Chatbot Based Public Sensoring to improve Situational Awareness

Hans Betke
Fraunhofer FOKUS
hans.betke@fokus.fraunhofer.de

Sascha Peitzsch
Fraunhofer FOKUS
sascha.peitzsch@fokus.fraunhofer.de

Johannes Boldt
Martin Luther University Halle-Wittenberg
johannes.boldt@wiwi.uni-halle.de

Dustin Reimann
Fraunhofer FOKUS
dustin.reimann@fokus.fraunhofer.de

Thomas Kox
Weizenbaum Institute
thomas.kox@weizenbaum-institut.de

ABSTRACT

In disaster management, any relevant information about the situation can help decision makers to take the right decisions and initiate appropriate response measures. The digitalization of society offers more and more opportunities to gather information from the public. As instant messengers are one of the most widely used communication applications, they offer a broad user base for the collection of situational information. To minimize the effort involved, chatbots offer a promising option for the automated acquisition of specific information via instant messengers. In this paper we present an information system under development for the collection and reproduction of image information for disaster management. We also present the results of a first UTAUT-based evaluation of the current state of development to get an impression of the usability and perceived usefulness of the approach.

Keywords

Situational Awareness, Situation Picture, Chatbot, Public Sensoring, Crowdsourcing

INTRODUCTION

People share an extremely large amount of information in the event of a disaster/crisis via social media (Fathi and Fiedrich 2023). To have access to this information and to disseminate their own information quickly and directly to citizens, many civil protection authorities (CPAs) also use social media and operate their own social media accounts. In addition, there are innovative endeavors to deal more efficiently with information about future developments by implementing new technologies in acute operations (Schütte and Kox 2021). The large amount of different information and social media platforms means a great deal of effort for CPAs to use them effectively and efficiently. For this reason, scientists have been working for several years on approaches to make social media and their services more usable for disaster management purposes (Reuter and Kaufhold 2018). One challenge for which no approach has yet been widely established in practice is the targeted acquisition of situation information from the population.

So called information crowdsourcing is generally not a new topic. Information crowdsourcing approaches are examples where the citizens act as sensors, providing data to interpret and use by scientists or government agencies. The roles as sensors can be passive, for example, downloading an app that allows data gathering via a smartphone, or involve active participation, for example, taking photos or providing other information to the extent that their role can also take on that of an interpreter. For example, gathering data may entail the participants performing some interpretation where basic training or guidance may be required. Beyond that, citizens involvement can go so far that the citizens play an active role in the problem definition or become part of the interpretation process (Haklay 2013; Vinnell et al. 2021).

Information crowdsourcing in disaster management offers the chance to gather previously unavailable data on e.g. meteorological phenomena (Kempf 2021) or earthquakes (Steed et al. 2019) and thus greatly add to existing observation capabilities of meteorological, geological or emergency services. In addition, crowdsourcing offers a low-cost approach to produce reliable and rapid results (Kox et al. 2021; Steed et al. 2019) and helping affected populations by providing geographic information for disaster response (Fathi and Fiedrich 2023). However, although promising approaches to targeted information crowdsourcing already exist, they are often limited by the reach of their users. For some approaches, users must have certain knowledge or skills, for example in dealing with geoinformation systems, but above all the approaches are mostly based on special software applications that must be installed separately and are not widely used. This means that much of the potential for obtaining information from the population cannot be utilized. Important aspects of the design of corresponding systems are user friendliness and simplicity of the implementation, as it is expected that most users will most likely not be able to accurately report desired phenomena on a professional scale (Kempf 2021).

One idea is therefore to make better use of systems that already have a large user base and enable information exchange, the social media. Instant messaging services such as WhatsApp, Facebook Messenger and Telegram are among the most frequently used applications worldwide (Kemp 2023). These enable simple and direct bidirectional communication with individuals and groups. However, not all CPAs can cope with the effort involved in communicating with many individual people, especially in highly stressful situations such as a disaster. The use of automation techniques in the form of conversational agents could therefore be an approach to ensure the practical applicability of instant messengers. Conversational agents (or chatbots) automatically respond to user input with suitable text messages and can support them in carrying out tasks or provide information themselves. In the area of crowdsourcing physical activities, there are already initial approaches to support the coordination of spontaneous volunteers in disaster response with chatbots (Gerstmann et al. 2019).

In this paper, we present the first steps in our research in progress on the development of targeted information crowdsourcing systems in disaster management using chatbots. To gain first impressions of the usefulness and accessibility of such systems, we have developed a simple chatbot with which a citizen can transmit photos of the situation taken with their smartphone with some meta information to CPAs. The CPA staff can access the information in the form of a dashboard. We have subjected this demonstrator to an initial expert evaluation based on a use case and present the results here. With this paper, we want to provide both scientists and practitioners with an initial assessment of the suitability of chatbot-based approaches for situational awareness and offer a simple solution for the implementation of a system in practical use. While doing so, we investigate the following research question:

RQ: Can chatbot-based situational awareness systems be a user-friendly addition to information retrieval in disaster management?

In the following sections, we first present related work in the field of chatbot-based approaches in disaster management, describe the implementation and features of the software artefact and show the results of an initial evaluation based on the UTAUT-method (Venkatesh et al., 2003). The paper ends with a conclusion summarizing the results and discussing the next steps of the research project.

RELATED WORK

Chatbots are text-based systems, which can communicate with their users via natural language (Gnewuch, Morana, Maedche 2017). They are particularly interesting due to their ability to integrate with other systems as they are mainly used on social media platforms, but also in other applications such as websites and mobile apps (Brandtzaeg and Følstad 2017). This makes them particularly valuable for use in disaster management, where communication via social media plays an important role (Reuter and Kaufhold, 2018). The application of chatbots for emergency and disaster management is an active field of research. In recent years, many different approaches for various use cases have been developed.

The approaches for chatbots in disaster management can be divided into two groups. The first group is concerned with informing and coordinating the general population. For example, Syed et al. (2020) designed an educational chatbot for small and medium sized companies to assist staff in learning about disaster preparedness, ranging from fires and blackouts to cyberattacks. The Richter chatbot on Facebook Messenger (Raymond 2016) provides users with earthquake and tsunami preparedness information to help them draw up an emergency plan for their household. The “Flood Ai” chatbot (Sermet 2018) teaches users from the public about floods and provides up-to-date information on water levels. Other important use cases involve providing information and guidance to the general population during an emergency (Crook 2016, Ghosh 2019, Ahmady 2020, Boné 2020, Ohtake 2021, Ouerhani 2020, Ovando-Leon 2022) and allowing affected people to contact and communicate with emergency response forces (Clegg 2017, Crook 2016).

