Agent-Based Modelling of the Emergence of Collective States Based on Contagion of Individual States in Groups

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Abstract. This paper introduces a neurologically inspired computational model for the dynamics and diffusion of agent states within groups. The model combines an individual model based on Damasio's Somatic Marker Hypothesis with mutual effects of group members on each other via mirroring of individual states such as emotions, beliefs and intentions. The obtained model shows how this combination of assumed neural mechanisms can form an adequate basis for the emergence of common group beliefs and intentions, while, in addition there is a positive feeling with these common states amongst the group members. A particular issue addressed is how certain types of states may affect other types of states, for example, emotions have an effect on beliefs and intentions, and beliefs may effect emotions.

1 Introduction

To express the impossibility of a task, sometimes the expression 'like managing a herd of cats' is used, for example, in relation to managing a group of researchers. This is meant to indicate that no single direction or decision will come out of such a group, no matter how hard it is tried. As an alternative, sometimes a reference is made to 'riding a garden-cart with frogs'. It seems that such a lack of coherence-directed tendency in a group is considered as something exceptional, a kind of surprising, and in a way unfair. However, as each group member is an autonomous agent with his or her own neurological structures, patterns and states, carrying for example, their own emotions, desires, preferences, and intentions, it would be more reasonable to expect that the surprise concerns the opposite side: how is it possible that so often, groups – even those of researchers – develop coherent directions and decisions, and, moreover, why do the group members in some miraculous manner even seem to feel good with these?

Models of social diffusion focus on the process of change within groups. Examples of social diffusion models found in the area of social sciences are: the diffusion of innovations (see e.g. [35]), social movements such as political interests and parties (see e.g. [22]), and crowd behavior, as for instance seen in emergency evacuation (see e.g. [28]). Diffusion models have also been developed in the domain of multi-agent systems in order to study and simulate the behavior of groups of agents. Hereby, models for the spread of information as well as models for the spread of emotions in agent groups have been expressed (see e.g. [36] and [4], [5], [16], respectively).

In this paper, inspired by the notion of mirroring from the neurological literature (e.g., [14], [23], [24], [31], [32], [33], [30]), first a generic agent-based model is presented for contagion of individual states *S* such as emotions, beliefs or intentions. The model is a generalization of work on emotion contagion as reported in [4] and [5]. It handles contagion of any individual state *S*, and takes into account personal characteristics for openness and expressivity for state *S*, for positive or negative biases for *S,* and for the extent of amplification for *S.* Moreover parameters are used for the interaction channels between pairs of agents. The generic model has been used for two more complex models each involving multiple types of internal state *S*, and involving specific forms of interaction between different types of states. These more complex models are also presented in the paper.

One of these two more complex models is a neurologically inspired computational modelling approach for the emergence of group decisions. It incorporates the ideas of somatic marking as a basis for individual decision making, see [2], [10], [12], [13] and mirroring of both emotions and intentions as a basis for mutual influences between group members, see [14], [23], [24], [31], [32], [33], [30]. The model shows how for many cases indeed, the combination of these two neural mechanisms, via the interaction between emotions and intentions, is sufficient to obtain the emergence of common group decisions on the one hand, and, on the other hand, to achieve that the group members have a positive feeling about these decisions.

The other more complex model presented formalizes and simulates the spread of different types of emotions and beliefs in a group. In the literature, results have been reported that indicate that the emotional state of a person influences the information processing ability (see e.g. [3], [26]). Hence, the emotions that are spread in a group and experienced by the individuals can influence how beliefs are spread. So, two interactions are considered: the influence of emotions upon spreading of beliefs, and the occurrence of emotions based on the beliefs. In order to exemplify the approach, extensive simulation runs have been performed in a evacuation domain with scenarios that include varying characteristics of the agents. The model is based on Frederickson's broaden-and-build theory [17], which states that positive emotions broaden people's mind-sets: the scopes of attention, cognition, action and the array of percepts, thoughts, and actions presently in mind are widened. The complementary narrowing hypothesis predicts the reverse pattern: negative emotions shrink people's thought-action repertoires. Support for the broaden and narrowing hypotheses can be found in [18].

The model presented here captures these dynamics between information and emotion. To illustrate, a message containing information about the location and spread of a fire can be expected to elicit fear. Feelings of fear will reinforce the focus of a person towards information relevant to the threat. Furthermore, numerous research studies have shown that information is able to affect emotions. For example, in many psychological experiments fear is elicited by imagery or text to study the process of fear itself or the internal or external signs of fear in humans, see [29]. Another area in psychological research studies fear appeal (persuasive messages that arouse fear) in which it is investigated if fear appeals can motivate behavior change across a variety of behaviors. See for example [37]. In [7] it is argued that the media can influence the perception of fear, via the type of information they spread. Moreover, studies of nonverbal behavior have showed results that emotions can be spread through nonverbal behavior [19]. One can conclude form these many viewpoints and disciplines that emotions, such as fear, can be spread through (non)verbal and textual communications and imagery.

The paper is organised as follows. In Section 2 a brief introduction of the neurological ideas underlying the approach is presented: mirroring and somatic marking. Next, in Section 3 the generic agent-based model is described in detail. Section 4 presents the more complex model for decision making in groups based on an interaction betweeen eomotions and intentions. In Section 5 a number of simulation results are shown and Section 6 addresses verification of the model against formally specified properties describing expected emerging patterns. In Section 7 the more complex model for the interplay between emotion and belief is introduced formally. Section 8 discusses extensive simulation results for this model. In Section 9 a mathematical analysis of the models is discussed. The paper is concluded with a discussion in Section 10.

2 Some Underlying Neurological Principles

For social interaction, recent neurological findings on the *mirroring function* of certain neurons have turned out to play an important role (e.g., [14], [23], [24], [31], [32], [33], [34], [30]). 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 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. For example, there is strong evidence that (already from an age of just 1 hour) sensing somebody else's face expression leads (within about 300 milliseconds) to preparing for and showing the same face expression ([21], p. 129-130). The idea is that these neurons and the neural circuits in which they are embedded play an important role in social functioning and in (empathic) understanding of others; (e.g., [14], [23], [34], [30]). The discovery of mirror neurons is often considered a crucial step for the further development of the discipline of social cognition, comparable to the role the discovery of DNA has played for biology, as it provides a biological basis for many social phenomena; cf. [23]. Indeed, when states of other persons are mirrored by some of the person's own states that at the same time are connected via neural circuits to states that are crucial for the own feelings and actions, then this provides an effective basic mechanism for how in a social context persons fundamentally affect each other's actions and feelings.

Given the general principles described above, the mirroring function can take place for different types of individual states. In the first place, via body and face expressions, mirroring of emotional states takes place. This type of mirroring occurs in both more complex models presented below in Section 4 and Section 7. A second way in which a mirroring function can occur is by mirroring of intentions or action tendencies of individuals 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. For example, in ([20], p.70) action tendencies are described as 'states of readiness to execute a given kind of action, [which] is defined by its end result aimed at or achieved'. This form of mirroring takes place in the model presented in Section 4. A third type of state for which mirroring can take place is for beliefs. Here verbal communication also may occur, but within a group the nonverbal responses may play an even more important role. This type of mirroring takes place in the model presented in Section 7.

Cognitive states of a person, such as sensory or other representations often induce emotions felt within this person, as described by neurologist Damasio, [11], [12]; for example:

> 'Even when we somewhat misuse the notion of feeling – as in "I feel I am right about this" or "I feel I cannot agree with you" – we are referring, at least vaguely, to the feeling that accompanies the idea of believing a certain fact or endorsing a certain view. This is because believing and endorsing *cause* a certain emotion to happen.' ([12], p. 93)

Damasio's *Somatic Marker Hypothesis*; cf. [2], [10], [12], [13], is a theory on decision making which provides a central role 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.' ([10], pp. 173-174)

Usually the Somatic Marker Hypothesis is applied to provide endorsements or valuations for options for a person's actions, thus shaping a decision process. Somatic markers may be innate, but may also by adaptive, related to experiences:

> 'Somatic markers are thus acquired through experience, under the control of an internal preference system and under the influence of an external set of circumstances which include not only entities and events with which the organism must interact, but also social conventions and ethical rules. ([10], p. 179)

In the computational model introduced in Section 4 somatic marking plays an important role in the spread of intentions in a group. In this model both emotion and intention mirroring effects are incorporated. 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.

In the model introduced in Section 7 mirroring of emotions and beliefs is addressed. Here another type of interaction between mirroring of two different types of states is addressed. In one direction, for example, emotions may affect the openness and biases of a person. In the other direction the beliefs affect emotions.

3 A Generic Agent-Based Model for Social Diffusion of Individual States

This section introduces the basic agent-based social diffusion model used as a point of departure for this research. This model is a generalization of two existing agent-based emotion contagion models: the absorption model and amplification model (cf. [4], [5]). The model formalizes different aspects and types of social diffusion of mental states, such as absorption, amplification, expressiveness and openness for cognitive and affective (e.g., information and emotion) states, which are inspired by theories on contagion mechanisms. For instance, in [1] Barsade describes an informal model of emotion contagion in which the valence (positive or negative) of the emotion and the energy level with which the emotion is expressed characterize the diffusion.

The basic building block of the model is the definition of the contagion strength between individuals within a group. This contagion strength between agents B and A for any particular state S is defined as follows:

$$\gamma_{SBA} = \varepsilon_{SB} \cdot \alpha_{SBA} \cdot \delta_{SA}. \qquad (1)$$

Here ε_{SB} is the personal characteristic *expressiveness* of the sender (agent B) for S, δ_{SA} the personal characteristic *openness* of the receiver (agent A) for S, and α_{SBA} the interaction characteristic *channel strength* for S from sender B to receiver A.

