Towards a Taxonomy for Conversational Agents in Disaster Management

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ABSTRACT

Conversational agents are a technology that is used today in many different ways, for example as chatbots or voice dialog systems. While they are mostly used for applications in the business sector, research is also focusing on their use in other areas, such as medicine or disaster management. Events in recent years, such as the global Covid pandemic and advances in the field of language learning models, have led to many new approaches. Taxonomies are a good way to provide researchers and practitioners with a good overview of this growing field of research by classifying new and existing approaches. In this paper we present the current results in a methodological approach to develop a taxonomy for the classification of conversational agent approaches in disaster management. We describe the data basis of a structured literature search, the implementation of the method and the current dimensions and characteristics of the emerging taxonomy.

Keywords

conversational agent, chatbot, taxonomy, classification, disaster management

INTRODUCTION

Software applications that use natural language processing to act as an interface between human users and information and communication systems (Dale, 2016) have been gaining in importance for years. These so-called conversational agents (CAs), also known as dialog systems, are already present in the everyday lives of many people, both in the form of voice assistants such as Alexa or Siri, as well as textually in the form of chatbots (Gnewuch et al., 2017). In 2018, there were already more than 300,000 chatbots in Facebook Messenger alone (Johnson, 2018), while the development and use of individual CAs by specialized providers such as Botpress or Voiceflow is becoming increasingly easy. Advances in the field of language learning models have led to the potential of this technology becoming increasingly utilizable (vom Brocke et al., 2018), with the result that there has recently been a veritable race between large IT companies such as Microsoft, Google and Meta to implement new applications in the field of CAs (Weise et al., 2023).

While many approaches of the past focused primarily on application areas in the fields of customer services or entertainment, new approaches are becoming increasingly diversified (Brandtzaeg & Følstad, 2017; Stieglitz et al., 2022). In the field of disaster and crisis management, CAs are also becoming an increasingly important technology that can be used for general information and communication tasks (e.g. Maniou & Veglis 2020), as well as for specific scenarios such as the Covid-19 pandemic (e.g. Rodswang et al. 2020). The constantly growing number of approaches in this field of application makes it increasingly difficult for scientists and practitioners to maintain an overview and distinguish key features.

To get a better overview of a research or application area and to classify existing approaches, taxonomies are a frequently used solution. Taxonomies are artifacts used in various scientific disciplines allow sequential classification of objects based on dimensions (Marradi, 1990). Several taxonomies have already been developed to classify CAs approaches from different perspectives. Janssen et al. (2020) focus on domain-specific chatbot applications, whereas Weber et al. (2021) present a taxonomy for CAs in education. Additional contributions provide conceptualizations of certain aspects of these systems like the taxonomy for social cues in CAs of Feine et al. (2019), as well as the exploration of chatbot relationship archetypes based on the time of interaction of Nißen et al. (2022).

However, to the best of our knowledge, there is no classification of CA approaches in the emerging area of disaster management. To address this research gap, in this paper we propose a taxonomy to classify approaches on conversational agents in disaster management. The results presented here are based on the methodological approach according to Nickerson et al. (2013) for the iterative development of taxonomies. By applying this method the following research question is to be specifically investigated in this research.

RQ: *Which dimensions and characteristics of a taxonomy describe current implementations of conversational agents in disaster management?*

However, as the research is still ongoing, the method has not yet been fully applied. The data basis for this taxonomy is provided by a structured literature analysis according to vom Brocke et al. (2009). For the complete research, we want to expand the database to include applied, non-scientifically documented applications and carry out a robust evaluation. Nevertheless, even in its current state of development, the taxonomy can support scientists in classifying existing and new approaches and offer practitioners possible criteria for selecting suitable solutions for their purposes.

The paper is structured as follows: in the second section, the current state of research on CAs is discussed. The methodological approach and its instantiation are presented in the third section before the taxonomy is described in the fourth section. Limitations and desiderata are discussed in the conclusion.

