An Agent-Based Model Predicting Group Emotion and Misbehaviours in Stranded Passengers

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Abstract. Airline passengers can get stranded in an airport due to a number of reasons. As a consequence, they might get frustrated. Frustration leads to misbehaving if a given individual is frustrated enough, according to the literature. In this work, an agent-based model of stranded passengers in an airport departure area is presented. Structured simulations show how personal and environmental characteristics such as age, gender and emotional contagion, among others, influence the frustration dynamics, number and type of misbehaviours in such a scenario. We also present simulation results with two implemented support models (a chatbot and multilingual staff) aiming to reduce the overall frustration level of passengers facing this type of situation. Important findings are that: men are more likely to use force than women, the crowd composition plays an important role in terms of misbehaviours, the effect of emotional contagion leads to more misbehaviours and a chatbot might be considered as an alternative for supporting stranded passengers.

Keywords: Computational modelling · Multi-agent based modelling · Emotional contagion · Misbehaviour prediction · Crime prevention · Chatbots

1 Introduction

On February 2017, as storm Doris battered European regions as UK and The Netherlands, hundreds of passengers, including holidaymakers and commuters, faced flight delays.[1,2] In such a situation in which passengers are stranded in a delimited area as a boarding gate lounge, it is always a challenge for the air companies as well as security professionals to deal with the fact that people may start to get frustrated and angry. Having people intimidating or yelling at others is a risk in such a scenario.

[1] Available on: https://goo.gl/ZrVeHT. Accessed 12 April 2017.
[2] Available on: https://goo.gl/8Me4ve. Accessed 12 April 2017.

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In previous work, a similar situation to the one stated above - stranded passengers in a train - was addressed by van der Wal et al. [21] In the current research it is described how this approach was adapted to deal with stranded passengers (in a boarding gate area) of a delayed flight.

The aim of this work is to propose a realistic domain model that: (1) can predict misbehaviours in stranded passengers at an airport boarding gate area and (2) that can be used by emergency management and prevention professionals as a preparation for or managing crowds during emergency scenarios. The word 'domain' refers to modelling the process as it is in reality. Besides that, we also implemented different 'support' models, added to the 'domain' model, to simulate the effects of a chatbot offering support or multi-lingual staff members on the group frustration level and number and types of misbehaviours.

Via the developed domain model we can predict how likely a given set of stranded passengers is to misbehave. This is calculated based on personal and environmental characteristics as gender, boarding time information, etc.

The rest of this paper is organized as follows. Section 2 provides concepts and lessons from the literature that were used to develop the models. Section 3 presents the developed formal domain and support models. Section 4 presents the structured simulation results to investigate the correctness of our models and to extract insights regarding the stranded passengers situation. Finally, Sect. 5 provides a discussion and our final conclusions.

2 Related Work

2.1 Computational Models of (Group) Emotions

Affective Computing is the field of developing and studying systems and devices that can interpret, simulate, process and recognize human emotion [16]. Marsella et al. [12] give an overview of the research on computational models of human emotions and emotional processes. They describe how the field of computational models of emotion is not mature yet, as there are very competing and complementary computational models. Often, such models do not seem to state their goals clearly or assumptions and design decisions are not articulated. They make a distinction between appraisal models, dimensional models and other approaches.

In appraisal theory, emotion is argued to arise from patterns of individual judgements concerning the relationship between events and an individual's beliefs, desires and intentions. This stems from the beliefs-desires-intention model for simulating agent behaviour and thoughts [9]. These judgements are formalised in variables representing aspects of the personal significance of events and can also trigger cognitive responses, or so called coping strategies. These models are mainly applied in human computer interaction applications, such as real-time interactive characters exhibiting emotions.

Dimensional theories argue that emotions should not be conceptualized as discrete entities, but as points in a continuous dimensional space. Dimensional computational models of emotions are applied in systems attempting to recognize human emotions and in animated character generation, as virtual avatars, in computer games or online therapies, that recognise the user's emotions to adjust the content of the game or therapy upon.