The second group focuses on supporting disaster response personnel and decision makers by e.g., facilitating data organization and access (Tsai 2019, Chen 2019, Tsai 2021a, Tsai 2021b). Another example for this is the coordination of spontaneous volunteers (Gerstmann et al. 2019, Ovando-Leon 2022). Furthermore, chatbots can also be applied for informational crowdsourcing. For instance, the chatbot 911bot, which was in practical use, (Crook 2016) was a Facebook Messenger based chatbot that allowed users to report emergencies to the authorities and provided information and advice to first responders. Additionally, it also allowed to send relevant pictures and videos to the authorities. Dharmapuri Sridhar (2017) investigated crowdsourcing situational information for flooding in Chennai, India and presented the web-based tool RiskMap for collecting and verifying crowdsourced information from social media. Participants can report flood-related information, such as location, flood height, and pictures of the flooding, by contacting chatbots on Twitter, Facebook, and Telegram. Tsai (2020) presented a system for the assessment of school building safety after natural hazards, such as earthquakes and typhoons, and for routine inspections. In this use case, people that are typically not structural engineering experts are assigned the task of assessing possible building damages. Hence, they are notified by a chatbot and guided through the inspection procedure and provided further assistance in the process. Furthermore, a dashboard showing the report results and assessed damages is used. This work is built upon in Kung (2020), where transfer learning is used to automatically extract the relevant information from the building damage reports. The chatbot SOCDA (Ohtake 2021) can be used to collect damage reports during natural disasters and can provide the public with relevant information, for example to aid in evacuations. SOCDA was tested in large-scale exercises in Japan in 2020 and 2021.

Despite the examples mentioned here along the entire disaster management lifecycle, the response to the refugee crisis in Germany has been characterized by the need for additional resources and the cooperation of various authorities and organizations under the leadership of a disaster management authority (Dittmer and Lorenz, 2019). Stieglitz et al. (2022) advise disaster managers not to rely on traditional chatbots, that simply gather information, but to deploy intelligent systems that ask information providers for more background information before passing it on to field teams.

Our work aims to build on these demands and previous chatbot implementations for data gathering during disasters and addresses the need to visualize the gathered data to disaster responders which can then be used to inform disaster response workers decision making processes. In the Research in Progress presented here, we explicitly do not consider any further features for analyzing and evaluating the information collected. In order to transfer the approach to practical use, it is important that the information collected is highly trustworthy. Possibilities for integrating existing methods that address this challenge on an organizational (e.g. Mehta et al., 2017) and technical level (e.g. Poblet et al., 2018) will be investigated in future publications.

SOFTWARE ARTIFACT

Our software demonstrator consists of two essential parts for the two user groups involved: A chatbot, the *BurningBot*, through which information providers from the population can transmit images of a situation including meta-information via the instant messenger Telegram, and a dashboard, called *Spell-Dashboard*, which visualizes this information on a situation map for disaster management. In the following, we explain the structure of the system before describing the features.

For a bot to be able to communicate via the Telegram Bot API, it must be registered with the Telegram internal tool BotFather. In the course of this, a name for the conversation ("spell-dashboard-burning-bot") and a username for linking ("@SpellDashboardBurningBot") are assigned and a token is created, which is required to authorize the bot and send requests to the Telegram Bot API. The bot is still active now and the given name can be used to find the chatbot in the Telegram search and to start a conversation. A *BurningBot* Listener Service, developed with Python, runs in the backend. This establishes a connection to the *BurningBot* via the bot token using the HTTP-based Telegram Bot API. The listener is also responsible for giving the *BurningBot* its functionality. All messages that the *BurningBot* sends to the user are defined in the service, such as requesting the image, location and direction. After all the necessary information has been received by the listener, it is converted into a JSON object together with some meta data (user ID, file ID, date and time) and forwarded to a PostgreSQL database. To enable the dashboard frontend to retrieve the data from the database, there is a *BurningBot* API service developed with NodeJS. The dashboard is an Angular application (v15) and runs on the Red Hat OpenShift Container Platform. All backend services, including those of the *BurningBot*, are provided via OpenShift. Communication between the frontend and the *BurningBot* API takes place via HTTP requests. End users on the disaster management side access the dashboard via HTTPS. Figure 1 shows the components and information flows of the system.

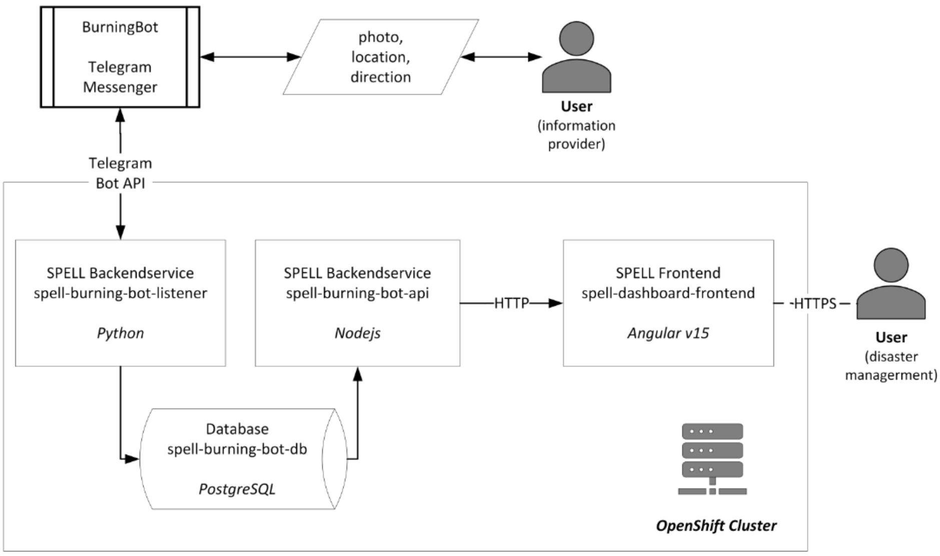

Figure 1. Component diagram of the BurningBot system demonstrator.