ON THE STATE OF CONVERSATIONAL AGENTS

Natural language processing as the basis technology for CAs has been a relevant topic in the field of information systems research for many decades. One of the earliest related computer programs was ELIZA, developed at MIT in the 1960s (Weizenbaum, 1966). It simulated psychotherapeutic dialogues by recognizing and responding to simple patterns in user input. Despite its lack of real intelligence, ELIZA impressed with its skillful pattern recognition and is considered an early example of chatbots. Text-based chatbots are a type of CAs alongside voice-based systems such as voice assistants (e.g. Siri, Alexa) (Gnewuch et al., 2017). Another category of CAs are so called embodied agents, which are visualized characters that often use facial expressions and gestures to provide a better user experience (Brave et al., 2005). Recent developments in this space are numerous and diverse, spanning various directions. One of these innovations is conversational dashboard systems, which allow users to interact with complex data visualizations using natural language (Ruoff et al., 2021). Another are conversational co-pilots which Microsoft, for example, is currently including in its product range (Dastin, 2023), as well as Coding Assistants (Ross et al., 2023) which automate tasks, advice, as well as collaborate with users.

An important theoretical approach in research on CAs is the social response theory (Gnewuch et al., 2017; Wambsganss et al., 2021). This states that people interact with computers as they do with other people, unconsciously applying social rules such as politeness, self-disclosure and trust, based on social cues such as conversation, interactivity and social roles. An important principle of this theory is that of reciprocity, which states that people respond to computers socially by attempting to "reciprocate" or "match" the computer's interaction or behavior (Nass & Moon, 2000; Reeves & Nass, 1996).This means that designers of CAs should consciously plan the conversational style of their applications, as the social characteristics of these systems have a significant influence on their use (Chattaraman et al., 2019).

Progress in the field of CAs is currently particularly dynamic. Systems such as OpenAI's Chat GPT are experiencing impressive growth. One million users registered for the service within five days of its launch - only Meta's "Threads" could reach so many users quicker (*Infographic*, 2023). They can also be easily integrated into existing systems such as websites, social media and messaging platforms like Facebook (Johnson, 2018). The latest developments are integrations of these systems into search engines, such as Bing Chat (*The Verge*, n.d.).

Social media has been an important control center for disaster response at least since the Central European flood 2013 (Albris, 2018). There, CAs have the potential to broadcast trustworthy information from civil protection authorities to the public (Stieglitz et al., 2022). They can also help overcome language barriers and provide reliable real-time information (Ahmady & Uchida, 2020). In addition, CAs have the potential to support the coordination of spontaneous helpers during a crisis and reduce the cognitive load on individuals (Gerstmann et al., 2019; M.-H. Tsai et al., 2019). Although research into the use of CAs in disaster management is still in its infancy and there is a lack of established design approaches, new approaches are constantly emerging and current findings indicate that the use of CAs in disaster management provide added value (Stieglitz et al., 2022). The aim of the research presented here is to take a deeper look at the developments to date to enable a classification of existing and new approaches in this rapidly growing field of research.

METHODOLOGICAL APPROACH

Taxonomy Development Following Nickerson et al. (2013)

To build our taxonomy for CAs in disaster management on a sound basis, we use the established methodology of Nickerson et al. (2013). This method prescribes a multi-stage, cyclical procedure with defined ending conditions for deriving dimensions and characteristics for a topic-specific taxonomy. The instantiation of the method in the context of our research, illustrated in Figure 1, is described below.