Among the other approaches are (1) anatomical approaches (models based on neural links and processes underlying emotional reactions), (2) rational approaches (that view emotions as a cognitive function with its own architectural constraints on how it operates) and (3) communicative theories of emotion (incorporating the dissociation between internal emotional processes and social emotion displays).

These computational models of emotion are mainly meant for individual emotions. Bosse et al. [2,3] have created a computational model for group emotions in which mental and emotional states can be socially distributed representing people being able to affect each other's states: the ASCRIBE model. The approach of Bosse et al. is a mix of computational social science and affective computing. The social contagion mechanisms are modelled and simulated, based on neurological findings as well (the anatomical perspective on computational models of emotions). Tsai et al. [20] evaluated computational emotional contagion models beforehand. The ASCRIBE model outperformed the other two models on reproducing real crowd panic scenes.

Concluding, in this paper a combination of the ASCRIBE model (social contagion of emotion) with an appraisal model (individual emotion) suits the goal of modelling frustration dynamics in stranded passengers best.

2.2 Chatbots and Multi-lingual Professionals Supporting People

Concerning the developed support models, we based ourselves on the literature to come up with the ideas of a chatbot and multi-cultural staff to regulate the overall frustration level of stranded passengers.

First, the concept of peer support, defined by Kim et al. [11] as people supporting each other within a social network context, has been addressed by researchers from Artificial Intelligence field. As examples for that we can point out the works conducted by: van der Zaan et al. [22], that provided a virtual buddy for helping victims of cyberbullying, and DeVault et al. [7], that developed virtual agents as depression therapists. In addition, Medeiros and Bosse [13] started to develop research about chatbots for messaging apps providing social support to users in order to help them to deal with everyday stressful situations. Hence, our paper addresses the role played by a chatbot in a network of people getting frustrated over time due to a flight delay and whose goal is to reduce the overall network frustration level. More precisely, a chatbot is a software that simulates human conversation through voice commands, text chats or both. Thus, during critical as well as emergency situations, an interaction with users and a chatbot would be useful to help people to receive instant instructions on how to handle the situation via providing social and/or practical support.

Second, we were also interested in investigating the role played by multilingual staff in our support model. A multicultural or at least bilingual staff may be helpful to effectively interact and respond to passengers' requests and claims

[23]. Indeed, verbal announcements and written information should be provided in English as well as the local language to increase clarity of communication, given the popularity of this language (according to Crystal [5], for example, it might be the case that approximately 2 billion people speak English).

3 Modelling a Flight Delay Situation

In this section, the formal domain and support models that were developed, are presented. Due to lack of space, only part of the formal definitions and code (written in NetLogo[3]) is presented. Nevertheless, for purposes of checking and replicating our simulations, the code is available on a GitHub repository[4].

3.1 Domain Model

Based on one of Fiumicino Airport's boarding areas[5], we designed an airport departure lounge in NetLogo with seats, restaurants, toilets, help desks and boarding gates. Then, we constructed a computational agent-based model in accordance with requirements provided by stakeholders from the H2020 IMPACT project[6]. In general terms, the model acts as follows: (1) as soon as there is no information regarding the boarding time, the passengers' frustration levels keep increasing over time; (2) when a given passenger reaches a frustration level equal or higher than 0.8, he or she will start to misbehave (it was decided it would be simpler to model the phenomena of becoming aggressive by implementing a standard frustration threshold for each passenger that triggers potential misbehavior rather than having different frustration thresholds for different groups); (3) a given passenger's frustration level growth rate depends on his or her personal characteristics (e.g. age, whether he or she is a commuter or a holidaymaker, etc.); (4) the intentions of a given passenger depend on his or her frustration level as well as respective personal characteristics; (5) the actions performed by a given passenger depend on his or her frustration level, personal characteristics and intention. A pseudocode for this model is given in Algorithm 1. As a basic setting (adjustable), the domain model runs for 2 h.

