

Towards an Online Emotional Support Agent: Identifying Emotional Support Strategies via Crowdsourcing

Socially Interactive Agents Track

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ABSTRACT

In this paper, an empirical study conducted with Amazon Mechanical Turk workers is presented that aims to make a correspondence between messages about stressful situations, which were shared via Twitter, and 5 different types of supportive replies to them. Around 10.00 tweets were collected and analyzed in the terms previously described. We performed statistical tests to determine possible correlations between causes of stress and supportive response strategies. We are about to use these findings to improve a previously implemented algorithm that automatically generates supportive messages to stressed users. This algorithm is the core of an agent, in the form of a chatbot, that would be able to interact with such stressed users as if it would belong to their social networks.

KEYWORDS

Social Agents; Chatbots; Social Media; Social Support; Crowdsourcing

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1 INTRODUCTION

The use of *Computer-Mediated Emotional Support* as a mechanism to help people in coping with stressful situations online has been addressed by different researchers [1, 2, 10–13]. However, helpful online emotional support is not always available for various reasons: users’ availability, privacy concerns, risk of facing stress as a consequence of providing support to stressed friends, etc. In this scenario, *Computer-Generated Emotional Support* in online social networks appears as an interesting alternative [3, 9]. Using the theory of emotional regulation proposed by Gross [4], a conceptual design of an algorithm to automatically produce supportive messages in accordance to stressful situations was previously introduced [6]. The algorithm uses five types of supportive strategies: *AD - Attentional Deployment*, *CC - Cognitive Change*, *GES - General Emotional Support*, *SM - Situation Modification* and *SS - Situation Selection*. Definitions of the strategies are also presented in [6].

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The current paper is part of a project that explores both advantages and disadvantages of using this solution to regulate emotions of stressed humans via social media. The main underlying idea is the concept of ‘artificial friends’: social agents that help people to deal with their ‘everyday problems’ via online social networks.

Using the API provided by the Telegram Messenger App, we developed an artificial friend in the form of a chatbot as a first effort in that direction [7]. Consequently, we conducted a pilot study to evaluate the acceptability of such an agent, which gave us promising results and interesting insights. One of the conclusions was that there was room for improvement of the algorithm used by our agent to classify incoming messages and to provide suitable supportive responses.

Therefore, the aim of the current research is to obtain more accurate insights regarding 1) the types of problems (stressful situations) human users share via online social networks, and 2) supportive strategies used by humans to regulate the stress of their peers. To achieve this, we performed a series of crowdsourcing experiments via Amazon Mechanical Turk, and the data obtained through the experiments are systematically analyzed (cf. [5]).

2 METHOD & RESULTS

As explained in [7], the stressful situations people share via social media can roughly be categorized into six classes: death, finances, health, relationships, school (or other educational environments) and work. Using the same keywords that our chatbot prototype uses to classify stressful situations into categories, plus indicators of negative sentiment and stress, we performed queries to collect tweets via Twitter’s official API¹. For instance, to collect tweets describing stressful situations about finances, the following query criteria were used: “money : (”, “money #stressed”, “debts : (”, “debts : (”, etc. Figure 1 shows the collected data.

Having the above described information in our database, we asked other participants to categorize the tweets into the same 6 classes of stressful situations (plus a category ‘other’). Figure 2 shows the result. Some examples of these tweets are presented in Table 1.

Next, we asked participants to provide replies to the filtered and classified tweets in two different ways. A first group had to select one out of five predefined replies we provided, each one related to one of the strategies mentioned earlier. We called this

¹All the code used to collect tweets can be accessed here: <https://git.io/vQLwB>. All the data obtained via the analysis was stored in a cloud MongoDB service. The data can be made available upon request.

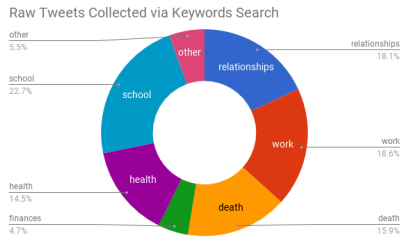


Figure 1: Distribution of tweets collected.

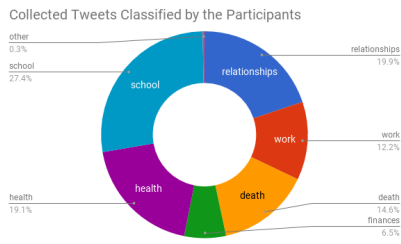


Figure 2: Distribution of tweets after categorization by the participants.

Table 1: Some examples of tweets collected via our keyword query approach.

Type of Situation	Examples of Tweets
Death	my great grandpa passed away earlier this year, and his birthday is on the 19th :(Sadly remembering a tragic event. When our Son passed away at birth 28 years ago today. :(
Finances	ugh i wish i found a duffel bag filled with money, that would solve all my problems :(I just need money :(
Health	Ingrid has kidney disease :(Someone pointed out that nasty bite I had last month could easily have been Lyme disease and now I'm nervous :(
Relationships	My crush isn't active on social networks :(i never did talk to my crush about the whole drunk holding hands thing :(i wanna but haven't had the opportunity
School	its 530am and ive been awake for the last hour looking at university admission requirements #stressed 6 page midterm due tomorrow, of course I leave it for the last minute! #Stressed
Work	Owwwwhhh I don't wanna work all day today :(I fuckings hate this job :(my family are heading out and I can't even be with them. I want to quit already

step 'Experiment 1'. Then, another group of participants had to come up with replies by themselves to the tweets. We refer to this step as 'Experiment 2'.