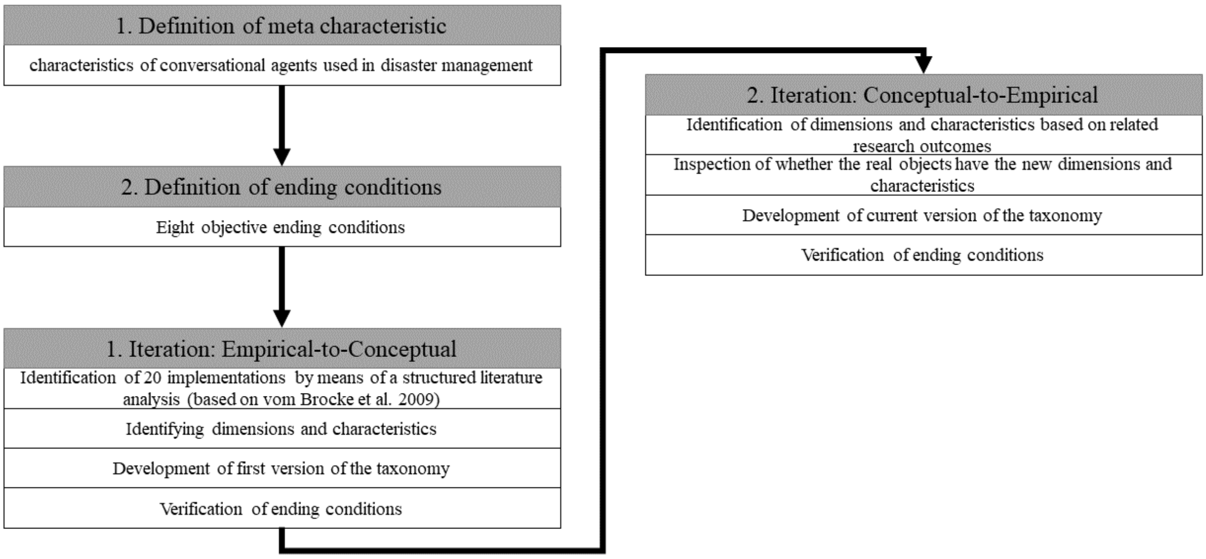

Figure 1. Procedure based on Nickerson et al. (2013)

The first step is the **definition of the meta-characteristic**. The aim here is to select a view of the objects to be examined (conversational agents in disaster management) from which all other characteristics can be derived (Nickerson et al., 2013). When defining the meta-characteristic, it is important to be clear about the objective and purpose of the taxonomy. In our case, the taxonomy is intended to be useful both for practitioners, who can use the taxonomy as a decision-making tool for the selection of suitable solutions, and for scientists from different disciplines who want to classify existing and new approaches and identify research gaps. The focus is on core features and application conditions, rather than specific technical or organizational aspects. The meta-characteristic was formulated in a correspondingly general manner: "characteristics of conversational agents used in disaster management."

The next step is to **define the ending conditions** of the iterative process for deriving new elements for the taxonomy. For this study the objective conditions (OEC) proposed by (Nickerson et al., 2013), which can be seen in Figure 2, are selected.

	Objective Ending Condition
1	All objects or a representative sample of objects have been examined
2	No object was merged with a similar object or split into multiple objects in the last iteration
3	At least one object is classified under every characteristics of every dimension
4	No new dimensions or characteristics were added in the last iteration
5	No dimensions or characteristics were merged or split in the last iteration
6	Every dimension is unique and not repeated (i.e., there is no dimension duplication)
7	Every characteristic is unique within its dimension (i.e., there is no characteristic duplication within a dimension)
8	Each cell (combination of characteristics) is unique and is not repeated (i.e., there is no cell duplication)

Figure 2. Objective ending conditions prescribed by (Nickeson et al., 2013)

In the following step the iterations for the development of characteristics and dimensions begin. These must be logical consequences of the meta-characteristic. A two-stage approach was chosen here, consisting of an initial "empirical-to-conceptual" step and a subsequent "conceptual-to-empirical" iteration. In the **first "empirical-to-conceptual" iteration** the required number of descriptions of CAs were created using a structured literature analysis, as recommended by Nickerson et al. (2013), to build the knowledge base. This is described in detail in the following section. A **second "conceptual-to-empirical" iteration** was then conducted to address dimensions related to important theoretical foundations, such as the Social Response Theory, which still need consideration. These are explored in categorizations of CAs in literature, as seen in the taxonomy presented by Janssen et al. (2020). Their taxonomy on domain-specific chatbots includes dimensions such as 'collaboration goal,' 'chatbot role,' 'relation duration,' and 'social cues' with their characteristics, which we adopt in this iteration (Janssen et al., 2020). These dimensions were used to examine the systems identified in the first cycle and assign them to the respective characteristics.