To calculate the level q_{SA} of an agent A for a specific state S the following calculations are performed. First, the overall contagion strength γ_{SA} from the group towards agent A is calculated:

$$\gamma_{SA} = \sum_{B \neq A} \gamma_{SBA} \qquad (2)$$

This value is used to determine the weighed impact $q_{SA}*$ of all the other agents upon state S of agent A:

$$q_{SA}* = \sum_{B \neq A} \gamma_{SBA} \cdot q_{SB} / \gamma_{SA} \qquad (3)$$

How much this external influence actually changes state S of the agent A is determined by two additional personal characteristics of the agent, namely the tendency η_{SA} to absorb or to amplify the level of a state and the bias β_{SA} towards positive or negative impact for the value of the state. The model to update the value of $q_{SA}(t)$ over time is then expressed as a combination of the absorption and amplification models. The result is a more general model of contagion for any state S:

$$q_{SA}(t + \Delta t) = q_{SA}(t) + \gamma_{SA} \cdot [\eta_{SA} \cdot [\beta_{SA} \cdot (1 - (1-q_{SA}*(t)) \cdot (1 - q_{SA}(t))) +$$
$$(1 - \beta_{SA}) \cdot q_{SA}*(t) \cdot q_{SA}(t)] + (1 - \eta_{SA}) \cdot q_{SA}*(t) - q_{SA}(t)] \Delta t \qquad (4)$$

The new value of the state is calculated from the old value, plus the change of the value based upon the contagion. This change is defined as the multiplication of the contagion strength times a factor for the amplification of information plus a factor for the absorption of information. The absorption factor (after $1 - \eta_{SA}(t))$) simply takes the difference between the incoming contagion and the current level. The amplification factor (part of the equation multiplied by $\eta_{SA}(t)$) depends on the tendency of the agent towards more positive (part of equation multiplied by $\beta_{SA}(t)$) or negative (part of equation multiplied by $(1-\beta_{SA}(t))$) information. Table 1 summarizes the most important parameters and states within the model.

Table 1 Parameters and states

q_{SA}	level for state *S* for agent *A*
ε_{SA}	extent to which agent *A* expresses state *S*
δ_{SA}	extent to which agent *A* is open to state *S*
η_{SA}	tendency of agent *A* to absorb or amplify state *S*
β_{SA}	positive or negative bias of agent *A* on state *S*
α_{SBA}	channel strenght for state *S* from sender *B* to receiver *A*
γ_{SBA}	contagion strength for *S* from sender *B* to receiver *A*

4 Modelling the Dynamics of Intentions and Emotions in Groups

In this section, based on the neurological principles of somatic marking and mirroring discussed in the previous section, the computational model for group decision making is introduced. To design such a model a choice has to be made for the grain-size: for example, it has to be decided in which level of detail the internal neurological processes of individuals are described. Such a choice depends on the aim of the model. In this case the aim was more to be able to simulate emerging patterns in groups of individuals, than to obtain a more detailed account of the intermediate neurological patterns and states involved. Therefore the choice was made to abstract to a certain extent from the latter types of intermediate processes. For example, the process of mirroring is described in an abstract manner by a direct causal relation from the emotional state shown by an individual to the emotional state shown by another individual, and the process of somatic marking is described by a direct causal relation for any individual from the emotional state for a certain option to the intention for this option (see Fig. 1). The model can easily be refined into a model that also incorporates more detailed intermediate internal processes, for example, based on recursive as-if body loops involving preparation and sensory neuron activations and the states of feeling the emotion, for example, as shown in [25].

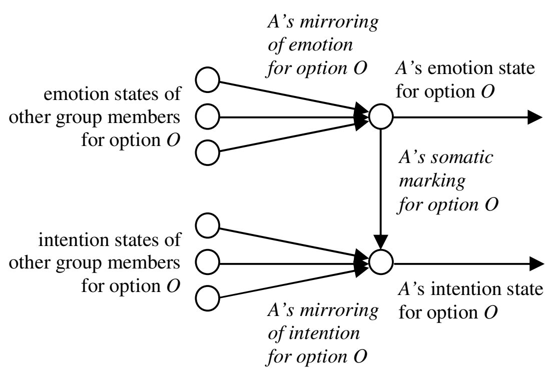

Fig. 1. Abstract causal relations induced by mirroring and somatic marking by person *A*

The abstract model for mirroring described above applies to both emotion and intention states *S* or an option *O*, but does not describe any interplay between them yet. Taking the Somatic Marker Hypothesis on decision making as a point of departure, not only intentions of others, but also one's own emotions affect one's own intentions. To incorporate such an interaction, the basic model is extended as follows: to update $q_{SA}(t)$ for an intention state *S* relating to an option *O*, both the intention states of others for *O* and the $q_{S'A}(t)$ values for the emotion state *S'* for *O* are taken into account. These intention and emotion states *S* and *S'* for option *O* are denoted by *OI* and *OE*, respectively:

Level of emotion for option *O* of person *A*:	$q_{OEA}(t)$
Level of intention indication for *O* of person *A:*	$q_{OIA}(t)$

The combination of the own (positive) emotion level and the rest of the group's aggregated intention is made by a weighted average of the two:

$$q_{OIA}^{**}(t) = (\omega_{OIA}/\omega_{OA})\, q_{OIA}^{*}(t) + (\omega_{OEA}/\omega_{OA})\, q_{OEA}(t)$$
$$\gamma_{OIA}^{*} = \omega\, \gamma_{OIA} \qquad (1)$$

where ω_{OIA} and ω_{OEA} are the weights for the contributions of the group intention impact (by mirroring) and the own emotion impact (by somatic marking) on the intention of *A* for *O*, respectively, and $\omega_{OA} = \omega_{OIA} + \omega_{OEA}$. Then the model for the intention and emotion contagion based on mirroring and somatic marking becomes:

$$q_{OEA}(t + \Delta t) = q_{OEA}(t) + \gamma_{OEA}[\,\eta_{OEA}(\beta_{OEA}\,(1 - (1-q_{OEA}{*}(t))(1-q_{OEA}(t))) + (1-\beta_{OEA})\, q_{OEA}{*}(t)\; q_{OEA}(t)) + (1 - \eta_{OEA})\, q_{OEA}{*}(t)\; - q_{OEA}(t)\;] \cdot \Delta t \tag{2}$$

$$q_{OIA}(t + \Delta t) = q_{OIA}(t) + \gamma_{OIA}{*}[\,\eta_{OIA}\,(\beta_{OIA}\,(1 - (1-q_{OIA}{**}(t))(1-q_{OIA}(t))) + (1-\beta_{OIA})\, q_{OIA}{**}(t)\; q_{OIA}(t)) + (1 - \eta_{OIA})\, q_{OIA}{**}(t)\; - q_{OIA}\,(t)] \cdot \Delta t \tag{3}$$

5 Simulation Results: Interaction Between Intentions and Emotions

The model has been studied in several scenarios in order to examine whether the proposed approach indeed exhibits the patterns that can be expected from literature. The investigated domain consists of a group of four agents who have to make a choice between four different options: A, B, C or D. The model has been implemented in Matlab by constructing three different scenarios which are characterized by different relationships (i.e., channel strength) between the agents. The scenarios used, involve two more specific types of agents: leaders and followers. Some agents have strong leadership abilities while others play a more timid role within the group. The general characteristics of leaders and followers as they were used in the experiments, which can be manifested differently within all agents, can be found in Table 2. The complete settings for the three scenarios can be found in Appendix A.

Table 2. Parameters and state variables for leaders and followers

	Leader *A*	**Follower *B***
emotion level	q_{OEA} high for particular O	-
intention level	q_{OIA} high for particular O	-
expressivity	ε_{SA} high	ε_{SB} low
channel strength	α_{SAB} high	α_{SAB} high
	α_{SBA} low	α_{SBA} low

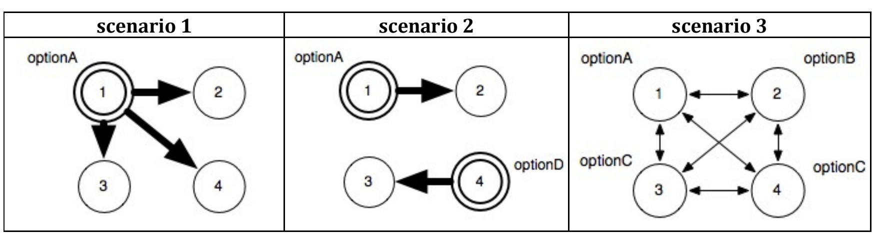

Fig. 2. Scenarios for the presented simulation experiments

The different scenarios are depicted in Fig. 2. Scenario 1 consists of a group of agents in which agent1 has strong leadership abilities and high channel strengths with all other agents. His initial levels of emotion and intention for option A, are very high. Scenario 2 depicts a situation where there are two agents with leadership abilities in the group, agent1 and agent4. Agent1 has strong channel strength to agent2, while agent4 has a strong connection to agent3. Agent1 has an initial state of high (positive) emotion and intention for option A, while agent4 has strong emotion and intention states for option D. Agent2 and agent3 have show no strong intentions and emotions for any of the options in their initial emotion and intention states. In Scenario 3 there are no evident leaders. Instead, all agents have moderate channel strengths with each other. A majority of the agents (agent3 and agent4) prefers option C, i.e., initially they have high intention and emotions states for option C. For both scenarios two variants have been created, one with similar agent characteristics within the group (besides the difference between leader and follower characteristics), and the second with a greater variety of agent personalities. In this section, only the main results using the greater variety in agent characteristics are shown for the sake of brevity. For the formal verification (Section 6) both have been used.

