such devices. In this case, the devices will (partially) overtake the role of emotions by providing information to human agents, which will increase the cohesiveness of groups and the consistency of their decision making. Because of this, the role of emotional influences, and thus differences between the *Conditions 1* and *2*, will be diminished. This supports *Hypothesis 4*.

To test *Hypothesis 5*, *Condition 1* was simulated 50 times with two more propagation radii: $r = 5$ and $r = 20$. It can be observed in Table 4 that the mean group size and the overall evacuation time grow with the increase of the interaction range. The two-sample t-test performed on the outcomes of two pairs of conditions - with the interaction range 5 and 10, and with the interaction range 10 and 20 - confirms *Hypothesis 5* with 95 % confidence.

Table 4. The mean overall evacuation time and the mean size of the groups emerging in the simulation of *Condition 1* with different interaction ranges. Standard deviation is provided in brackets.

Interaction range, r	5	10	20
Mean group size, gs	17 (4.8)	27 (8.1)	54 (10.2)
Mean overall evacuation time in seconds	156.2 (24.3)	164.1 (31.6)	201.4 (32.2)

6 Conclusion

Many empirical studies indicated [7, 9, 19, 22] that emotions play an important role in social decision making. In this paper the role of emotions in group dynamics in large crowds has been investigated. To this end, based on the literature from social psychology and domain knowledge five hypotheses were formulated. To verify these hypotheses a computational model for social decision making was developed. This model is based on a number of neurological theories and principles supplementing each other in a consistent manner. By simulation based on this model and performing the two-sample t tests on the results all these hypotheses were confirmed. In particular, human agents equipped with personal assistants were recognised as leaders in groups emerging in evacuation. Evacuation with larger groups proceeded more slowly than with smaller groups. Spread of emotions in a crowd increased resistance of agent groups to opinion changes. Acceptance of a different decision option occurred gradually, as also described in the literature [21, 22]. Furthermore, spread of emotions in a group increased its cohesiveness. This result is also supported by the literature (e.g., see [22]). Emotional influences were, however, attenuated by an increasing number of personal assistant devices.

The modelling perspective followed aims at a cognitive and affective modelling level, but takes inspiration from the underlying mechanisms as described at a neurological level. Modeling causal relations discussed in neurological literature in a cognitive/affective level model does not take specific neurons into consideration but uses more abstract mental states. This is a way to use results from the large and more and more growing amount of neurological literature for the cognitive/affective modelling level. This method can be considered as lifting neurological knowledge to a higher level of description. In a more detailed manner, in [3], such a perspective is discussed: '… we can expect that injection of some neurobiological details back into folk psychology would fruitfully enrich the latter, and thus allow development of a more fine-grained folk-psychological account that better matches the detailed functional profiles that neurobiology assigns to its representational states.' [3]. Here Bickle suggests that by relating a (folk) psychological to a neurobiological account, the psychological account can be enriched. The type of higher level model that results from adopting principles from the neurological level may inherit some characteristics from the neurological level. In particular this holds for the Hebbian learning principle adopted here. Another, even more basic element inherited from this 'lifting' perspective is the use of numbers to indicate the strength of the considered states. This is more common in neural modelling perspectives, but here also applied at a higher level. Such a gradual way of modelling allows for the type of cyclic and adaptive processes addressed here, which would be impossible using an approach based on a binary states.

To generate emotions the OCC model has been used in the paper. However, there also exist other approaches to emotional modelling, such as the basic emotions approach [34] and the dimensional approach [35]. The former approach is similar to the OCC model in distinguishing a set of basic emotions (e.g., happiness, anger). The latter approach distinguishes a few dimensions (e.g., valence and arousal) to characterise different emotions; e.g., fear is characterised by a negative valence and a high arousal. Both these approaches can be incorporated in our model by defining appropriate evaluation functions, as discussed in Sect. 4.2.

In the literature [11] it is recognized that humans often employ diverse emotion regulation mechanisms (e.g., to cope with fear and stress). These mechanisms involve interplay between cognitive and affective processes. In the future the proposed model will be extended with an emotion regulation component.

Furthermore, in real evacuation communication lines might be broken and information relay may be significantly delayed. Such scenarios were not considered in this paper and are left for future work.

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