The agent's age and gender affect the selection of actions. According to literature, young men are more prone to exert aggressive behaviour compared to any other age group or gender [15]. Based on the frustration level in combination with the characteristics of the passenger, an intention and an action is chosen. The higher the frustration level, the more aggressive the behaviour and men are more likely than women to express aggression [1,4]. This is modelled with different chances to misbehave, for each passenger type. The chance a passenger will yell, intimidate or use force, depends on both gender and age. The chances of misbehaviours were based on the statistics of disruptive behaviour on board

[3] Available on: https://ccl.northwestern.edu/netlogo/. Accessed 30 April 2017.
[4] Available on: https://git.io/vH5ma. Accessed 14 June 2017.
[5] Available on: https://goo.gl/HS95SI. Accessed 30 April 2017.
[6] Available on: http://www.impact-csa.eu/. Accessed 14 June 2017.

Algorithm 1 Pseudo code for the domain model.

```
procedure MainLoop(void)
    time ← 0:00 a.m.
    repeat
        UpdateFrustration()
        ▷ Updating the passenger's frustration level according to the pre-defined rules, taking into account: the individual's personal characteristics, boarding time and availability of toilets and restaurants.

        UpdateIntention()
        ▷ Updating the individual's intention according to his characteristics and frustration. The possible values are: "to enjoy the trip", "to seek for information" and "to become aggressive".

        ActionSelection()
        ▷ Selecting the individual's action according to his characteristics and intention. The possible values are: "to go to a restaurant", "to go to the toilet", "to walk", "to sit", "to ask questions", "to yell", "to intimidate", and "to use force". This procedure is called every 2 minutes.

        EmotionalContagion()
        ▷ Spreading the effect of emotional contagion among passengers in a radius of 5 meters.

        time ← time + 1s
    until time = 2:00 a.m.
```

of UK airlines[7]. Therefore, we assumed that male passengers are more likely to misbehave than female passengers for each type of misbehaviour.

In agent-based modelling, agent behaviour might be modelled with some randomness in order to make it more realistic [24]. To accomplish this, an internal random constant assuming values between -0.04 and 0.04 called `INT_THRESHOLD` was created in every stranded passenger. It is aimed to simulate internal personal characteristics that differentiate the passengers from each other as individuals.

In the model, the passengers are divided into different clusters of culturally similar nationalities based on previous research [18]. Data concerning the percentage of English speakers for each country in each cluster were then obtained, where available, from multiple verified and official sources compiled by Wikipedia[8]. We then calculated a weighted average percentage of English speakers in each cluster – using the population sizes of each cluster's constituent countries – and these were the values used in the simulation model to determine the percentage of passengers from each cluster who could understand an English instruction by a staff member or public announcement.

Social contagion of frustration, according to the concept of social identity [8,10,17], also plays a role in our model. Passengers compare themselves to others and the more similar (based on age, gender and traveller type) they are, the more they can infect others' frustration levels. This influence is causing a strengthening or diminishing of the frustration experienced. This mechanism is based on social identification theory [19] and emotional contagion [3]. The formula in the current model works as follows for passengers in a radius of 5 meters: if 2 passengers are travelling together, one will fully affect the other's frustration level; if 2 passengers are not travelling together, the influence one exerts on the other's frustration level is proportional to the similarity between them considering 4 personal characteristics (age, gender, nationality cluster and traveller type); therefore, if 2 passengers that are not travelling together have the same age, gender, nationality cluster and if both are commuters, one will

[7] Available on: https://goo.gl/lBUK5H. Accessed 30 April 2017.
[8] Available on: https://goo.gl/vrEQip. Accessed 30 April 2017.

fully affect other's frustration level, i.e., 4 times more than if they had only the same gender, for instance.