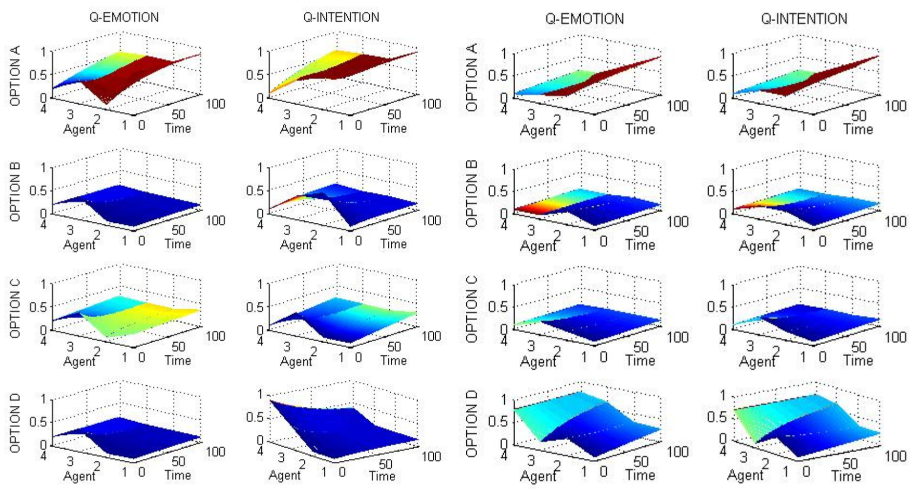

Fig. 3. Simulation results for scenario 1 (left) and scenario 2 (right)

The results of scenario 1 clearly show how one influential leader can influence the emotions and intention in a group. This is shown in the left graph of Fig. 3, here the z-axis shows the value for the respective states, and the x-and y-axes represent time and the various agents. The emotion and intention of the leader (in this case agent1) spread through the network of agents, while the emotions and intentions of other agents hardly spread. Consequently, the emotions and intentions for option A, which is the preferred option of the leader, develop to be high in all agents. As can be seen in the figure, there are small differences between the developments of emotions and intentions of the agents. This is because they have different personality characteristics, which are reflected in the settings for the scenario (see Appendix A). Depending on their openness, agents are more or less influenced by the states of others. Those agents with low openness (such as agent4) are hardly influenced by intentions and emotions of others.

In scenario 2 (as shown in the right graph of Fig. 3), the leader has somewhat positive emotions about option C as well, which explains the small but increasing spread of emotions (and after a while also intentions) concerning option C through the social network. Even though agent3 and agent2 both have a moderate intention for option B, their only strong channel strength is with each other, causing only some contagion between the two of them. Their intention does not spread because of a low expressive nature and low amplification rate of both agents. The patterns found in the simulation of scenario 2 are similar to the ones of scenario 1, with the addition that both leaders highly dominate the spread of the emotions and intentions. The figure shows that the emotions and intentions of agent2 turn out to depend highly on the emotions and intentions of agent1, whereas the emotions and intentions of agent3 highly depend on those of agent4. As can be seen in the figure, any preferences for option D and C by agent2 and agent3 quickly grow silent.

Scenario 3 shows how a group converges to the same high emotions and intentions for an option when there is no authority. In general, the graphs show that when there is no clear leadership, the majority determines the option with highest emotion and intentions in all agents. Option C, initially preferred by agent4 and agent3, eventually is the preferred option for all. However, the emotions and intentions for option A also spread and increase, though to a lesser extent. This is due to the fact that agent1 has strong feelings and intentions for option A and a high amplification level for these states. Furthermore, he has a significant channel strength with agent3, explaining why agent3 has the most increasing emotions and intentions for option A. However, the majority has the most important vote in this scenario.

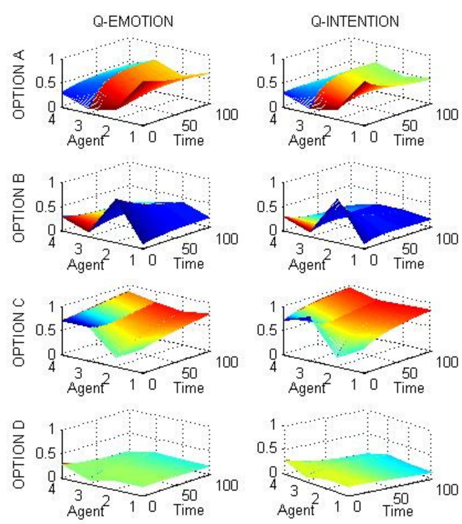

Fig. 4. Simulation results for scenario 3

Furthermore, some general statements can be made about the behaviour of the model. In case a leader has high emotions but low intentions for a particular option, both the intentions and emotions of all followers will increase for that option. On the other hand, if a leader has high intentions for a particular option, but not high emotions for that option, this intention will not spread to other agents.

6 Verification of Properties Specifying Emerging Patterns

This section addresses the analysis of the group decision making model by specification and verification of properties expressing dynamic patterns that emerge. The purpose of this type of verification is to check whether the model behaves as it should, by automatically verifying such properties against the simulation traces for the various scenarios. In this way the modeller can easily detect inappropriate behaviours and locate sources of errors in the model. A typical example of a property that may be checked, is whether no unexpected situations occur, such as a variable running out of its bounds (e.g., $q_A(t) > 1$, for some time point t and agent A), or whether eventually an equilibrium value is reached, but also more detailed expected properties of the model such as compliance to the theories found in literature.

A number of dynamic properties have been identified, formalized in the Temporal Trace Language (TTL), cf. [6] and automatically checked. The TTL software environment includes a dedicated editor supporting specification of dynamic properties to obtain a formally represented temporal predicate logical language TTL formula. In addition, an automated checker is included that takes such a formula and a set of traces as input, and verifies automatically whether the formula holds for the traces. The language TTL is built on atoms referring to *states* of the world, *time points* and *traces*, i.e. trajectories of states over time. In addition, *dynamic properties* are temporal predicate logic statements that can be formulated with respect to traces based on a state ontology.

Below, a number of the dynamic properties that were identified for the group decision making model are introduced, both in semi-formal and in informal notation (where state(γ, t) |= p denotes that p holds in trace γ at time *t*). The first property counts the number of subgroups that are present. Here, a subgroup is defined as a group of agents having the same highest intention. Each agent has 4 intention values (namely one for each of the four options that exist), therefore the number of subgroups that can emerge are always: 1, 2, 3 or 4 subgroups.

P1 –number of subgroups

The number of subgroups in a trace γ is the number of options for which there exists at least one agent that has an intention for this option as its highest valued intention.

P1_number_of_subgroups(γ:TRACE) ≡ sum(I:INTENTION, case(highest_intention(γ, I), 1, 0)

where

highest_intention(γ:TRACE, I:INTENTION) ≡
∃A:AGENT [∀R1:REAL state(γ, te) |= has_value(A, I, R1)
⇒ ∀I2:INTENTION≠I, ∀R2:REAL [state(γ, te) |= has_value(A, I2, R2) ⇒ R2 < R1]]

In this property, the expression case(p, 1, 0) in TTL functions such that if property p holds it is evaluated to the second argument (*1* in this example), and to the third argument (*0* in this example) if the property does not hold. The sum operator simply adds these over the number of elements in the sort over which the sum is calculated (the intentions in this case). Furthermore, when tb or te are used in the property, they denote the begin or end time of the simulation, whereby in te an equilibrium is often reached. Property P1 can be used to count the number of subgroups that emerge. A subgroup is defined as a group of agents that each have the same intention as their intention with highest value. This property was checked on multiple traces that each belong to one of the three scenario's discussed in the simulation results section. For the traces for both variants of scenario 1: , a single subgroup was found, for scenario 2: two subgroups were found, and for scenario 3, a single subgroup was found, which is precisely according to the expectations.

The second property counts the number of agents in each of the subgroups, using a similar construct.

P2– subgroup size

The number of agents in a subgroup for intention I is the number of agents that have this intention as their highest intention.

P2_subgroup_size(γ:TRACE, I:INTENTION) ≡ sum(A:AGENT, case(highest_intention_for(γ, I, A), 1, 0))

where

highest_intention_for(γ:TRACE, I:INTENTION, A:AGENT) ≡
∀R1:REAL [state(γ, te) |= has_level(A, I, R1)
⇒ ∀I2:OPTION≠I, ∀R2:REAL [state(γ, te) |= has_level(A, I2, R2) ⇒ R2 < R1]]

In the traces for scenario1 the size of the single subgroup that occurred was 4 agents. For scenario 2 two subgroups of 2 agents were found. Finally, in scenario 3 only a single subgroup combining 4 agents has been found. These findings are correct; they indeed correspond to the simulation results.

The final property, P3, expresses that an agent is a leader in case its intention values have changed the least over the whole simulation trace, as seen from his initial intention values and compared to the other agents (thereby assuming that these agents moved towards the intention of the leader that managed to convince them of this intention).

P3–leader

An agent is considered a leader in a trace if the number of intentions for which it has the lowest change is at least as high as all other agents.

P3_leader (γ:TRACE, A:AGENT) ≡
∀A2:AGENT ≠A
sum(I:INTENTION, case(leader_for_intention(γ, A, I),1,0)) ≥
sum(I:INTENTION, case(leader_for_intention(γ, A2, I),1,0))

where

leader_for_intention(M:TRACE, A:AGENT, I:INTENTION) ≡
∀R1, R2: REAL [[state(γ, tb) |= has_value(A,I, R1) & state(γ, te) |= has_value(A, I, R2)]
⇒ ∀R3, R4: REAL, ∀A2:AGENT ≠A
[state(γ, tb) |= has_value (A2, I, R4) & state(γ, te) |= has_value (A2, I, R3)
⇒ |R2-R1|< |R3-R4|]]

Using this definition, only agent 1 qualifies as a leader in scenario 1. For scenario 2 only agent 4 is a leader. Finally, in scenario 3 both agent 1 and agent 3 are found to be leaders as they both have equal intentions for which they change the least.