The *BurningBot* is a rule-based conversational agent that queries a photo and the corresponding location and direction of the shot in a three-stage conversation. The *BurningBot* first introduces itself and briefly explains how it works and the purpose of information retrieval. It then asks participants to upload an image that will be used as a source of information for CPAs. After the participant has uploaded a picture, the *BurningBot* asks for the participant's location and explains how to share it in the Telegram messenger. If the users have shared their location, the *BurningBot* asks for the cardinal direction in which the picture was taken and provides information on how this can be determined. After entering the cardinal direction, the *BurningBot* thanks the user and the entire conversation can be restarted to share more pictures. An example conversation in German is shown in Figure 2.

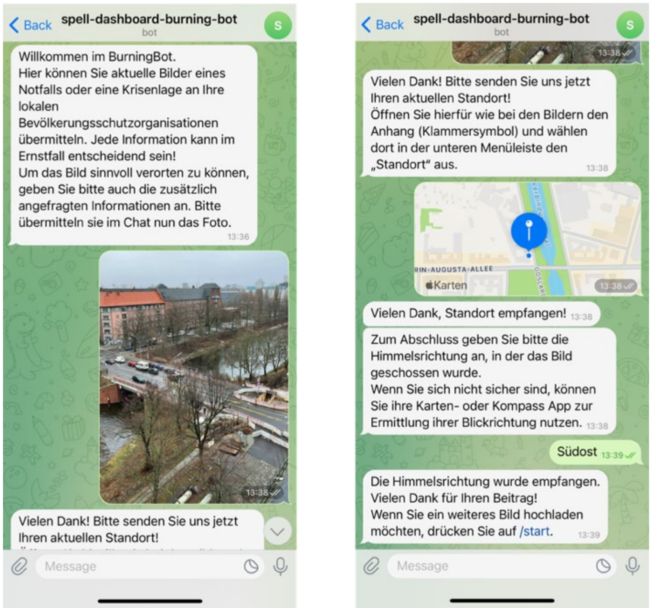

Figure 2. Screenshots of an example interaction with the BurningBot.

The second part of the evaluation involves the visualization of the results on a dashboard that was developed in the context of the SPELL project (https://spell-plattform.de/en/). The participants are provided with the internet address and login information for the dashboard. After login, the participants are presented with a dashboard landing page, where they can select the "*Lage Berlin*" (translation: "situation picture Berlin") dashboard. They are presented with a panel that shows where participants submitted pictures. A screenshot of an exemplary map is shown in Figure 3.

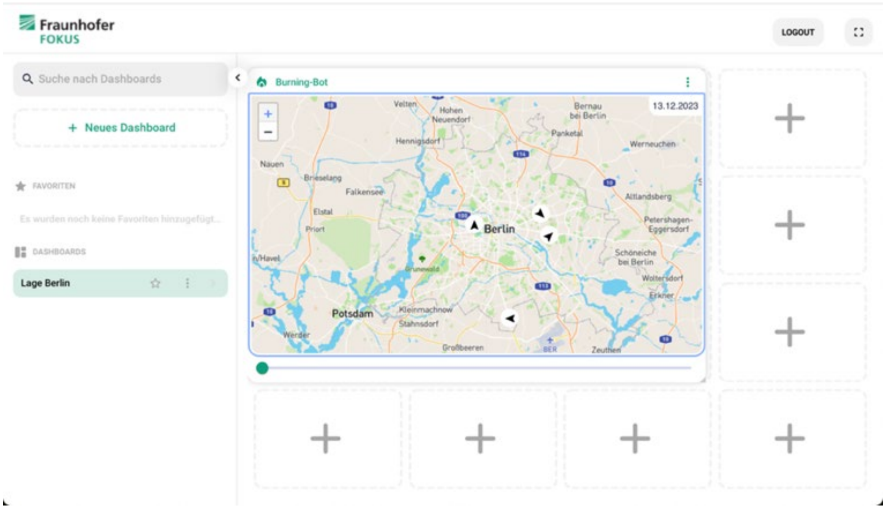

Figure 3. BurningBot panel with map showing locations of submissions.

The slider widget below the map can be used to display the submission status for different times. The positions of the submissions are shown with circle markers, which also indicate the viewing directions of the pictures. Detailed information of the single submissions can be seen by clicking on one of the markers. Figure 4 shows an example submission.

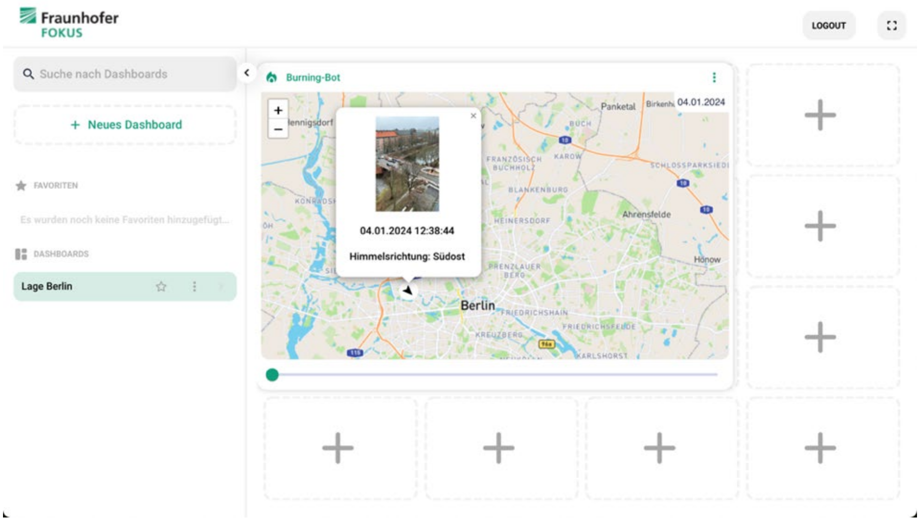

Figure 4. BurningBot panel with detailed information of an example submission.