The following is an example of a formal rule we used in our domain model. Consider: P as a set containing all the passengers, $p \in P$ as a given passenger, the functions $g : P \rightarrow G = \{$"male", "female"$\}$, $ag : P \rightarrow AG = \{$"young", "adolescent", "adult", "elder"$\}$ and $i : P \rightarrow I = \{$"to enjoy the trip", "to seek for information", "to misbehave"$\}$ as gender, age group and intention of the passenger p, respectively. Besides, consider the function $yell : P \rightarrow \mathbb{R}$ as the chance p has to yell when he or she is intending to become aggressive (i.e., $i(p) =$ "*to misbehave*"). Hence, the chance a given male passenger has to yell when intending to misbehave (30%) is defined as follows: $\forall p \in P \wedge g(p) = \text{"}male\text{"} \wedge ag(p) = \text{"}adult\text{"} \wedge i(p) = \text{"}to\ misbehave\text{"} \Rightarrow yell(p) = 0.3$. Figure 1 shows how this rule is implemented in NetLogo. A conceptual representation of the domain model is presented in Fig. 2.

```
ask passengers with [intention = "to become aggressive" and gender = "M" and age_group = "adult"] [
  set chance random 100
  ; ...
  if chance >= 16 and chance <= 45 [ ; 30%
    set action "to yell"
    ; ...
  ]
]
```

Fig. 1. Excerpt of NetLogo code regarding the chance a given adult male passenger will yell when he is intending to misbehave (i.e., to become aggressive).

3.2 Support Models

In previous research, a model of how people are collectively coping with stressful situations within social networks was developed [14]. The authors realized that, by providing support to peers, a given individual might also get stressed as a consequence of such an emotional effort. As an attempt to deal with this implication, the idea of a chatbot emerged from a study about strategies used by social network users when helping their friends to cope with stress online [13]. Based on these previous works, we came up with the concept of a supportive chatbot for stranded passengers in the current model. It is assumed a reasonable idea that some passengers might get even more stressed by receiving such a type of support, since its efficacy needs more concrete results. Therefore, when a given stranded passenger receives support from the chatbot, in 80% of cases his or her frustration level will become lower than before. On the other hand, in 20% of cases, it will become higher than before.

Finally, we also implemented the concept of multi-lingual staff as a support strategy. In our model, when a given staff member is able to speak more than one language, the chance a given passenger will get less frustrated by talking to him or her is 3 times higher than if he or she had no such a multi-cultural background.

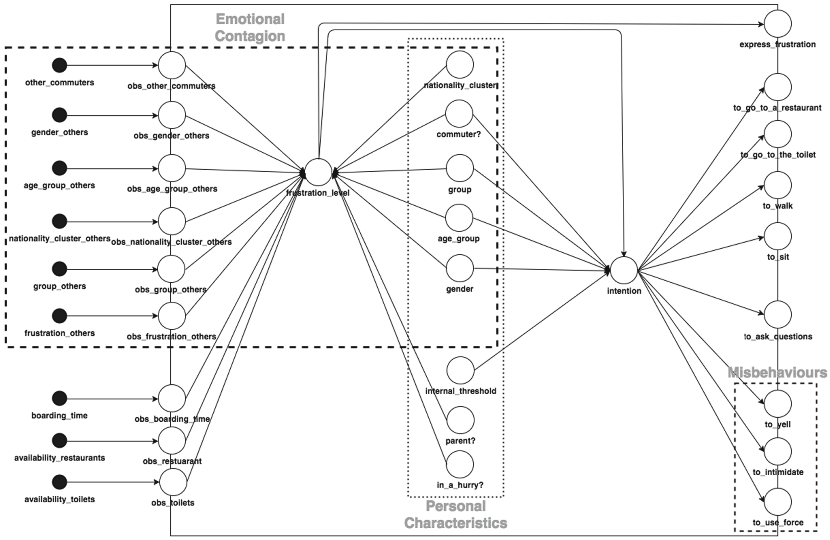

Fig. 2. Representation of the stranded passengers' domain model at a departure gate at Fiumicino Airport. A given passenger's internal states are located within the big (non-dashed) rectangle.

4 Experimental Analysis

In order to answer our research questions and check our hypotheses, we performed structured simulations with our model, adjusting parameters in a structured way (10 runs per configuration as there was not enough variance to need more repetitions).