7 Modelling the Dynamics of Beliefs and Emotions in Groups

The agent-based social diffusion model introduced in Section 2 can be applied to both emotion and beliefs, but does not describe any interplay between diffusion of different states. For example, not only emotions of others, but also beliefs may affect emotions. On the other hand, strong emotions may affect personal characteristics for belief diffusion such as openness and expressivity. To incorporate such interactions, the basic model is extended as follows:

1. To update q_{SA} for one state S, also the $q_{S'B}$ values for some other state S' may be taken into account.
2. Some of the personal characteristics for a state S may be determined dynamically depending on values $q_{S'B}$ for a certain other state S'.

The Effect of Emotion upon Belief

To model the effect of emotions on belief diffusion, below the personal characteristics δ_{SA}, η_{SA} and β_{SA} for a belief state S are not assumed constant, but are instead modeled in a dynamic manner, depending on emotions. As can be seen in the adopted model, multiple factors that influence diffusion of a state S have been distinguished. One can divide these into three different categories: state q_{SA}, personal characteristics ε_{SA}, δ_{SA}, η_{SA}, β_{SA} and interaction characteristic α_{BA}. One additional category is introduced here, namely belief state characteristics r_{SA} denoting how relevant, and p_{SA} denoting how positive a belief state S is for agent A. Examples of settings for an evacuation scenario can be found in Table 3.

The intensity of the emotional state of a person will affect his ability to receive information, thereby possibly affecting individual agent characteristics. In this case the focus is on one type of emotion, namely fear. A high level of fear contributes to the levels of β_{SA}, η_{SA} and δ_{SA}. However, if fear is low, the value of the parameters should be dominated by their initial values that represent the personal characteristics of the agent instead. First the effect of fear upon the openness for a belief state S (characterized by a relevance r_{SA} and a positiveness p_{SA} for A) is expressed:

$$\delta_{SA}(t+\Delta t) = \delta_{SA}(t) + \mu\cdot(1/1+e^{-\sigma(q_{fear,A}(t)\ -\ \tau)})\cdot[(1-(1-r_{SA})\ q_{fear,A}(t))\ -\delta_{SA}(t)]\cdot\Delta t \qquad (8)$$

Table 3 Types Of Information

		positivity of information (p) [0-1]	
		0	*1*
relevance for survival (r) [0-1]	*0*	"The toilets are out of order"	"Local authorities have been informed"
	1	"All rear exits are obstructed"	"The front emergency exit is clear"

If $q_{fear,A}$ is lower than threshold τ (on the interval [0,1]), it will not contribute to the value of δ_{SA}. If $q_{fear,A}$ has a value above τ, the openness will depend on the relevance of the information: when the relevance is high, openness will increase, while if the relevance is low, openness will decrease. In all formulae, μ is an adaptation parameter. This proposed model corresponds to theories of emotions as frames for selective processing, as described in [17]**,** [27]. A distinction between amplification values for different types of information is also made, depending on the emotional state fear. The dynamics for the characteristic $\eta_{SA}(t)$ that model the amplification or absorption of belief state S are described as follows:

$$\eta_{SA}(t+\Delta t) = \eta_{SA}(t\ ) + \mu\cdot(1/1+e^{-\sigma(q_{fear,A}(t)\ -\ \tau)})\cdot[r_{SA}\cdot(1-p_{SA})\cdot(q_{fear,A}(t) - \eta_{SA}(t))]\cdot\Delta t \qquad (9)$$

The emotion of fear only has an influence when it is above the threshold. In that case the parameter only changes for relevant, non-positive information for which the parameter starts to move towards the value for the emotion of fear (meaning this type of belief will be amplified). This property represents an interpretation of [8] on how emotion can result in selective processing of emotion-relevant information.

The bias of an agent is also influenced by its emotion, but in addition depends on the content of the information, which can be either positive or negative:

$$\beta_{SA}(t+\Delta t) = \beta_{SA}(t) + \mu\cdot(1/1+e^{\sigma(\ q_{fear,A}(t)\ -\ \tau)})\cdot(1-q_{fear,A}(t)\ )\cdot((1-p_{SA})-\beta_{SA}(t))\cdot\Delta t \qquad (10)$$

Again, the bias is not influenced by fear if its value is low. In case fear is high, p_{SA} has a high impact on the bias: a low positiveness inhibits the bias, while a high positiveness increases the bias. The agent thus has a bias towards negative belief in case it has a high level of fear, which corresponds with the narrowing hypothesis from Frederickson's broaden-and-build theory in [17].

The Effect of Belief upon Emotion

After modeling the influence of emotion upon the belief contagion in the previous section, the opposite direction is investigated in this section: emotions being influenced by belief. This influence is modeled by altering the overall weighed impact of the contagion of the emotional state for fear. This is expressed as follows:

$$q_{Sfear,A}^* = \nu \cdot (\sum_{B \neq A} \gamma_{SfearBA} \cdot q_{SfearB} / \gamma_{SfearA}) + (1-\nu) \cdot (\sum_{Sinfo} \omega_{Sinfo,A} \cdot (1 - p_{SinfoA}) \cdot r_{SinfoA} \cdot q_{Sinfo,A}) \quad (11)$$

Table 4 Six scenarios for diffusion

Initial settings	emotion → info	emotion ↔ info
high fear levels	scenario 1	scenario 4
low fear levels	scenario 2	scenario 5
mixed fear levels	scenario 3	scenario 6

Here the influence depends on the impact from the emotion fear by others (the first factor, with weight ν) in combination with the influence of the belief present within the agent. In this case, belief has an increasing effect on fear if it is relevant and non positive.

8 Simulation Results: Interaction Between Beliefs and Emotions

In order to see whether the approach indeed exhibits the patterns that can be expected from literature, a case study has been conducted in the domain of emergency evacuation. The states as shown in Table II have been used in combination with the emotion of fear. Furthermore, the value of the channel strength α_{SBA} has been made dependent upon the distance:

$$\alpha_{SBA} = 1-(1/(1+e^{-4\sigma(d_{AB}-\tau)}) \quad (12)$$

This formula expresses that a belief is only perceived in case the distance between agent A and B (d_{AB}) is below the distance threshold (τ).

The full model has been implemented in Matlab, and six different scenarios have been created (see Table 5). The complete settings for the three scenarios can be found in Appendix B.

In the scenarios, the emotional levels have been varied. The influence of belief upon emotion has been left out of to allow the sole analysis of the influence of emotions upon belief contagion. In each scenario, 4 agents have been used. The most important results are discussed below. Note that for all scenarios the value for the maximum distance ($\tau_{distance}$) has been set to 4, which represents that one can not hear or see a (non)verbal communication properly anymore when it is farther than the distance of 4. The threshold value for fear (τ_{fear}) is set to 0.5.

Scenario 1. First the general scenario and the interpretation of the values of the parameters is briefly described. In scenario 1, all agents initially are unaware of any danger and thus have low fear ($q_{fear} = 0.1$). Each agent has access to one out of four types of information (the four types can be made out of the four combinations of high/low relevance versus high/low positiveness of information). That is, agent 1 is located near the front exit and observes it is clear. Agent 2 just read on his phone that local authorities have been informed that there is smoke emerging from the building. Agent 3 just received word that all rear exits are blocked and agent 4 noticed that the toilets are out of order.

Table 5 Parameter Settings For Scenario 1

Parameter	q_{fear}	q_{HH}	q_{LH}	q_{HL}	q_{LL}
A1 (init q)	*0.1*	*1*	*0.1*	*0.1*	*0.1*
A2 (init q)	*0.1*	*0.1*	*1*	*0.1*	*0.1*
A3 (init q)	*0.1*	*0.1*	*0.1*	*1*	*0.1*
A4 (init q)	*0.1*	*0.1*	*0.1*	*0.1*	*1*
A1 (δ)	*0.5*	*0.5*	*0.5*	*0.5*	*0.5*
A2 (δ)	*0.5*	*0.5*	*0.5*	*0.5*	*0.5*
A3 (δ)	*0.5*	*0.5*	*0.5*	*0.5*	*0.5*
A4 (δ)	*0.5*	*0.5*	*0.5*	*0.5*	*0.5*
A1 (η)	*0.5*	*0.3*	*0.3*	*0.3*	*0.3*
A2 (η)	*0.5*	*0.8*	*0.8*	*0.8*	*0.8*
A3 (η)	*0.5*	*0.1*	*0.1*	*0.1*	*0.1*
A4 (η)	*0.5*	*0.2*	*0.2*	*0.2*	*0.2*
A1 (β)	*0.5*	*0.1*	*0.1*	*0.1*	*0.1*
A2 (β)	*0.5*	*0.5*	*0.5*	*0.5*	*0.5*
A3 (β)	*0.5*	*0.9*	*0.9*	*0.9*	*0.9*
A4 (β)	*0.5*	*0.3*	*0.3*	*0.3*	*0.3*

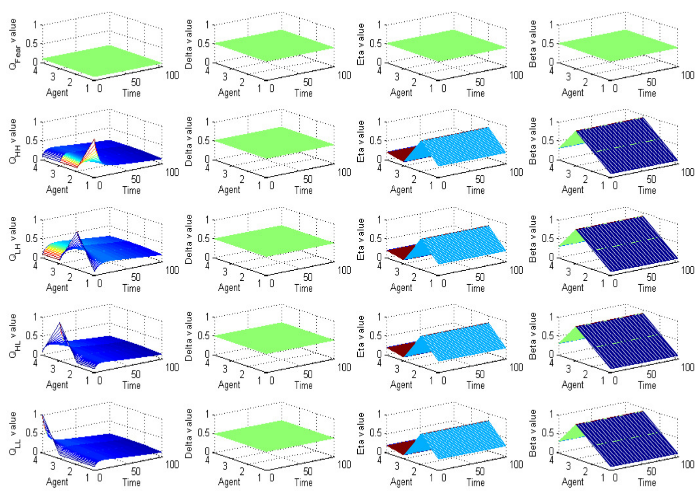

Fig. 5 Simulation results of scenario 1

In order to clearly demonstrate the functioning of the model, all agents in this scenario have the same openness for all information and fear states (0.5) and they have the same amplification rate for fear (0.5). However, they differ in their amplification rate for information they receive. Agent 1, agent 3 and agent 4 all have relatively low amplification rates for all belief states, while agent 2 is more expressive and has a strong amplification for all belief states. In this scenario, agent 1 and agent 3 have a low bias for all types of belief and are not easily primed by it. Agent 2 has an average bias for all belief states and agent 3 is easily primed by any kind of belief. Details on the translation of this information into parameter settings can be found in Table 5. Fig. 5 shows the simulation results for scenario 1. The rows in the figure represent the various states: the first row shows values for the state fear (q_{fear}), row 2 represents the state of highly relevant, positive information (q_{HH}), row 3 of low relevant, positive information (q_{LH}), row 4 of highly relevant, negative information (q_{HL}) and row 5 shows values for the state of low relevant, negative information (q_{LL}). The columns represent the values for the state itself, and those for the openness, amplification, and bias for that state. Analysis of the simulation results leads to the following conclusions. First, the perceived fear remains constant for all agents, since this scenario does not capture the influence of belief on emotion. The same holds for the individual values for openness, amplification and bias due to the fact that fear is so low that it does not influence the contagion of the belief. Second, all types of information are quickly relayed to the other agents but after some time there is a slow decay of all types of belief.