After the second iteration, the eight objective ending criteria were examined, we found that criterion OEC4 was not yet met, revealing that further iterations are necessary. As this paper is a presentation of research in progress, the procedure ends at this point. We are aware that further iterations are necessary, and an evaluation of the taxonomy will take place in future steps. The methodological instantiation described here forms the basis for the considerations on the preliminary taxonomy in the following main section.

Knowledge Base from Structured Literature Search

The first iteration of the taxonomy creation is based on a knowledge base consisting of a set of descriptions of CAs. Structured processing is recommended to set this up in a way that is comprehensible to third parties. We chose to build our knowledge base using a structured literature analyses following vom Brocke et al. (2009). The method includes a 5-step procedure: 1) definition of review scope, 2) conceptualization of topic, 3) literature search, 4) literature analysis, 5) research agenda (Brocke et al., 2009).

Starting with the **definition of review scope,** vom Brocke et al. propose a procedure based on the taxonomy of Cooper (1988) which was instantiated in Figure 3.

Characteristic	Categories			
focus	research outcome	research method	theories	applications
goal	integration	criticism		central issues
organization	historic	conceptual		methodical
perspective	neutral representation		espousal of position	
audience	specialized scholars	general scholars	practitioners/politicians	general public
coverage	exhaustive	exhaustive and selective	representative	central/pivotal

Figure 3. Instantiation of the Taxonomy for the "definition of review scope" according to Cooper (1988)

Based on this, the focus was placed on applications with the aim of addressing the central issues. The organization should be conceptual, whereby a neutral perspective should be adopted. Practitioners as well as specialized researchers in the fields of disaster management and conversational systems were identified as the target group, who should be offered an exhaustive and selective coverage of the topic.

In the next phase, the **conceptualization of topic**, working definitions of the most important terms were created and an overview of the existing literature in the field of CAs in disaster management was compiled. The findings from this step were used to develop a better understanding and a relevant search string.

As part of the **literature search,** the scientific databases SpringerLink, ISCRAM, ScienceDirect, Wiley and Google Scholar were searched. Publications containing the search string in abstract, title or keywords were to be identified within the search. This is *(chatbot OR "conversational agent" OR "chat bot" OR "dialogue system") AND ("disaster" OR "crisis" OR "emergency")* and was formed from the core terms derived in the previous steps. In the Wiley and ScienceDirect databases, the search described above could be carried out via the website. For the other databases, additional steps had to be taken. The SpringerLink database had to be addressed programmatically using an Application Protocol Interface (API) to perform a full-text search. The title, abstract and keyword searches were then carried out using a Python script. The ISCRAM database did not provide the desired search functionalities either, but since it specializes in information systems in disaster control, a full-text search was also carried out on the site using Google Scholar. Finally, a title search was carried out using the search string in Google Scholar. This database also offered no possibility to search in abstract or keywords.

After the search process, in the **literature analysis,** the titles and abstracts of the results were checked according to previously defined exclusion criteria. These are (1) not in English, (2) not peer-reviewed, (3) no concrete description of a CA artifact and (4) the described artifact has not been implemented at least once. This process resulted in a total of 88 identified publications with 20 descriptions of specific CA implementations, which formed the knowledge base for the taxonomy's development. The entire literature search and the results of the individual analysis can be seen in Figure 4.