EVALUATION

To get a first impression of the usability, the perceived usefulness, and user-friendliness of the *BurningBot* and the dashboard system demonstrator, we conducted a UTAUT-based evaluation (Unified Theory of Acceptance and Use of Technology; Venkatesh et al., 2003) of the current state of development. We surveyed people with a background in computer science and with a connection to disaster management as a proxy for the two actual user groups: volunteers, which contribute situational information, and disaster managers, who utilize the submitted information. The questionnaire is based on items and constructs from Venkatesh et al. (2003). The perceived likelihood of adopting the technology is dependent on the effect of four constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions, moderated by age, gender, experience and voluntariness of use (Venkatesh et al., 2003). Certain UTAUT items that do not fit the context of our specific application were not included as they did not fit the purpose of the tool. For example, the item "*If I use the system, I will increase my chances of getting a raise*" was excluded since both the dashboard and the chatbot are not intended to provide economic benefits for the volunteers and disaster managers in our scenario. The items "*It scares me to think that*

I could lose a lot of information using the system by hitting the wrong key” and “*I could complete a job task using the system if I had just the built-in help facility for assistance*” were also omitted. Similarity, the item groups that measure the factors “*social influence*” and “*facilitating conditions*” do not transfer to the scenario at hand and were not used. The questionnaire contained 14 items of the UTAUT, measuring performance expectancy, attitude towards using technology, effort expectancy, self-efficacy, anxiety, and behavioral intent to use the technology. Eight additional items from a questionnaire from Sindhuja p and Dastidar, (2009), which is derived by the Purdue Usability Testing Questionnaire (PUTQ) by Lin et al. (1997) were included to obtain information about user satisfaction and perception of the software design.

The resulting questionnaire contained consequently 22 items for the dashboard and 22 items for the chatbot, which were translated to German. All thematic items consisted of 5-point Likert scales ranging from -2 (strongly disagree) to 2 (strongly agree). In addition, we added demographic items about age and gender. However, we did not include items about the level of education and profession of the participants. The survey was conducted online. Participants could answer items about the chatbot, the dashboard or both systems subsequently. In choosing the sample size, we followed the so-called "10±2 rule" (Hwang and Salvendy, 2010), which states that 8 to 12 respondents are sufficient for evalutation of usefulness of an artifact or technology The experts interviewed all had at least a bachelor's degree, with specialized knowledge in either disaster management, information systems design or both. Finally, 22 questionnaires were completed between December 2023 and January 2024. Ten of the completed questionnaires related to the dashboard while 12 referred to the chatbot. Participants were between 25 and 55 years old. Nine participants identified themselves as female and 13 as male. Due to the preliminary nature of this report, we are only reporting a selection of the data collected, with a focus on the items from UTAUT. All other analyses are currently work in progress.

Performance Expectancy

The performance expectations (Figure 5) for both the bot and the dashboard were generally reported as very high. 50% (dashboard) and 42% (bot) strongly agreed and an additional 40% (dashboard) and 50% (bot) agreed with the statement “*I would find the system useful in my job*” (median value dashboard: 1.5; bot: 1). In addition, 30% (dashboard) and 42% (bot) strongly agreed and additional 30% (dashboard) and 42% (bot) agreed with the statement “*Using the system enables me to accomplish tasks more quickly*” (median value dashboard and bot both: 1).

Figure 5. Survey results for performance expectancy.

Effort Expectancy

Also, effort expectancy (Figure 6) for both the bot and the dashboard were generally reported as very high. 70% (dashboard) and 75% (bot) of the participants strongly agreed and an additional 20% (dashboard) and 25% (bot) agreed with the statement “*It would be easy for me to become skillful at using the system*” (median value dashboard and bot both: 2). 50% (dashboard) and 83% (bot) of the participants strongly agreed and an additional 30% (dashboard) and 8% (bot) agreed with the statement “*I would find the system easy to use*” (median value dashboard:

1.5; bot: 2). 50% (dashboard) and 92% (bot) of the participants strongly agreed and an additional 30% (dashboard) and 8% (bot) agreed with the statement "*Learning to operate the system is easy for me*" (median value dashboard: 1.5; bot: 2).

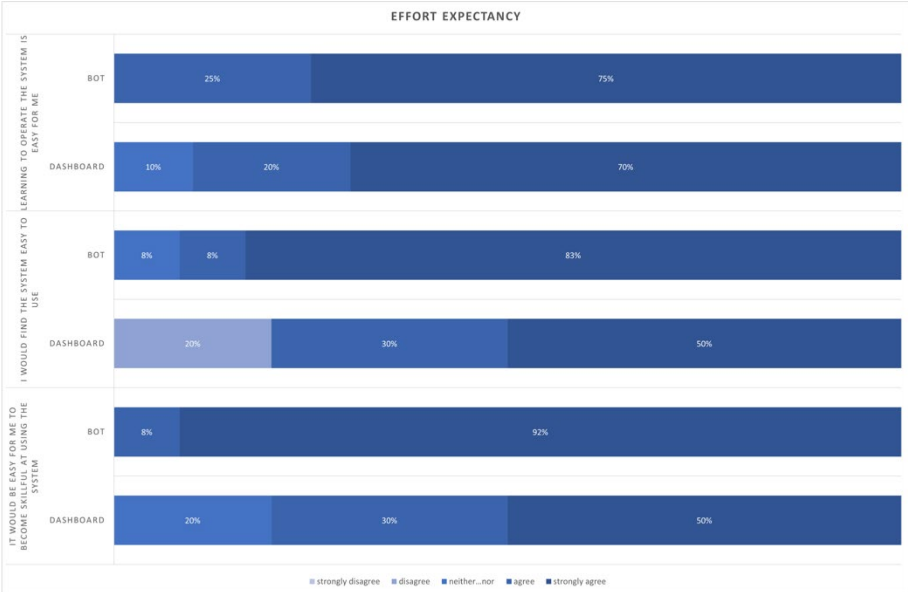

Figure 6. Survey results for effort expectancy.

Attitude Towards Technology

The attitude towards the presented technology (Figure 7) was to some degree indifferent: 50% (dashboard) and 25% (bot) of the participants agreed and an additional 8% (bot) strongly agreed with the statement "*Working with the system is fun*", while 40% (dashboard) and 58% (bot) neither agreed nor disagreed with the statement (median value dashboard: 0; bot: 0.5). However, 20% (dashboard) and 8% (bot) of the participants strongly agreed and an additional 60% (dashboard) and 67% (bot) agreed with the statement "*I like working with the system*" (median value dashboard and bot both: 1). 80% (dashboard) and 83% (bot) of the participants strongly disagreed and an additional 20% (dashboard) and 8% (bot) disagreed with the statement "*Using the system is a bad idea*". 8% of the participants who answered the questionnaire related to the bot, however, agreed with the statement (median value dashboard and bot both: -2).