All environmental and personal factors were kept constant among simulations and they are as follows: 2 h of simulation time (delay), unknown boarding time throughout the hour delay, cultural clusters evenly distributed, 50% chance of misbehaving towards staff or other passenger, age distribution according to De Wulf [6], presence of children 'on', effect of emotional contagion 'on', 50% men and 50% women, 50% commuters and 50% holidaymakers, toilets and restaurants 'available', effect of chatbot 'off', non-multilingual staff, 50% of passengers in a hurry, 50% travelling alone, 50%, 30% and 20% travelling in groups of 2, 3 and 4, respectively and, finally, the total amount of passengers equal to 250. Only the factors and levels stated in each subsequent experimental setup were systematically varied.

Concerning the effect of gender, we had the following research question: what is the effect of gender on number and types of misbehaviour? We checked 2 hypotheses to answer this question: (1) Men will show more misbehaviours in total than women; (2) There will be differences in types of misbehaviour for men and women. We simulated changing gender, crowdedness (number of passengers) and boarding time. All factors and levels were reproduced, only the most important findings are presented here, namely the difference between 100% males and 100% females.

The results show us that: men and women misbehaved equally much (see Fig. 3) and, when the passengers are misbehaving: (1) men are more likely to use force and to yell than women and (2) women are more likely to intimidate than men (see Fig. 4). Interestingly, men and women misbehaved equally. This could be explained by the fact that, in our model, the growth rate of the frustration level function for a given passenger depends on other personal characteristics different than gender as age, traveller type, etc. and, besides that, all the passengers have the same frustration threshold that determines if they will start to misbehave. Also interesting is the difference in types of misbehaviours between men and women. A difference was expected, but it was unknown which types of misbehaviours would be dominant for men and women. These results can give an insight to how men and women can differ in their types of misbehaviours, to better estimate the risks for certain crowd compositions.

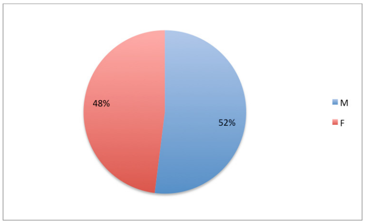

Fig. 3. Effect of gender on misbehaviours.

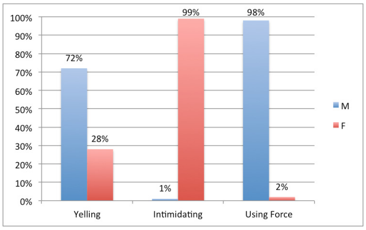

Fig. 4. Effect of gender on types of misbehaviours.

For crowd composition and the definitions of conditions 1 (emotional contagion 'on', more groups with 4 people than 2 and 3 and most of the passengers having the same nationality cluster) and 2 (emotional contagion 'off', number of groups of people travelling together and nationality clusters evenly divided), we had this research question: what is the effect of crowd composition on number and types of misbehaviour? We checked this hypothesis: It is expected that passengers will misbehave more in condition 1 than in 2. We simulated changing crowdedness, groups of passengers, cultural clusters and emotional contagion effect. Even though we reproduced all the combinations for the parameters, we only checked the results regarding the stated conditions since we were aiming to check the differences between populations of passengers with very strong and very weak social ties (conditions 1 and 2, respectively).

Indeed, people misbehaved more in condition 1 than condition 2 (in general as well as for every type of misbehaviour). See Figs. 5 and 6. We verified, therefore, that group frustration level reaches higher values faster in condition 1 than condition 2 and, as a consequence, passengers tend to misbehave more in condition 1 than in condition 2. This conclusion can be explained by emotional contagion. The model was developed taking into account that the effect of emotional contagion influences the passengers' frustration levels more if they have similar personal characteristics such as nationality clusters and they are travelling together within the same group of passengers.