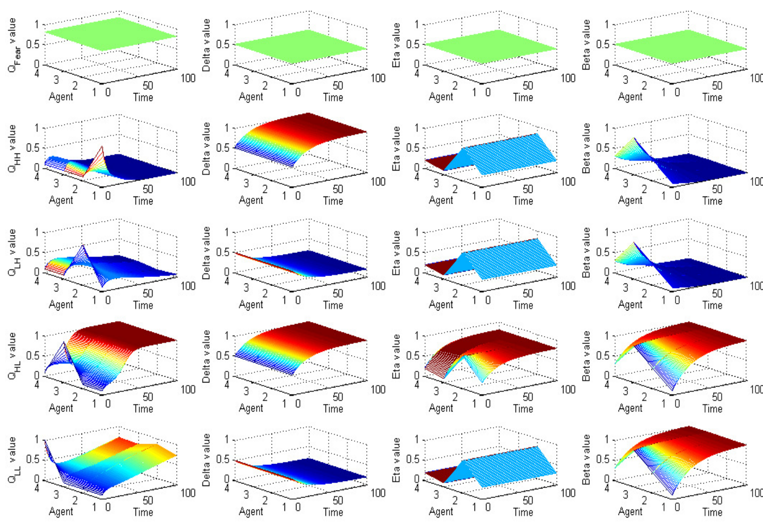

Fig. 6. Simulation results of scenario 2

Scenario 2. The only difference between scenario 1 and 2 is the initial level of fear, which is low for all agents in scenario 1, but high for all agents in scenario 2. In the simulation of scenario 2, which can be found in Fig. 6, different patterns emerge. Although the fear is still a constant factor, the high state of fear of all agents affects their values of openness, amplification and bias for particular belief states. For example, all values increase of the parameters for highly relevant, negative information. While the levels for positive information decrease or stay constant over time, the levels for negative information show a significant increase due to these changes of the parameters.

Scenario 3. In scenario 3 the agents all have different personalities and different levels of fear and belief, represented by different personal settings for all parameters. Simulation results show that due to the personal settings, some agents develop higher fear levels over time than others. See Fig. 7.

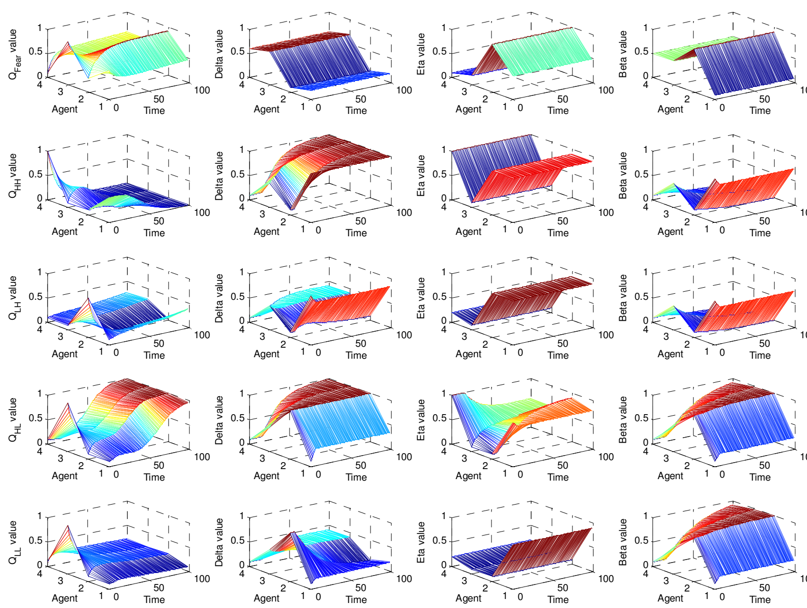

Fig. 7. Simulation results of scenario 3

Scenario 4, 5, and 6. Simulations 4, 5 and 6 also take the influence of belief upon the level of fear into account. In these scenarios, the value for the weights of the influence of the belief state upon fear is set to 0.1, 0.7, 0.1, and 0.1 for q_{HH}, q_{LH}, q_{HL} and q_{LL} respectively. Furthermore, the value for ν has been set to 0.5. The initial settings of scenario 4, 5 and 6 are the same as scenario 1, 2 and 3, respectively. Since in the presented model the belief directly affects the emotion (and not the openness, amplification and bias), only the *q*-values will be discussed. They are displayed in Fig. 8. For the scenario with low fear (scenario 4) the q_{fear} increases slightly for all agents due to availability of belief. However, just as the belief levels decay, the q_{fear} levels decrease again after some time. More interesting are the results from scenario 5 and 6. The results of the simulation of scenario 5 show that (i) negative information - in particular relevant negative information - spreads quickly through the network of agents, and (ii) the spread of q_{fear} first decreases and then spreads again causing an increase of this level for each of the agents. Note that the increase of q_{HL} and, in a somewhat lesser extent, q_{LL} cause the higher levels of q_{fear}. Looking at the simulation results of scenario 6 two main observations can be made. First, the q_{fear} of agent1, agent 3 and agent 4 does not increase as much as it did in scenario 5, due to the fact that they have lower values for negative

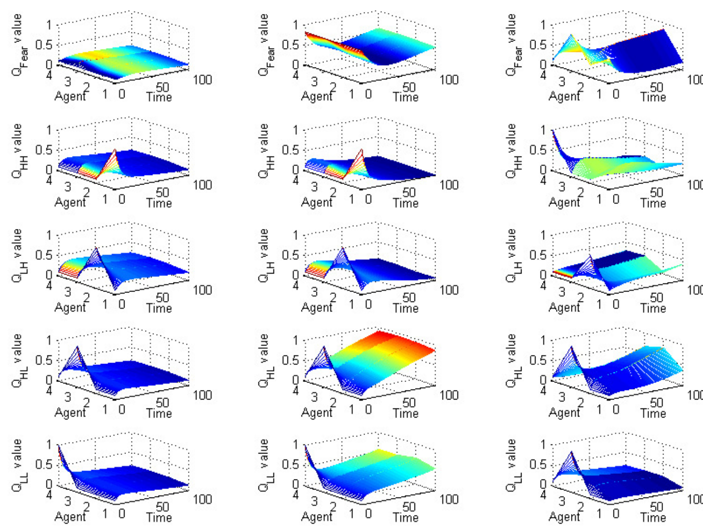

Fig. 8. The q-values for scenario 4 (leftmost column), 5 (center column), and 6 (rightmost column)

information states than agent 2. Second, q_{fear} is reduced as the agents obtain more positive information and soon after increases when the obtained information has a less positive content.

9 Mathematical Analysis of Equilibria and Monotonicity

In this section for the presented models a mathematical analysis will be discussed of equilibria, and monotonicity.

9.1 Mathematical analysis for the first model

During simulations it turns out that eventually equilibria are reached: all variables approximate values for which no change occurs anymore. Such equilibrium values can also be determined by mathematical analysis of the differential equations for the model:

$$dq_{OEA}(t)/dt = \gamma_{OEA}[\, \eta_{OEA}(\beta_{OEA}\,(1 - (1\text{-}q_{OEA}{}^{*}(t))(1\text{-}q_{OEA}(t))) + (1\text{-}\beta_{OEA})\, q_{OEA}{}^{*}(t)\;\; q_{OEA}(t)) + (1 - \eta_{OEA})\, q_{OEA}{}^{*}(t)\; - q_{OEA}(t)\;]\;\cdot \Delta t \quad (4)$$

$$dq_{OIA}(t)/dt = \gamma_{OIA}{}^{*}\,[\, \eta_{OIA}\,(\beta_{OIA}\,(1 - (1\text{-}q_{OIA}{}^{**}(t))(1\text{-}q_{OIA}(t))) + (1\text{-}\beta_{OIA})\, q_{OIA}{}^{**}(t)\;\; q_{OIA}(t)) + (1 - \eta_{OIA})\, q_{OIA}{}^{**}(t)\; - q_{OIA}(t)]\;\cdot \Delta t \quad (5)$$

Putting $dq_{OEA}(t)/dt = 0$ and $dq_{OIA}(t)/dt = 0$ and assuming γ_{OEA} and $\gamma_{OIA}{}^{*}$ nonzero, provides the following equilibrium equations for each agent A.

$$\eta_{OEA}(\beta_{OEA}\,(1\text{-}(1\text{-}q_{OEA}{}^*)(1\text{-}q_{OEA})) + (1\text{-}\beta_{OEA})\,q_{OEA}{}^*\,q_{OEA}) + (1 - \eta_{OEA})\,q_{OEA}{}^* - q_{OEA} = 0 \qquad (6)$$
$$\eta_{OIA}\,(\beta_{OIA}\,(1\text{-}(1\text{-}q_{OIA}{}^{**})(1\text{-}q_{OIA})) + (1\text{-}\beta_{OIA})\,q_{OIA}{}^{**}\,q_{OIA}) + (1 - \eta_{OIA})\,q_{OIA}{}^{**} - q_{OIA} = 0 \qquad (7)$$

For given values of the parameters η_{OEA}, β_{OEA}, η_{OIA}, and β_{OIA} , these equations may be solved analytically or by standard numerical approximation procedures. Moreover, by considering when $dq_{OEA}(t)/dt > 0$ or $dq_{OEA}(t)/dt < 0$ one can find out when $q_{OEA}(t)$ is strictly increasing and when strictly decreasing, and similarly for $q_{OIA}(t)$. For example, for equation (2), one of the cases considered is the following.