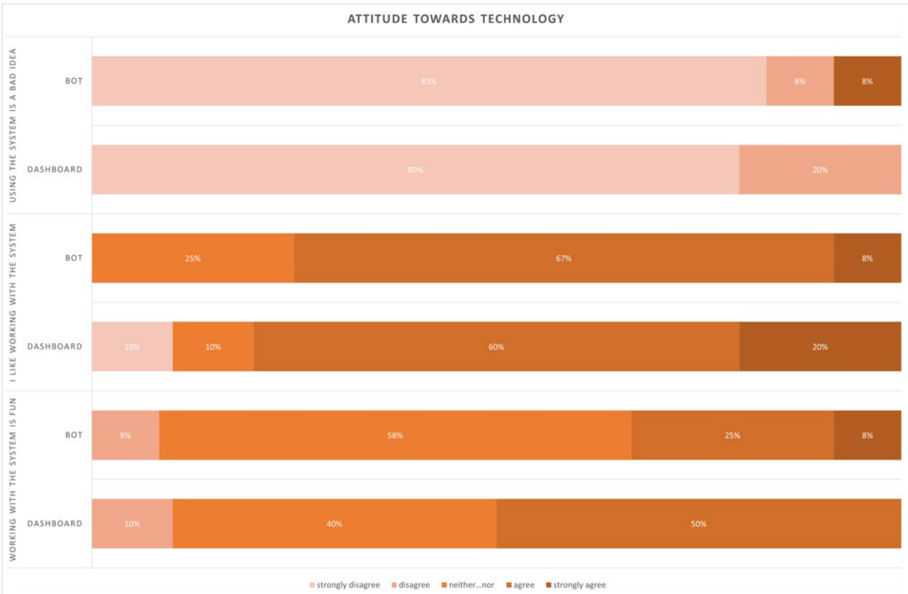

Figure 7. Survey results for attitude towards technology.

Self-Efficacy

Self-efficacy (Figure 8) was measured by asking three questions each starting with "*I could complete a job or task using the system...*" followed by a more specific statement. First, 50% (dashboard) and 67% (bot) of the participants strongly agreed and an additional 50% (dashboard) and 25% (bot) agreed, while 8% of the participants who answered the questionnaire related to the bot disagreed with the statement "*...if there was no one around to tell me what to do as I go"* (median value dashboard: 1.5; bot: 2). Second, 100% (dashboard) and 92% (bot) of the participants strongly agreed and an additional 8% (bot) agreed with the statement "*...if I could call someone for help if I got stuck*" (median value dashboard and bot both: 2). Third, 50% (dashboard) and 67% (bot) of the participants strongly agreed and an additional 30% (dashboard) and 25% (bot) agreed with the statement "*...if I had a lot of time to complete the job for which the software was provided*". However, of the participants who answered the questionnaire related to the dashboard 10% disagreed and an additional 10% strongly disagreed with the statement (median value dashboard: 1.5; bot: 2).

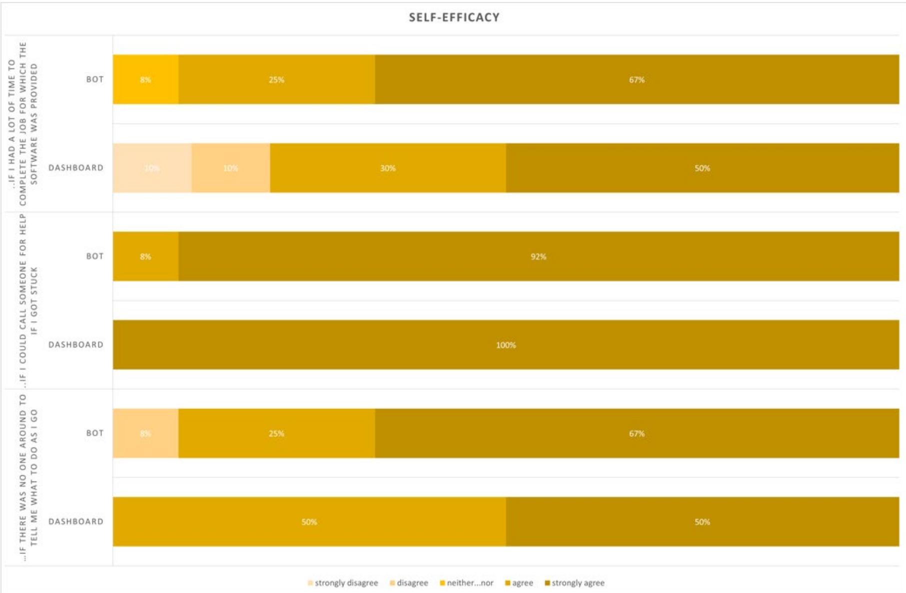

Figure 8. Survey results for self-efficacy.

Behavioral Intention to Use the System

The stated intention to use the bot was indifferent (Figure 10). 42% of the participants neither agreed nor disagreed, while 33% agreed and 17% disagreed with the statement "*I intend to use the system in the next 3 months*" (median value: 0). Regarding the stated intention to use the dashboard, 40% of the participants strongly agreed and an additional 40% agreed with the statement, while 10% each neither agreed nor disagreed or disagreed with the statement (median value bot: 0; dashboard: 1).

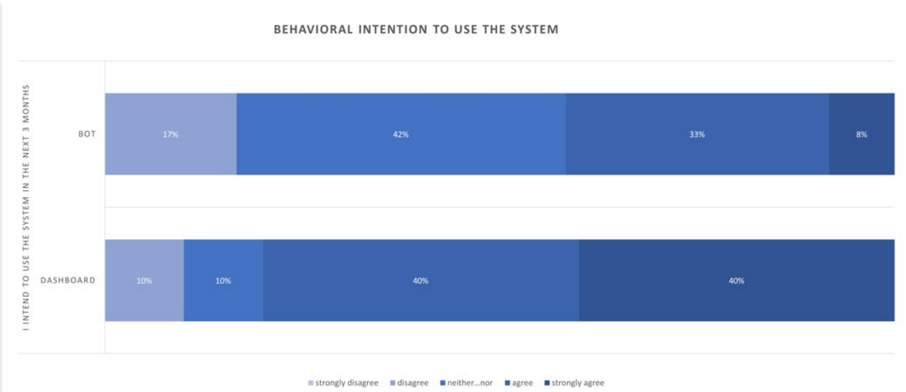

Figure 10. Survey results for behavioral intention to use the system.