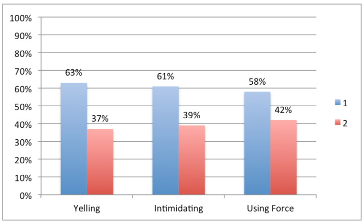

Fig. 5. Effect of crowd composition conditions (1 and 2) on types of misbehaviours

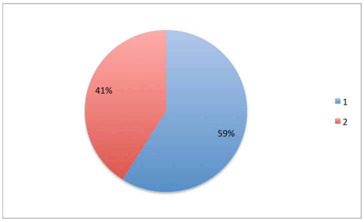

Fig. 6. Effect of crowd composition conditions (1 and 2) on misbehaviours

For the effect of emotional contagion, we had the following research question: what is the effect of emotional contagion on passengers' misbehaviours? We checked the following hypothesis: it is expected that passengers will start to misbehave faster when the effect of emotional contagion is 'on' than when it is 'off'. Here we used all the default values for the parameters and we only changed the effect of emotional contagion ('on' and 'off'). On average, passengers misbehaved 8.95 times when the emotional contagion was 'on' versus 0 times when it was 'off'. Besides that, they always started to misbehave sooner with the emotional contagion 'on' than when it was 'off' (Fig. 9 shows an execution of this simulation to illustrate what was stated). These are interesting findings, as they indicate that through emotional contagion there appear more misbehaviours. This is something emergency managers and prevention professionals should take into account. Perhaps in some cases certain passengers should be separated from each other, to avoid emotional contagion between them and consequently misbehaviours that follow out of that.

For the effects of a chatbot and multi-lingual staff, we had the following research questions: (1) What is the effect of a chatbot on overall frustration level and misbehaviours? (2) What is the effect of a multi-lingual staff on frustration levels and misbehaviours? To answer these questions we checked the following hypotheses: (1) More misbehaviours are expected when the chatbot is 'off' than when it is 'on'; (2) Less misbehaviours are expected 'with' multi-lingual staff than 'without'. We simulated changing crowdedness and (1) chatbot or (2) staff and cultural clusters of the passengers – depending on the research question.

Indeed, passengers misbehaved more when the chatbot was 'off' than when it was 'on' (see Fig. 7). Interestingly, we found no statistical difference in terms of misbehaviours when we compared multi-lingual versus non-multi-lingual staff (see Fig. 8). We were not expecting this result and an explanation could be that in the period of asking questions, the multi-lingual staff couldn't lower the frustration levels enough to avoid the passengers from reaching higher levels and misbehaving. In reality, this seems similar to the situation where after a certain level of frustration, talking to the staff makes no difference on the passengers' frustration levels. We presume it is reasonable to think that passengers would like practical information about what to do rather than simple supportive messages or generic instructions when they are already frustrated. Finally, the overall frustration level of the passengers always tended to be lower when the chatbot was 'on' than when it was 'off' (Fig. 10 shows an execution of this simulation to illustrate what was stated). Such a chatbot is always available for the users that have access to it. Additionally, as we mentioned in Sect. 2, there are some insights on the literature about chatbots being useful for helping people to cope with stress. Therefore, that is why we believe that having better results for a chatbot than for a multi-lingual staff might be reasonable and we developed our model taking this into account. Nevertheless, this should be investigated further using real data and being simulated in different scenarios.

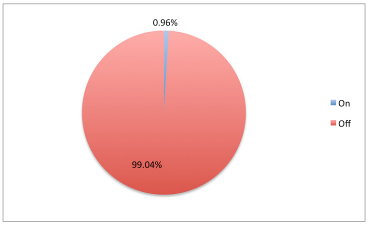

Fig. 7. Effect of a chatbot (on/off) on misbehaviours

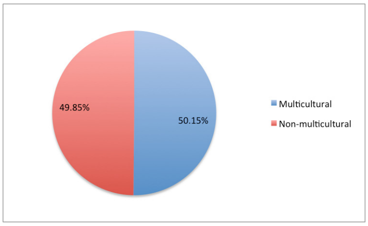

Fig. 8. Effect of a multicultural staff on misbehaviours

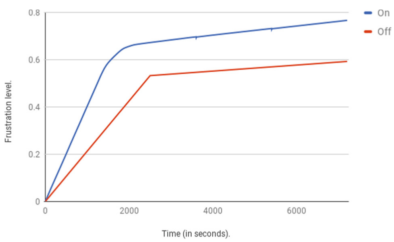

Fig. 9. Passengers' overall frustration level over time. 2 scenarios: with (on) and without (off) emotional contagion.