Case $\eta_{OIA} = 1$ and $\beta_{OIA} = 1$

For this case, equation (2) reduces to $(1\text{-}(1\text{-}q_{OIA}{}^{**})(1\text{-}q_{OIA})) - q_{OIA} = 0$. This can easily be rewritten via $(1\text{-}\ q_{OIA}\ )\ \text{-}(1\text{-}q_{OIA}{}^{**})(1\text{-}q_{OIA}) = 0$ into $q_{OIA}{}^{**}(1\text{-}q_{OIA}) = 0$. From this, it can be concluded that equilibrium values satisfy $q_{OIA}{}^{**}= 0$ or $q_{OIA} = 1,$ and q_{OIA} is never strictly decreasing, and is strictly increasing when $q_{OIA}{}^{**} > 0$ and $q_{OIA} < 1$. Now the condition $q_{OIA}{}^{**} = 0$ is equivalent to

$$(\omega_{OIA}/\omega_{OA})\,q_{OIA}{}^* + (\omega_{OEA}/\omega_{OA})\,q_{OEA} = 0 \;\Leftrightarrow\; q_{OIA}{}^* = 0 \text{ if } \omega_{OIA} > 0 \text{ and } q_{OEA} = 0 \text{ if } \omega_{OEA} > 0$$

where $q_{OIA}{}^* = 0$ is equivalent to $\sum_{B\neq A} \gamma_{OIBA} \cdot q_{OIB} / \gamma_{OIA} = 0 \;\Leftrightarrow\; q_{OIB} = 0$ for all $B{\neq}A$ with $\gamma_{OIBA} > 0$. Assuming both ω_{OIA} and ω_{OEA} nonzero, this results in the following:

equilibrium: $q_{OIA} = 1$ or $q_{OIA} < 1$ and $q_{OEA} = 0$ and $q_{OIB} = 0$ for all $B{\neq}A$ with $\gamma_{OIBA} > 0$
strictly increasing: $q_{OIA} < 1$ and $q_{OEA} > 0$ or $q_{OIB} > 0$ for some $B{\neq}A$ with $\gamma_{OIBA} > 0$

Table 6. Equilibria cases for an agent A with both $\omega_{OEA} > 0$, $\omega_{OIA} > 0$, and $\gamma_{OEBA} > 0$ for all B

		$\eta_{OIA} = 1$ $\beta_{OIA} = 1$		$\eta_{OIA} = 1$ $\beta_{OIA} = 0.5$	$\eta_{OIA} = 1$ $\beta_{OIA} = 0$	
		$q_{OIA} = 1$	$q_{OIA} < 1$ $q_{OEA} = 0$ $q_{OIB} = 0$ for all $B \neq A$	$q_{OIA}{}^{**} = q_{OIA}$	$q_{OIA} = 0$	$q_{OIA} > 0$ $q_{OEA} = 1$ $q_{OIB} = 1$ for all $B \neq A$
$\eta_{OEA} = 1$ $\beta_{OEA} = 1$	$q_{OEA} = 1$	$q_{OEA} = 1$ $q_{OIA} = 1$	none	$q_{OEA} = 1$ $q_{OIA}{}^{**} = q_{OIA}$	$q_{OEA} = 1$ $q_{OIA} = 0$	$q_{OEA} = 1$ $q_{OIA} > 0$ $q_{OIB} = 1$ for all $B \neq A$
	$q_{OEA} < 1$ $q_{OEB} = 0$ for all $B \neq A$	$q_{OEA} < 1$ $q_{OIA} = 1$ $q_{OEB} = 0$ for all $B \neq A$	$q_{OEC} = 0$ for all C $q_{OIA} < 1$ $q_{OIB} = 0$ for all $B \neq A$	$q_{OEA} < 1$ $q_{OIA}{}^{**} = q_{OIA}$ $q_{OEB} = 0$ for all $B \neq A$	$q_{OEA} < 1$ $q_{OIA} = 0$ $q_{OEB} = 0$ for all $B \neq A$	none
$\eta_{OEA} = 1$ $\beta_{OEA} = 0.5$	$q_{OEA}{}^* = q_{OEA}$	$q_{OEA}{}^* = q_{OEA}$ $q_{OIA} = 1$	$q_{OEC} = 0$ for all C $q_{OIA} < 1$ $q_{OIB} = 0$ for all $B \neq A$	$q_{OEA}{}^* = q_{OEA}$ $q_{OIA}{}^{**} = q_{OIA}$	$q_{OEA}{}^* = q_{OEA}$ $q_{OIA} = 0$	$q_{OEC} = 1$ for all C $q_{OIA} > 0$ $q_{OIB} = 1$ for all $B \neq A$
$\eta_{OEA} = 1$ $\beta_{OEA} = 0$	$q_{OEA} = 0$	$q_{OEA} = 0$ $q_{OIA} = 1$	$q_{OEA} = 0$ $q_{OIA} < 1$ $q_{OIB} = 0$ for all $B \neq A$	$q_{OEA} = 0$ $q_{OIA}{}^{**} = q_{OIA}$	$q_{OEA} = 0$ $q_{OIA} = 0$	none
	$q_{OEA} > 0$ $q_{OEB} = 1$ for all $B \neq A$	$q_{OEA} > 0$ $q_{OIA} = 1$ $q_{OEB} = 1$ for all $B \neq A$	none	$q_{OEA} > 0$ $q_{OIA}{}^{**} = q_{OIA}$ $q_{OEB} = 1$ for all $B \neq A$	$q_{OEA} > 0$ $q_{OIA} = 0$ $q_{OEB} = 1$ for all $B \neq A$	$q_{OIA} > 0$ $q_{OEC} = 1$ for all C $q_{OIB} = 1$ for all $B \neq A$

For a number of cases such results have been found, as summarised in Table 6. This table considers any agent A in the group. Suppose A is the agent in the group with highest q_{OEA}, i.e., $q_{OEB} \leq q_{OEA}$ for all $B \neq A$. This implies that $q_{OEA}^* = \sum_{B \neq A} \gamma_{OEBA} \cdot q_{OEB} / \gamma_{OEA} \leq \sum_{B \neq A} \gamma_{OEBA} \cdot q_{OEA} / \gamma_{OEA} = q_{OEA} \sum_{B \neq A} \gamma_{OEBA} / \gamma_{OEA} = q_{OEA}$. So in this case always $q_{OEA}^* \leq q_{OEA}$. Note that when $q_{OEB} < q_{OEA}$ for some $B \neq A$ with $\gamma_{OEBA} > 0$, then $q_{OEA}^* = \sum_{B \neq A} \gamma_{OEBA} \cdot q_{OEB} / \gamma_{OEA} < \sum_{B \neq A} \gamma_{OEBA} \cdot q_{OEA} / \gamma_{OEA} = q_{OEA} \sum_{B \neq A} \gamma_{OEBA} \cdot / \gamma_{OEA} = q_{OEA}$. Therefore $q_{OEA}^* = q_{OEA}$ implies $q_{OEB} = q_{OEA}$ for all $B \neq A$ with $\gamma_{OEBA} > 0$. Similarly, when A has the lowest q_{OEA} of the group, then always $q_{OEA}^* \geq q_{OEA}$ and again $q_{OEA}^* = q_{OEA}$ implies $q_{OEB} = q_{OEA}$ for all $B \neq A$ with $\gamma_{OEBA} > 0$. This implies, for example, for $\eta_{OEA} = 1$ and $\beta_{OEA} = 0.5$, assuming nonzero γ_{OEBA}, that always for each option the members' emotion levels for option O will converge to one value in the group (everybody will feel the same about option O).

9.2 Mathematical analysis for the second model

In this section it is analyzed which are equilibria values that occur. In particular it is focused on the characteristics in the model and the fear state.