Anxiety

Respondents showed no anxiety or concern (Figure 9) about using the dashboard or the bot. 50% (dashboard) and 67% (bot) of the participants strongly disagreed and an additional 40% (dashboard) and 17% (bot) disagreed, while 10% (dashboard) and 17% (bot) neither agreed nor disagreed with the statement "*I feel apprehensive about using the system*" (median value dashboard: -1.5; bot: -2). 50% (dashboard) and 92% (bot) of the participants strongly disagreed and an additional 40% (dashboard) and 8% (bot) disagreed, while 10% of the participants who answered the questionnaire related to the dashboard agreed with the statement "*The system is somewhat intimidating to me*" (median value dashboard: -1.5; bot: -2).

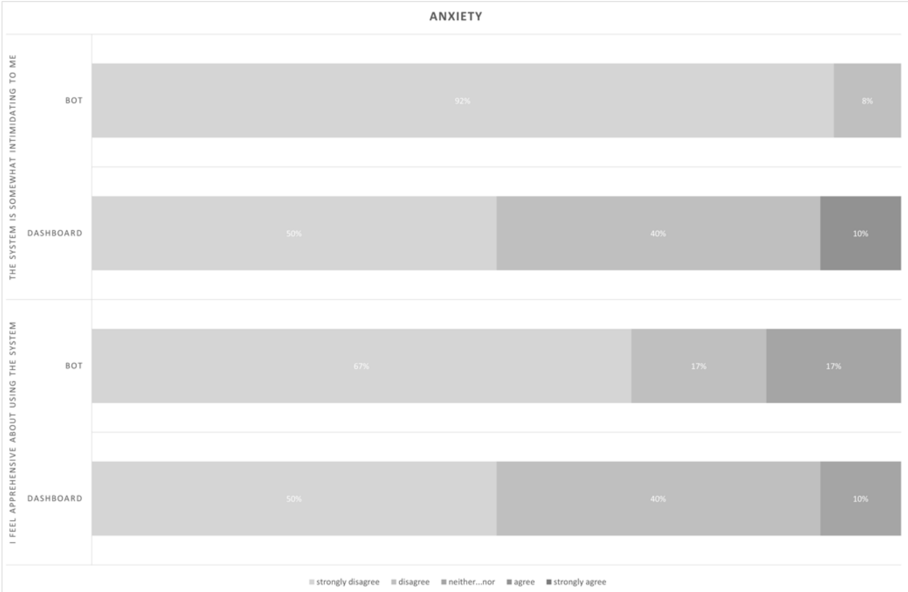

Figure 9. Survey results for anxiety.

Additional Items on Satisfaction and Perception of the Software Design

Regarding the questions on satisfaction with the software design of the dashboard and the bot, we present a selection of the items here (Figure 11). In general, the participants were satisfied with the software design. 40% of the participants strongly agreed and an additional 30% agreed with the statement "*I like the design of the dashboar*d." 10%, however, strongly disagreed with the statement and 20% were indecisive (median value: 1). In addition, 30% of the participants strongly agreed and an additional 30% agreed with the statement "*The dashboard provides clarity and consistency of wording*". Again, 10% strongly disagreed with the statement and 30% were indecisive (median value: 1).

Regarding the color scheme and the arrangement of the dashboard, participants gave positive feedback. First, 40% of the participants strongly agreed and an additional 50% agreed with the statement "*Color codes used in the dashboard are easily distinguishable*" (median value: 1). Second, 50% of the participants strongly agreed and an additional 40% agreed with the statement "G*rouping and ordering of menu options [in the dashboard] are logical*" (median value: 1.5). Third, 30% of the participants strongly agreed and an additional 40% agreed with the statement "*I can find easily what I'm looking for on the dashboard*", while 10% each strongly disagreed, disagreed or were indecisive (median value: 1).

The participants were not sure whether frequent and regular use of the dashboard and the bot was necessary to handle the technology. 20% (dashboard) of the participants strongly agreed and an additional 20% (dashboard) and 17% (bot) agreed with the statement "*The user needs to be a frequent user*", while 20% (dashboard) and 17% (bot) neither agreed nor disagreed with the statement. In contrast, 20% (dashboard) and 33% (bot) of the participants strongly disagreed and an additional 20% (dashboard) and 33% (bot) disagreed with the statement (median value dashboard: 0; bot: -1).

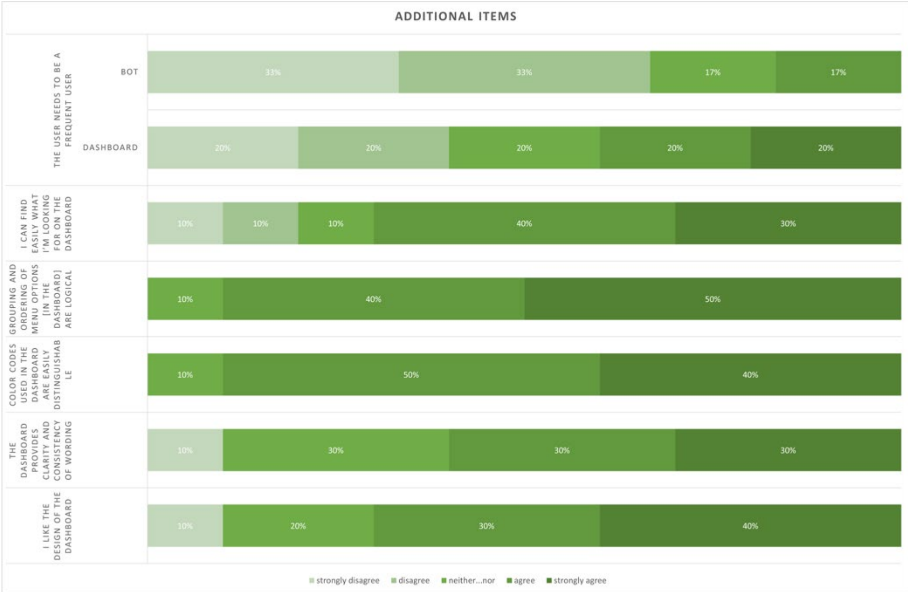

Figure 11. Survey results for additional items.