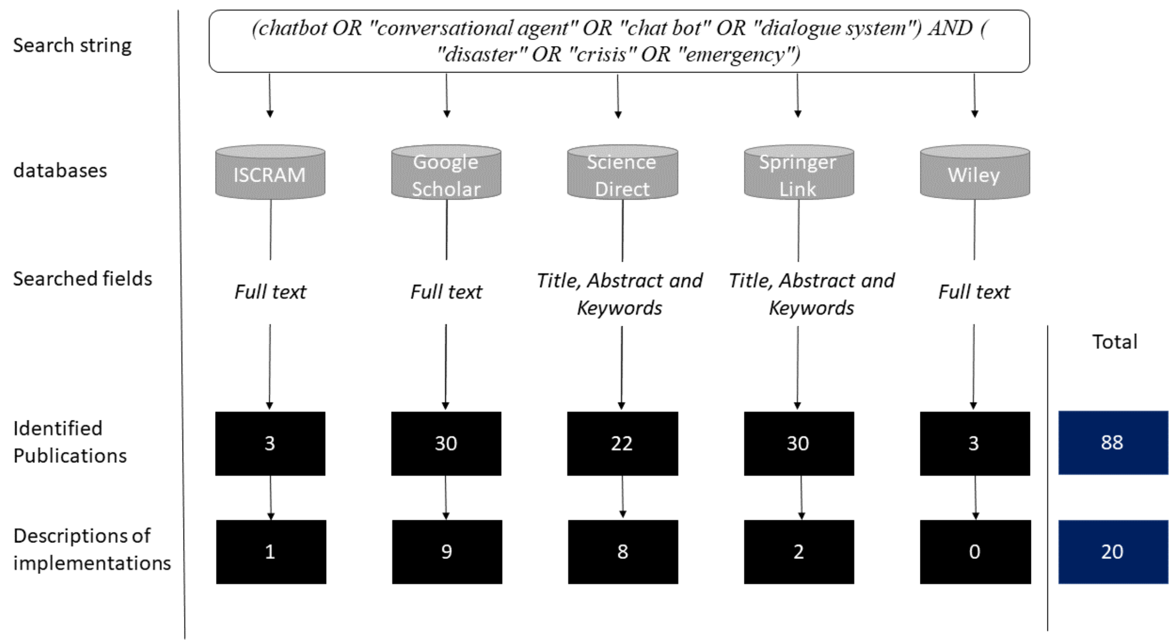

Figure 4. Literature Search Processing and Results

In this paper, the fifth step, formulation of a research agenda, is omitted as the focus on the methodology for taxonomy design renders it redundant.

A TAXONOMY FOR CONVERSATIONAL AGENTS IN DISASTER MANAGEMENT

This section describes the taxonomy in its current state of research. As part of the taxonomy development, 13 dimensions were identified. For reasons of clarity, these are divided into four categories and will be presented here. The developed taxonomy can be seen in Figure 5. Six of the included dimensions are exclusive, these are marked in the figure with an asterisk (*). The numbers in brackets after the characteristics indicate how many of the CA approaches from the knowledge base they apply to. Due to incomplete descriptions of the approaches, not all of them could be classified in every dimension.

Dimension		Characteristics			
Application Background	User*	Hospitals (2)	Disaster Management Authority (5)	Public Bodies (6)	Private Sector (2)
	Target Group*	General Population (12)	Affected (2)	Specific groups of the general population (4)	Disaster Management Officer (2)
	Type of Disaster*	Flood (4)	Pandemic (12)	Unspecific (4)	
Communication Goals and Language Processing	Intended Use	Coordination (6)	Information (13)	Education (1)	Decision Support (3)
	Conversational Goal*	Task-oriented (9)	Chatter (11)		
	Language Comprehension	Rule-based (7)	Natural (15)		
Interaction	Input Interaction	Text-based (16)	Voice-based (3)	Buttons (5)	Multimedia (2)
	Output Interaction	Text-based (16)	Voice-based (4)	Multimedia (6)	Facial Expression(1)
	Integration	Messenger Platform (10)	Native (8)	Smart Home Device (1)	
		Telephone (1)	Augmented Reality Device (1)		
	Human in the Loop	Forwarding to a Hotline (2)	Request to Adapt the Content (1)	No Described Functionality (17)	
Social Aspects	Role Model	Facilitator (9)	Peer (2)	Expert (9)	
	Relationship Length*	Short-term Relationship (12)	Long-term Relationship (8)		
	Social Cues*	Present (9)	Not Present (7)		