Analysis of $\delta_{Sinfo\ A}(t)$, $\beta_{Sinfo\ A}(t)$ and $\eta_{Sinfo\ A}(t)$

The openness $\delta_{Sinfo,A}$ is described in differential equation format by

$$d\,\delta_{Sinfo,A}(t)/\,dt \;=\; \mu_{\delta_{Sinfo,A}}\,(1/1+e^{-\sigma(q_{fear,A}(t)\,-\,\tau)})\cdot [(1-(1-r_{Sinfo\ A})\;\; q_{fear,A}(t)) - \delta_{Sinfo\ A}(t)]$$

It is assumed that $\mu_{\delta_{Sinfo,A}} > 0$. First of all, it follows that when $q_{fear,A} < \tau$, then always $d\delta_{Sinfo,A}(t)/dt = 0$, so for these cases any value for $\delta_{Sinfo,A}$ is an equilibrium. Next, assuming $q_{fear,A} \geq \tau$, it holds:

$\delta_{Sinfo,A}$ is in **equilibrium**	iff	$[(1-(1-r_{Sinfo\ A})\;\; q_{fear,A}) - \delta_{Sinfo\ A}(t)] = 0$
$\delta_{Sinfo,A}$ is **strictly increasing**	iff	$[(1-(1-r_{Sinfo\ A})\;\; q_{fear,A}) - \delta_{Sinfo\ A}(t)] > 0$
$\delta_{Sinfo,A}$ is **strictly decreasing**	iff	$[(1-(1-r_{Sinfo\ A})\;\; q_{fear,A}) - \delta_{Sinfo\ A}(t)] < 0$

From this the following equilibrium values can be determined (see also Table 7, upper part):

$q_{fear,A} < \tau$ and any value for $\delta_{Sinfo,A}$ or

$q_{fear,A} \geq \tau$ and $\delta_{Sinfo,A} = 1-(1-r_{Sinfo\ A})\;\; q_{fear,A}$

For example, $q_{fear,A} = 1 \Rightarrow \delta_{Sinfo\ A}(t) = r_{Sinfo\ A}$ and $r_{Sinfo\ A} = 1$ and $q_{fear,A} \geq \tau \Rightarrow \delta_{Sinfo\ A} = 1$. The following monotonicity conditions hold for $q_{fear,A}(t) \geq \tau$

$\delta_{Sinfo\ A}(t)$ is **strictly increasing**	iff	$\delta_{Sinfo\ A}(t) < 1-(1-r_{Sinfo\ A})\;\; q_{fear,A}(t)$
$\delta_{Sinfo\ A}(t)$ is **strictly decreasing**	iff	$\delta_{Sinfo\ A}(t) > 1-(1-r_{Sinfo\ A})\;\; q_{fear,A}(t)$

These conditions show that $\delta_{Sinfo\ A}(t)$ is attracted by the value $1-(1-r_{Sinfo\ A})\;\; q_{fear,A}(t)$, so when $q_{fear,A}(t)$ is stable, this value is a stable equilibrium for $\delta_{Sinfo\ A}(t)$. Similarly the equilibrium values of the characteristics $\beta_{Sinfo,A}$ and $\eta_{Sinfo,A}$ can be determined as shown in Table V. Moreover, as above it can be shown that β_{SinfoA} is attracted by the value $1-p_{SinfoA}$, and $\eta_{Sinfo\ A}(t)$ is attracted by the value $q_{fear,A}(t)$, so they both are stable.

Analysis of $q_{Sfear,A}(t)$

The fear state is described by

$$dq_{SfearA}(t)/dt = \gamma_A \cdot [\eta_{SfearA} \cdot (\beta_{SfearA} \cdot (1 - (1 - q_{SfearA}^*) \cdot (1 - q_{SfearA})) + (1 - \beta_{SfearA}) \cdot q_{SfearA}^* \cdot q_{SfearA}) + (1 - \eta_{SfearA}) \cdot q_{SfearA}^* - q_{SfearA}]$$

Then the equilibrium equations become:

$$\eta_{SfearA} \cdot (\beta_{SfearA} \cdot (1 - (1 - q_{SfearA}^*) \cdot (1 - q_{SfearA})) + (1 - \beta_{SfearA}) \cdot q_{SfearA}^* \cdot q_{SfearA}) + (1 - \eta_{SfearA}) \cdot q_{SfearA}^* = q_{SfearA}$$

In general the equation is too complex to be solved symbolically, but for some cases it can be solved; see Table 7 (lower part).

Special case $\eta_{SfearA} = 1$ and $\beta_{SfearA} = 1$

This case concerns an amplifying agent for fear with an increasing orientation. For this case the analysis shows that there is a strong tendency for q_{SfearA} to reach value *1*. It will only not reach *1* if there are extreme circumstances that there is full absence of negative group impact: none of the other group members transfer any bad information or fear (see Table 7).

Special case $\eta_{SfearA} = 1$ and $\beta_{SfearA} = 0$

This case concerns an amplifying agent for fear with a decreasing orientation. For this case the analysis shows that there is a strong tendency for q_{SfearA} to reach value *0*. It will only not reach *0* if there are extreme circumstances in the sense that there is full presence of negative group impact: all other group members do transfer bad information and fear. See Table V.

Special case $\eta_{SfearA} = 0$

This case concerns an absorbing agent for fear. For this case the analysis shows that there is a strong tendency for q_{SfearA} to reach some value between *0* and *1*. It will only reach *0* or *1* if there are extreme circumstances that not any of the other group members does transfer any bad information or fear, or if all of them transfer both in a maximal sense. The value reached between *0* and *1* is some form of average of the values of the other group members.

Table 7 Equilibrium values. UPPER: values for $q_{fear,A}$. LOWER: values for $\delta_{Sinfo\ A}$, $\beta_{Sinfo\ A}$, η_{Sinfo}

<table>
<tr><th></th><th>$q_{fear,A} = 0$</th><th>$0 < q_{SfearA} < 1$</th><th>$q_{fear,A} = 1$</th></tr>
<tr><td>$\eta_{SfearA}=1$ $\beta_{SfearA}=1$</td><td colspan="2">any value < 1 for q_{SfearA} iff there is full absence of negative group impact</td><td>$q_{fear,A} = 1$</td></tr>
<tr><td>$\eta_{SfearA}=1$ $\beta_{SfearA}=0$</td><td>$q_{fear,A} = 0$</td><td colspan="2">any value > 0 for q_{SfearA} iff there is full presence of negative group impact</td></tr>
<tr><td>$\eta_{SfearA} = 0$</td><td>$q_{fear,A} = 0$, and there is full absence of negative group impact</td><td>$q_{SfearA}^* = q_{SfearA}$</td><td>$q_{fear,A} = 1$, and there is full presence of negative group impact</td></tr>
<tr><td></td><td>$q_{fear,A} = 1$</td><td>$\tau \leq q_{SfearA} < 1$</td><td>$q_{SfearA} < \tau$</td></tr>
<tr><td>$\delta_{Sinfo\ A}$</td><td>$\delta_{Sinfo,A} = r_{Sinfo\ A}$</td><td>$\delta_{Sinfo,A} = 1 - (1 - r_{Sinfo\ A})\ q_{fear,A}$</td><td>any value for $\delta_{Sinfo,A}$</td></tr>
<tr><td>$\beta_{Sinfo\ A}$</td><td>any value for $\beta_{Sinfo\ A}$</td><td>$\beta_{Sinfo\ A} = 1 - p_{Sinfo\ A}$</td><td>any value for $\beta_{Sinfo\ A}$</td></tr>
<tr><td>$\eta_{Sinfo\ A}$</td><td>$r_{Sinfo\ A} > 0$ and $p_{Sinfo\ A} < 1$ and $\eta_{Sinfo\ A} = q_{fear,A}$</td><td>any value for $\eta_{Sinfo\ A}$</td><td></td></tr>
</table>

Equilibria for q_{SfearA}

The equilibrium equation: $q_{SfearA}* = q_{SfearA}$. For the cases $q_{SfearA}* = q_{SfearA} = 0$ and $q_{SfearA}* = q_{SfearA} = 1$ the terms of the double summation for $q_{SfearA}*$ can be handled as above, thus providing the conditions as depicted in Table 7.

10 Discussion

In this paper, an agent-based modelling approach has been presented, to model contagion of different types of individual agent states, which may have mutual interaction. First, a generic model for contagion of a single type of state was described. This generic model has been inspired by the neurological concept of mirroring (see e.g. [24], [30]). Previous emotion contagion models have been used as well as a source of inspiration (cf. [4], [5], [15], [16]). Emotion contagion, has been shown to occur in many cases varying from emotions in small groups to panicking crowds (cf. [1]). The generic model introduced unifies the models for emotion contagion and generalises to contagion of any type of individual state. The agent-based approach used differs from the approach of the computational models from social science such as in ([35], [22], [28]), which model the complex spread of innovations as diffusion that is asymmetric in time, irreversible, and nondeterministic. Next, two more specialised and more complex models were presented involving contagion of multiple types of states for which mutual interaction takes place.

As a first more complex model, a model was presented for the emergence of collective decision making in groups. In this model contagion of emotions and intentions and their interaction play a main role. The model has been based not only on the neurological concept of mirroring (see e.g. [24], [30]) but also on the Somatic Marker Hypothesis of Damasio (cf. [2], [10], [12], [13]). This provides an interaction between the two types of states, in the form of influences of emotions upon intentions. Several scenarios have been simulated by the model to investigate the emerging patterns, and also to look at leadership of agents within groups. The results of these simulation experiments show patterns as desired and expected. In order to be able to make this claim more solid, a formal verification of the simulation traces have been performed, showing that the model indeed behaves properly. By a mathematical analysis, equilibria of the model have been determined.

As a second more complex model, a model has been presented which incorporates the effect of emotions upon the spreading of belief as well as the effect of belief upon emotions. This work has been inspired by a number of theories and observations as found in literature (cf. [1], [7], [8], [17], [27], [37]). The model has been evaluated by a case study in the domain of emergency evacuations, and was shown to exhibit the patterns that could be expected based upon the literature. Also for this model by a mathematical analysis equilibria have been determined.

For future work, an interesting element will be to scale up the simulations and investigate the behaviour of agents in larger scale simulations. Furthermore, modelling a more detailed neurological model is also part of future work, thereby defining an abstraction relation mapping between this detailed level model and the current model. As part of further work it can also be considered to model how mood can affect (systematic) information processing, for example in case of a depression. In [9] such mechanisms are discussed. Other ideas for future work consist of extending the current model for multiple emotions affecting each other and beliefs as well and vice versa. Moreover, models addressing contagion of more than two different types of states and their interaction will be addressed.