For the results of both experiments, we performed chi-squared tests to determine whether the distributions of support strategies over types of stressful situations were following a random distribution or not. It turned out that, in both cases, with significance level of at least 95%, we can state that the distributions are not random. Hence, we conclude that the types of stressful situations affect the support strategies selected by the participants while replying the tweets. The contingency tables for both experiments are represented in the form of bar charts in Figures 3 and 4, respectively. The results suggest that CC (for work and school) and GES are the most often used strategies. These results are comparable to the conclusion stated in [8], indicating that people tend to prefer socio-affective support. The results for finances and relationships need further investigation.

Finally, using a simulation-based approach, we identified for each stressful situation which of the strategies were selected significantly more often than average (this is indicated by the red arrows in Figures 3 and 4).

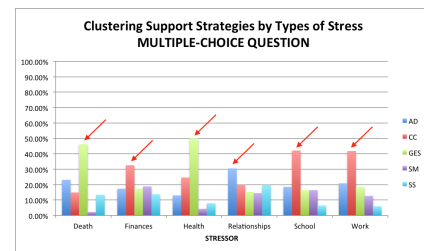


Figure 3: Results of the first experiment.

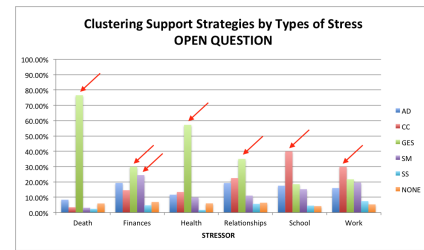


Figure 4: Results of the second experiment.

Based on these results, we now aim to improve the algorithm of our chatbot, since we can now base the choice on which support strategy to select in a particular situation on empirical findings. Currently, we are working on a new version of the chatbot. Here, not only the algorithm for selecting the supportive responses will be improved, but also the way the bot does it, as we are using IBM Watson to build the dialogues, which uses sophisticated AI techniques. Eventually, the aim is to systematically evaluate the final version of our agent.

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REFERENCES

- [1] D.O. Braithwaite, V.R. Waldron, and J. Finn. 1999. Communication of social support in computer-mediated groups for persons with disabilities. *Health Communication* 11 (1999), 123–151.
- [2] Scott E Caplan and Jacob S Turner. 2007. Bringing theory to research on computer-mediated comforting communication. *Computers in human behavior* 23, 2 (2007), 985–998.
- [3] David DeVault, Ron Artstein, Grace Benn, Teresa Dey, Ed Fast, Alesia Gainer, Kallirroi Georgila, Jon Gratch, Arno Hartholt, Margaux Lhomme, et al. 2014. SimSensei Kiosk: A virtual human interviewer for healthcare decision support. In *Proceedings of AAMAS 2014*. IFAAMAS, 1061–1068.
- [4] James J Gross. 2002. Emotion regulation: Affective, cognitive, and social consequences. *Psychophysiology* 39, 3 (2002), 281–291.
- [5] Peter Kindness, Judith Masthoff, and Chris Mellish. 2017. Designing emotional support messages tailored to stressors. *International Journal of Human-Computer Studies* 97 (2017), 1–22.
- [6] Lenin Medeiros and Tibor Bosse. 2016. Empirical Analysis of Social Support Provided via Social Media. In *International Conference on Social Informatics*. Springer, 439–453.
- [7] Lenin Medeiros and Tibor Bosse. 2017. An Empathic Agent that Alleviates Stress by Providing Support via Social Media. In *Proceedings of the 16th Conference on Autonomous Agents and MultiAgent Systems*. International Foundation for Autonomous Agents and Multiagent Systems, 1634–1636.
- [8] Lisanne S Pauw, Disa A Sauter, Gerben A Van Kleef, and Agneta H Fischer. 2017. Sense or sensibility? Social sharers evaluations of socio-affective vs. cognitive support in response to negative emotions. *Cognition and Emotion* (2017), 1–18.
- [9] Janneke M van der Zwaan, Virginia Dignum, and Catholijn M Jonker. 2012. A conversation model enabling intelligent agents to give emotional support. In *Modern Advances in Intelligent Systems and Tools*. Springer, 47–52.
- [10] J.B. Walther and S. Boyd. 2002. Attraction to computer mediated social support. *Communication technology and society: Audience adoption and uses* (2002), 153–188.
- [11] Marsha White and Steve M Dorman. 2001. Receiving social support online: implications for health education. *Health education research* 16, 6 (2001), 693–707.
- [12] Kevin Wright. 2002. Social support within an on-line cancer community: An assessment of emotional support, perceptions of advantages and disadvantages, and motives for using the community from a communication perspective. *Journal of Applied Communication Research* 30, 3 (2002), 195–209.
- [13] K.B. Wright and S.B. Bell. 2003. Health-related support groups on the Internet: Linking empirical findings to social support and computer-mediated communication theory. *Health Psychology* 8 (2003), 39–54.