Limitations

Not just because of the provisional nature of the software, there are several limitations to this study: The evaluation only included part of the evaluation items, was conducted with only a few test persons and not under real-life conditions. It can be assumed that the statements will change under these conditions. The current prototype, for example, does not provide any information on the expected extent of contributions during a real-life crisis event. However, as lay persons networks made up of e.g. voluntary weather observers (Kox et al. 2021), or digital volunteers and professionalized digital volunteers institutionalized in established CPAs (Fathi and Fiedrich 2023) also form a community of practice and their willingness to engage in such a crowdsourcing task should not be underestimated (Kox et al. 2021). Additionally, in a real-life emergency context we would expect a bias between urban over rural areas, as it can be expected that the density of crowd observations will be higher in higher populated urban regions (Meier et al. 2017).

CONCLUSION

In this paper, we used a software demonstrator to investigate how potential users evaluate chatbot-based applications for situational awareness in disaster management. The approach presented here uses citizens and their mobile devices as sensors that interact with the object of interest to some extent, but do not provide any interpretative services. The participants in this use case mainly take the roles as *active sensors* by taking photos and providing context information. Images transmitted via chatbot with location and time stamp are displayed to decision-makers in disaster management in the form of a map-based dashboard. Both frontends were evaluated by expert groups based on established methods for evaluating technology acceptance after they had familiarized themselves with the system in a simple use case. The results showed a generally positive assessment of the user-friendliness and perceived usefulness of the system for both user groups.

Performance expectations and effort expectancy for both the bot and the dashboard were generally reported as very high. The respondents showed no anxiety or concern about using either of these technologies. The software design of the dashboard was generally evaluated positively. However, the stated intention to use the bot was indifferent, suggesting that other factors, which were not covered in this study, still might be affecting this variable. The factors "*social influence*" and "*facilitating conditions*" were omitted in this preliminary study and might be included in future research.

Despite the limitations of this work, such as the limited number of participants in the evaluation in the current research in progress and the fact that the software demonstrator only has basic functionalities, the clearly positive assessment of the system and the idea behind it suggests that corresponding solutions could offer significant practical added value and make further research in this area appear promising. In future research steps, we want to extend the existing demonstrator to investigate chatbot-based querying and dashboard-supported evaluation of different types of information. To better assess the added value and acceptance of such systems in practice, we are aiming for an evaluation in the context of a larger disaster control exercise with more realistic operating conditions and a larger number of participants. We want to methodically summarize the design knowledge acquired in the course of this work for the implementation of such systems in a design theory to provide scientists and practitioners with a suitable starting point for the implementation of their own systems. Another research question that has been investigated for several years in the field of information gathering via social media concerns the IT-supported evaluation of the information collected. In addition, using sophisticated data analysis tools for automatic classification the crowdsourced information could help to build up databases of disaster impact that could not otherwise be created.

ACKNOWLEDGMENTS

This work is funded by the German Federal Ministry for Economic Affairs and Climate Action under grant No. FKZ 01MK21005B SPELL. The contribution of Thomas Kox was part of the joint project "Weizenbaum Institute for the Networked Society" (FKZ 16DII131), funded by the German Federal Ministry of Education and Research. We thank all people who participated in the evaluation of the dashboard and the chatbot.

REFERENCES

Ahmady, S. E., and Uchida, O. (2020). Telegram-based chatbot application for foreign people in Japan to share disaster-related information in real-time. In *2020 5th International Conference on Computer and Communication Systems* (ICCCS)(pp. 177-181). IEEE.

Boné, J., Ferreira, J. C., Ribeiro, R., and Cadete, G. (2020). Disbot: A Portuguese disaster support dynamic knowledge chatbot. In *Applied Sciences*, 10(24), 9082.

Brandtzaeg, P.B., Følstad, A. (2017). Why People Use Chatbots. In Kompatsiaris, I., et al. *Internet Science. INSCI 2017. Lecture Notes in Computer Science*, vol 10673. Springer, Cham. https://doi.org/10.1007/978-3-319-70284-1_30

Chen, J. Y., Tsai, M., Yang, C., Chan, H., and Kang, S. (2019). Chatbot System for Data Management: A Case Study of Disaster-related Data. In *ISARC. Proceedings of the International Symposium on Automation and Robotics in Construction* (Vol. 36, pp. 306-309). IAARC Publications.

Clegg, J. (2017). Rescue. io: A chatbot solution for emergency situations. In *Square One Labs* https://medium. com/square-one-labs/rescue-io-a-chatbot-solution-toemergency-situations-dd267f174554.

Crook, J. (2016). *911bot is a chat bot that could save your life*. https://techcrunch.com/2016/05/08/911bot-is-a-chat-bot-that-could-save-your-life

Dittmer, C. and Lorenz, D. (2019). Disaster situation and humanitarian emergency – in-between responses to the refugee crisis in Germany. *International Migration*, 59(3), 96-112. https://doi.org/10.1111/imig.12679

Dharmapuri Sridhar, M. P. (2017). *Real-time flood mapping for disaster management decision support in Chennai* (Doctoral dissertation, Massachusetts Institute of Technology).

Fathi, R., and Fiedrich, F. (2024). Digital Volunteers in Disaster Management. In D. Burghardt, E. Demidova, and D. A. Keim (Eds.), *Volunteered Geographic Information: Interpretation, Visualization and Social Context* (pp. 265–276). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-35374-1_13.

Gerstmann, S., Betke, H., and Sackmann, S. (2019). Towards Automated Individual Communication for Coordination of Spontaneous Volunteers. In *Proceedings of the 16th Annual Global Conference on Information Systems for Crisis Response and Management (ISCRAM 2019), Spain*.

Ghosh, P., Raihan, M., Islam, M. T., and Rahaman, M. E. (2019). Safeguard: A prototype of an application programming interface to save the disaster affected people. In *2019 10th International Conference on Computing, Communication and Networking Technologies* (ICCCNT) (pp. 1-5). IEEE.