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Appendix A Settings for the Scenarios in Section 5

Scenario 1			agent 1	agent 2	agent 3	agent 4
q (initial state)	**emotion**	optionA	0.9	0.1	0.5	0.2
		optionB	0.1	0.1	0.5	0.2
		optionC	0.3	0.1	0.5	0.2
		optionD	0.1	0.1	0.5	0.2
	intention	optionA	0.9	0.7	0.5	0.1
		optionB	0.1	0.7	0.5	0.1
		optionC	0.1	0.1	0.5	0.1
		optionD	0.1	0.1	0.5	0.9
δ (open-ness)	**emotion**	optionA	0.1	0.9	0.9	0.2
		optionB	0.1	0.9	0.9	0.2
		optionC	0.1	0.9	0.9	0.2
		optionD	0.1	0.9	0.9	0.2
	intention	optionA	0.1	0.9	0.9	0.2
		optionB	0.1	0.9	0.9	0.2
		optionC	0.1	0.9	0.9	0.2
		optionD	0.1	0.9	0.9	0.2
η (amplify / absorb)	**emotion**	optionA	0.9	0.1	0.2	0.9
		optionB	0.1	0.1	0.2	0.9
		optionC	0.9	0.1	0.2	0.9
		optionD	0.1	0.1	0.2	0.9
	intention	optionA	0.9	0.1	0.2	0.9
		optionB	0.1	0.1	0.2	0.9
		optionC	0.9	0.1	0.2	0.9
		optionD	0.1	0.1	0.2	0.9
β (bias)	**emotion**	optionA	0.9	0.1	0.5	0.6
		optionB	0.1	0.1	0.5	0.6
		optionC	0.9	0.1	0.5	0.6
		optionD	0.1	0.1	0.5	0.6
	intention	optionA	0.9	0.8	0.5	0.6
		optionB	0.1	0.8	0.5	0.6
		optionC	0.9	0.1	0.5	0.6
		optionD	0.1	0.1	0.5	0.6
ε (expressiveness)			1	0.4	0.1	1
α (connection)		agent1	-	0.1	0.1	0.1
		agent2	1	-	0.9	0.1
		agent3	1	0.9	-	0.1
		agent4	1	0.1	0.1	-

Scenario 2			agent 1	agent 2	agent 3	agent 4
q (initial state)	**emotion**	optionA	0.9	0.3	0.2	0.1
		optionB	0.1	0.3	0.1	0.1
		optionC	0.1	0.2	0.3	0.1
		optionD	0.1	0.4	0.2	0.8
	intention	optionA	0.9	0.3	0.3	0.1
		optionB	0.1	0.3	0.3	0.1
		optionC	0.1	0.2	0.4	0.1
		optionD	0.1	0.4	0.1	0.7
δ (openness)	**emotion**	optionA	0.1	0.8	0.9	0.3
		optionB	0.1	0.8	0.9	0.3
		optionC	0.1	0.8	0.9	0.3
		optionD	0.1	0.8	0.9	0.3
	intention	optionA	0.1	0.8	0.3	0.3
		optionB	0.1	0.8	0.3	0.3
		optionC	0.1	0.8	0.3	0.3
		optionD	0.1	0.8	0.3	0.3
η (amplify/ absorb)	**emotion**	optionA	0.9	0.5	0.2	0.7
		optionB	0.9	0.5	0.2	0.7
		optionC	0.9	0.5	0.2	0.7
		optionD	0.9	0.5	0.2	0.7
	intention	optionA	0.9	0.5	0.2	0.7
		optionB	0.9	0.5	0.2	0.7
		optionC	0.9	0.5	0.2	0.7
		optionD	0.9	0.5	0.2	0.7
β (bias)	**emotion**	optionA	0.9	0.3	0.6	0.7
		optionB	0.9	0.3	0.5	0.7
		optionC	0.9	0.3	0.4	0.7
		optionD	0.9	0.3	0.5	0.8
	intention	optionA	0.9	0.3	0.6	0.7
		optionB	0.9	0.3	0.5	0.7
		optionC	0.9	0.3	0.4	0.7
		optionD	0.9	0.3	0.5	0.8
ε (expressiveness)			1	0.1	0.1	0.8
α (connection)		agent1	-	0.1	0.1	0.1
		agent2	1	-	0.1	0.1
		agent3	0.1	0.1	-	0.8
		agent4	0.1	0.1	0.1	-

Scenario 3			agent 1	agent 2	agent 3	agent 4
q (initial state)	**emotion**	optionA	*0.9*	*0.2*	*0.1*	*0.3*
		optionB	*0.1*	*0.9*	*0.1*	*0.3*
		optionC	*0.5*	*0.2*	*0.7*	*0.7*
		optionD	*0.2*	*0.2*	*0.1*	*0.1*
	intention	optionA	*0.9*	*0.2*	*0.1*	*0.1*
		optionB	*0.1*	*0.9*	*0.1*	*0.1*
		optionC	*0.5*	*0.2*	*0.9*	*0.9*
		optionD	*0.2*	*0.2*	*0.1*	*0.1*
δ (openness)	**emotion**	optionA	*0.5*	*0.1*	*0.9*	*0.3*
		optionB	*0.5*	*0.1*	*0.9*	*0.3*
		optionC	*0.5*	*0.1*	*0.9*	*0.7*
		optionD	*0.5*	*0.1*	*0.9*	*0.3*
	intention	optionA	*0.5*	*0.1*	*0.9*	*0.3*
		optionB	*0.5*	*0.1*	*0.9*	*0.3*
		optionC	*0.5*	*0.1*	*0.9*	*0.7*
		optionD	*0.5*	*0.1*	*0.9*	*0.3*
η (amplify/ absorb)	**emotion**	optionA	*0.9*	*0.5*	*0.2*	*0.8*
		optionB	*0.2*	*0.5*	*0.2*	*0.8*
		optionC	*0.2*	*0.5*	*0.2*	*0.8*
		optionD	*0.2*	*0.5*	*0.2*	*0.8*
	intention	optionA	*0.9*	*0.5*	*0.1*	*0.8*
		optionB	*0.2*	*0.5*	*0.1*	*0.8*
		optionC	*0.2*	*0.5*	*0.1*	*0.8*
		optionD	*0.2*	*0.5*	*0.1*	*0.8*
β (bias)	**emotion**	optionA	*0.5*	*0.5*	*0.9*	*0.2*
		optionB	*0.5*	*0.5*	*0.9*	*0.2*
		optionC	*0.5*	*0.5*	*0.9*	*0.9*
		optionD	*0.5*	*0.5*	*0.9*	*0.2*
	intention	optionA	*0.5*	*0.5*	*0.9*	*0.2*
		optionB	*0.5*	*0.5*	*0.9*	*0.2*
		optionC	*0.5*	*0.5*	*0.9*	*0.9*
		optionD	*0.5*	*0.5*	*0.9*	*0.2*
ε (express iveness)			*0.9*	*0.7*	*0.1*	*0.5*
α (connec tion)		agent1	-	*0.3*	*0.5*	*0.7*
		agent2	*0.1*	-	*0.5*	*0.5*
		agent3	*0.8*	*0.8*	-	*0.2*
		agent4	*0.6*	*0.5*	*0.2*	-

Appendix B Settings for the Scenarios in Section 8

Scenario 1 and 2		Fear sc1 / sc2	Information high r, high p	Information low r, high p	Information high r, low p	Information low r, low p
q (initial state)	Agent1	*0.1 / 0.8*	*1*	*0.1*	*0.1*	*0.1*
	Agent2	*0.1 / 0.8*	*0.1*	*1*	*0.1*	*0.1*
	Agent3	*0.1 / 0.8*	*0.1*	*0.1*	*1*	*0.1*
	Agent4	*0.1 / 0.8*	*0.1*	*0.1*	*0.1*	*1*
δ (open ness)	Agent1	*0.5*	*0.5*	*0.5*	*0.5*	*0.5*
	Agent2	*0.5*	*0.5*	*0.5*	*0.5*	*0.5*
	Agent3	*0.5*	*0.5*	*0.5*	*0.5*	*0.5*
	Agent4	*0.5*	*0.5*	*0.5*	*0.5*	*0.5*
η (amplify/ absorb)	Agent1	*0.5*	*0.3*	*0.3*	*0.3*	*0.3*
	Agent2	*0.5*	*0.8*	*0.8*	*0.8*	*0.8*
	Agent3	*0.5*	*0.1*	*0.1*	*0.1*	*0.1*
	Agent4	*0.5*	*0.2*	*0.2*	*0.2*	*0.2*
β (bias)	Agent1	*0.5*	*0.1*	*0.1*	*0.1*	*0.1*
	Agent2	*0.5*	*0.5*	*0.5*	*0.5*	*0.5*
	Agent3	*0.5*	*0.9*	*0.9*	*0.9*	*0.9*
	Agent4	*0.5*	*0.3*	*0.3*	*0.3*	*0.3*
Scenario 3						
q (initial state)	Agent1					
	Agent2	*0.3*	*0.1*	*0.8*	*0.1*	*0.1*
	Agent3	*0.9*	*0.1*	*0.1*	*1*	*1*
	Agent4	*0.1*	*1*	*0.1*	*0.1*	*0.1*
δ (open ness)	Agent1	*0.2*	*1*	*1*	*0.1*	*0.1*
	Agent2	*0.1*	*0.1*	*0.1*	*1*	*1*
	Agent3	*0.7*	*0.5*	*0.5*	*0.5*	*0.5*
	Agent4	*0.6*	*0.1*	*0.1*	*0.1*	*0.1*
η (amplify/ absorb)	Agent1	*0.5*	*0.9*	*0.9*	*0.9*	*0.9*
	Agent2	*1*	*0.9*	*0.9*	*0.9*	*0.1*
	Agent3	*0.2*	*0.1*	*0.1*	*0.1*	*0.1*
	Agent4	*0.1*	*1*	*0.2*	*1*	*0.2*
β (bias)	Agent1	*0.1*	*0.9*	*0.9*	*0.1*	*0.1*
	Agent2	*0.9*	*0.1*	*0.1*	*0.9*	*0.9*
	Agent3	*0.5*	*0.5*	*0.5*	*0.5*	*0.5*
	Agent4	*0.5*	*0.1*	*0.1*	*0.1*	*0.1*