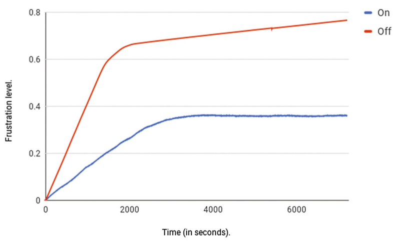

Fig. 10. Passengers' overall frustration level over time. 2 scenarios: with (on) and without (off) support from a chatbot.

5 Discussion

The aim of this work was to provide a computational agent-based domain model of stranded passengers at an airport to help stakeholders in dealing with these passengers. Besides that, we also investigated the effects of 2 support models (a supportive chatbot and multi-lingual staff) aiming to decrease the overall frustration level of the passengers in such a situation. We tried to do so by constructing these models according to the concepts found in the literature as well as requirements provided by stakeholders. Via the domain model we developed we can predict how likely a given set of stranded passengers is to misbehave. This can be calculated based on passengers and environments characteristics such as age, gender, nationality and amount of information.

Strengths of this work are: the inclusion of the socio-cultural aspects in the crowd modelling, the specific communication solution under analysis, both domain and support models being based on input (concepts) from specialist stakeholders and empirical findings from the literature, the facts that we carefully designed the simulation experiments and we have showed that it is useful to implement new emergency communication strategies and to estimate their effectiveness. The main weakness of this work is the fact that there are many cultural aspects that may play a role in this scenario, so we could not model all of them since it would become too complex to analyze. Although, it is an advantage to have a well defined parameters setting and they were most relevant to the stakeholders. Furthermore, the results coming out of the simulations cannot be taken for granted. Therefore, they will remain estimations. However, because they are based on a set of concepts taken from the literature, research and interaction with stakeholders, we believe they are representative enough as estimations.

As future work, we suggest (among others): to investigate the effect of a different layout, to investigate the effect of the number of staff members, to address multiple delayed flights and to come up with more cultural aspects and to investigate them in such a context.

We believe the implications of this work to be as follows. Transport operators, emergency managers and prevention professionals can use this kind of agent-based models to see what happens and choose the best solution at design time, to support periodic safety and security risk assessments and mandatory risk assessment when something changes in the environment, procedures and/or when new communication measures/technologies are put in place. Also, policy makers could use these models to support the identification of mandatory regulations and standards with respect to communication for emergency prevention and management.

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References

1. Berkowitz, L.: Frustration-aggression hypothesis: examination and reformulation. Psychol. Bull. **106**(1), 59 (1989)
2. Bosse, T., Duell, R., Memon, Z.A., Treur, J., van der Wal, C.N.: Agent-based modeling of emotion contagion in groups. Cogn. Comput. **7**(1), 111–136 (2015)