Gnewuch, U., Morana, S. and Maedche, A. 2017. *Towards Designing Cooperative and Social Conversational Agents for Customer Service*.

Haklay, M. (2013). Citizen science and volunteered geographic information: Overview and typology of participation. In D. Sui, S. Elwood, & M. Goodchild (Eds.), Crowdsourcing Geographic Knowledge: Volunteered Geographic Information (VGI) in Theory and Practice (Vol. 9789400745, pp. 1–396). Springer. https://doi.org/10.1007/978-94-007-4587-2

Hwang, W. and Salvendy, G. (2010) Number of people required for usability evaluation, *Communications of the ACM*, 53, 5, 130–133.

Kemp, S. (2023). *DIGITAL 2023: Global Overview Report*, https://datareportal.com/reports/digital-2023-global-overview-report

Kempf, H. (2021). Experience from large-scale crowdsourcing via weather apps. In *Australasian Journal of Disaster and Trauma Studies*, 25(3), 87–93.

Kox, R., Wentzel, G., Böttcher, L., and Freundl, G. (2021). Build and Measure: Students report weather impacts and collect weather data using self-built weather stations. In *Australasian Journal of Disaster and Trauma Studies,* 25(3), 79–86.

Kung, H. K., Hsieh, C. M., Ho, C. Y., Tsai, Y. C., Chan, H. Y., and Tsai, M. H. (2020). Data-augmented hybrid named entity recognition for disaster management by transfer learning. In *Applied Sciences*, 10(12), 4234.

Lin, H. X., Choong, Y. Y., and Salvendy, G. (1997). A proposed index of usability: A method for comparing the relative usability of different software systems. In *Behaviour & Information Technology, 16*(4–5), 267–277.

Mehta, A. M., Bruns, A., & Newton, J. (2017). Trust, but verify: social media models for disaster management. *Disasters*, 41(3), 549-565.

Meier, F., Fenner, D., Grassmann, T., Otto, M., and Scherer, D. (2017). Crowdsourcing air temperature from citizen weather stations for urban climate research. In *Urban Climate*, 19, 170–191. https://doi.org/10.1016/j.uclim.2017.01.006

Ohtake, K. (2021). Reseach and Development on Technologies for Real-time Analysis of Social Wisdom. In *NICT NEWS 2021*, 3, 8-9.

Ouerhani, N., Maalel, A., and Ben Ghézela, H. (2020). SPeCECA: a smart pervasive chatbot for emergency case assistance based on cloud computing. In *Cluster Computing*, 23, 2471-2482.

Ovando-Leon, G., Veas-Castillo, L., Gil-Costa, V., and Marin, M. (2022). Bot-Based Emergency Software Applications for Natural Disaster Situations. In *Future Internet*, 14(3), 81.

Poblet, M., García-Cuesta, E., & Casanovas, P. (2018). Crowdsourcing roles, methods and tools for data-intensive disaster management. *Information Systems Frontiers*, 20(6), 1363-1379.

Raymond, P. (2016). *Meet Richter: Earthquake Preparation Bot*. https://chatbotslife.com/meet-richter-earthquake-preparation-made-a-little-simpler-d143128a544

Reuter, C., and Kaufhold, M. A. (2018). Fifteen years of social media in emergencies: a retrospective review and future directions for crisis informatics. In *Journal of Contingencies and Crisis Management*, 26(1), 41-57.

Schütte, P., and Kox, T. (2022). Vor die Lage—Jetzt und morgen. Herausforderungen von BOS im Umgang mit neuen Technologien und Digitalisierung. In Fekete, A. (Ed) *Kritische Infrastruktur und Versorgung der Bevölkerung* (pp. 19–22). Springer International Publishing.

Sermet, Y., and Demir, I. (2018). An intelligent system on knowledge generation and communication about flooding. In *Environmental modelling & software*, 108, 51-60.

Sindhuja p, P. N., and Dastidar, S. G. (2009). Impact of the Factors Influencing Website Usability on User Satisfaction. In *Journal of Management Research, 8*(12), 54-66.

Syed, H. A., Schorch, M., and Pipek, V. (2020). Disaster learning aid: A chatbot centric approach for improved organizational disaster resilience. In *Information Systems for Crisis Response and Management Conference; Virginia Tech: Blacksburg, VA, USA* (pp. 448-457).

Steed, R. J., Fuenzalida, A., Bossu, R., Bondár, I., Heinloo, A., Dupont, A., Saul, J., and Strollo, A. (2019). Crowdsourcing triggers rapid, reliable earthquake locations. In *Science Advances*, 5(4), eaau9824. https://doi.org/10.1126/sciadv.aau9824

Stieglitz, S., Hofeditz, L., Brünker, F., Ehnis, C., Mirbabaie, M., and Ross, B. (2022). Design principles for conversational agents to support Emergency Management Agencies. In *International Journal of Information Management*, *63*, 102469.

Tsai, M. H., Chan, H. Y., Chan, Y. L., Shen, H. K., Lin, P. Y., and Hsu, C. W. (2021a). A chatbot system to support mine safety procedures during natural disasters. In *Sustainability*, 13(2), 654.

Tsai, M. H., Yang, C. H., Chen, J. Y., and Kang, S. C. (2021b). Four-stage framework for implementing a chatbot system in disaster emergency operation data management: A flood disaster management case study. In *KSCE Journal of Civil Engineering*, 25(2), 503-515.

Tsai, M. H., Chan, H. Y., and Liu, L. Y. (2020). Conversation-based school building inspection support system. In *Applied Sciences*, 10(11), 3739.

Tsai, M. H., Chen, J. Y., and Kang, S. C. (2019). Ask Diana: A keyword-based chatbot system for water-related disaster management. In *Water*, 11(2), 234.

Venkatesh, V., Morris, M. G., Davis, G. B., and Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. In *MIS Quarterly, 27*(3), 425-478. https://doi.org/10.2307/30036540

Vinnell, L. J., Becker, J. S., Scolobig, A., Johnston, D. M., Marion L. Tan, and McLaren, L. (2021). Citizen science initiatives in high-impact weather and disaster risk reduction. In *Australasian Journal of Disaster and Trauma Studies*, 25(3), 55–60.