3. Bosse, T., Hoogendoorn, M., Klein, M.C.A., Treur, J., van der Wal, C.N., Van Wissen, A.: Modelling collective decision making in groups and crowds: integrating social contagion and interacting emotions, beliefs and intentions. Auton. Agents Multi-Agent Syst. **27**, 1–33 (2013)
4. Challenger, R., Clegg, C.W., Robinson, M.A.: Understanding Crowd Behaviours. Supporting Theory and Evidence, vol. 2. The Stationery Office (TSO), London (2010)
5. Crystal, D.: Two thousand million? Engl. Today **24**(01), 3–6 (2008)
6. De Wulf, M.: Population pyramids of the world from 1950 to 2100 (2016)
7. DeVault, D., Artstein, R., Benn, G., Dey, T., Fast, E., Gainer, A., Georgila, K., Gratch, J., Hartholt, A., Lhommet, M., et al.: SimSensei Kiosk: a virtual human interviewer for healthcare decision support. In: Proceedings of the 2014 International Conference on Autonomous Agents and Multi-agent Systems, pp. 1061–1068. IFAAMAS (2014)
8. Drury, J., Cocking, C., Reicher, S.: Everyone for themselves? A comparative study of crowd solidarity among emergency survivors. Br. J. Soc. Psychol. **48**(3), 487–506 (2009)
9. Georgeff, M., Pell, B., Pollack, M., Tambe, M., Wooldridge, M.: The belief-desire-intention model of agency. In: Müller, J.P., Rao, A.S., Singh, M.P. (eds.) ATAL 1998. LNCS, vol. 1555, pp. 1–10. Springer, Heidelberg (1999). doi:10.1007/3-540-49057-4_1
10. Jackson II, R.L., Hogg, M.A.: Encyclopedia of Identity, vol. 1. Sage, Thousand Oaks (2010)
11. Kim, H.S., Sherman, D.K., Taylor, S.E.: Culture and social support. Am. Psychol. **63**(6), 518 (2008)
12. Marsella, S., Gratch, J., Petta, P., et al.: Computational models of emotion. Bluepr. Affect. Comput. Sourceb. Man. **11**(1), 21–46 (2010)
13. Medeiros, L., Bosse, T.: Empirical analysis of social support provided via social media. In: Spiro, E., Ahn, Y.-Y. (eds.) SocInfo 2016. LNCS, vol. 10047, pp. 439–453. Springer, Cham (2016). doi:10.1007/978-3-319-47874-6_30
14. Medeiros, L., Sikkes, R., Treur, J.: Modelling a mutual support network for coping with stress. In: Nguyen, N.-T., Manolopoulos, Y., Iliadis, L., Trawiński, B. (eds.) ICCCI 2016. LNCS, vol. 9875, pp. 64–77. Springer, Cham (2016). doi:10.1007/978-3-319-45243-2_6
15. Mileti, D.S.: Factors related to flood warning response. In: US-Italy Research Workshop on the Hydrometeorology, Impacts, and Management of Extreme Floods, pp. 1–17. Citeseer (1995)
16. Picard, R.W.: Affective Computing. MIT Press, Cambridge (1995)
17. Reicher, S., Drury, J.: Social identity and social change: rethinking the context of social psychology (1996)
18. Ronen, S., Shenkar, O.: Mapping world cultures: cluster formation, sources and implications. J. Int. Bus. Stud. **44**(9), 867–897 (2013)
19. Tajfel, H.: Social Identity and Intergroup Relations. Cambridge University Press, Cambridge (2010)
20. Tsai, J., Bowring, E., Marsella, S., Tambe, M.: Empirical evaluation of computational emotional contagion models. In: Vilhjálmsson, H.H., Kopp, S., Marsella, S., Thórisson, K.R. (eds.) IVA 2011. LNCS, vol. 6895, pp. 384–397. Springer, Heidelberg (2011). doi:10.1007/978-3-642-23974-8_42

21. van der Wal, C.N., Couwenberg, M., Bosse, T.: Getting frustrated: modelling emotional contagion in stranded passengers. In: Benferhat, S., Tabia, K., Ali, M. (eds.) IEA/AIE 2017. LNCS, vol. 10350, pp. 611–619. Springer, Cham (2017). doi:10.1007/978-3-319-60042-0_67
22. van der Zwaan, J.M., Dignum, V., Jonker, C.M.: A conversation model enabling intelligent agents to give emotional support. In: Ding, W., Jiang, H., Ali, M., Li, M. (eds.) Modern Advances in Intelligent Systems and Tools. Studies in Computational Intelligence, vol. 431, pp. 47–52. Springer, Heidelberg (2012). doi:10.1007/978-3-642-30732-4_6
23. Veenema, T.G.: Disaster Nursing and Emergency Preparedness: for Chemical, Biological, and Radiological Terrorism and Other Hazards. Springer Publishing Company, New York (2012)
24. Wilensky, U., Rand, W.: An Introduction to Agent-Based Modeling: Modeling Natural, Social, and Engineered Complex Systems with NetLogo. MIT Press, Cambridge (2015)