Figure 5. Taxonomy for Conversational Agents in Disaster Management

Category: Application Background

This category is intended to summarize all dimensions that deal with the primary actors and the overall situation in which the CA is used.

The **user** dimension describes the people and organizations that operate and administer the system. *Hospitals* are an example of this, but CAs are also used in the *private sector* (Jang & Lee, 2023; Sarbay et al., 2023). In contrast, the system designed for *disaster management authorities* by Tsai et al. attempts to provide a simple interface to retrieve up-to-date information on the current situation (M.-H. Tsai et al., 2019). A final characteristic is users in *public bodies*, such as government agencies or universities (Balderas et al., 2023).

The **target group** dimension describes which user group should be reached by the system. This can be the *general population*, whereas other systems try to address *disaster management officers* (Chan & Tsai, 2019; Nomura et al., 2020). The user group *Specific groups of the general population* can be illustrated by the "Emergency Reporter" system, which was created with the participation of indigenous groups to give them an opportunity to interact with the disaster management authorities (C.-H. Tsai et al., 2023). *Affected people* are also identified as a target group by systems (Syed et al., 2020).

The **disaster type** dimension describes the type of crisis in question, with a distinction being made between various types. A first example is the *flood*, but many CAs have also been identified that deal with *pandemics*, especially the Covid-19 pandemic (Sermet & Demir, 2018; Yoneoka et al., 2020). However, there are also systems that can be used *unspecifically* in several different types of crises. One example of this is DisBot, which uses knowledge accessed via social media to support citizens and first responders in disaster scenarios, improving community resilience and decision-making (Boné et al., 2020).

Category: Communication Goals and Language Processing

Strategic intentions of the system and the planned results of the interaction are relevant factors of CAs.

The **Intended Use** dimension refers to the purpose for which the CA was developed and which specific tasks or functions it should fulfill. The *Information* characteristic emphasizes the role of the CA as a source of information. The agent can for example provide real-time updates on hazardous situations, evacuation instructions and other relevant information to keep the public informed (Sermet & Demir, 2018). Used for *coordination,* a CA can ensure efficient communication and resource allocation during a disaster situation (Konstantoudakis et al., 2023). *Decision support* is another application in which the CA was developed to support decision-makers in disaster management with relevant data and semi-automated processes (Lai et al., 2020). Finally, a CA can be used in the field of *education* to prepare for disaster situations. By providing training materials, the agent helps to raise awareness and prepare for potential disasters (Syed et al., 2020).

The dimension of the **Conversational Goal** refers to the overarching goals or intentions that are pursued during the interaction with the user. A distinction is made here between CAs that act in a *task-oriented* manner and collaborate with the user (Tsai et al., 2023), and those that are *chatter,* as is the case with a simple question-answer scheme, for example (Goh et al., 2006; Konstantoudakis et al., 2023).

The **Language Comprehension** dimension of CAs describes how they process the user's utterances. *Natural language understanding* enables a CA to interpret the natural language of the user. This method enables versatile and human-like communication, as the agent can react to different expressions and formulations (Syed et al., 2020). In contrast, *rule-based language understanding* is based on predefined rules or scripts that the CAt uses to understand and respond to user utterances (C.-H. Tsai et al., 2023).

Category: Interaction

Interaction with a CA can be designed in very different ways. Dimensions in this category describe various aspects of the exchange of information between CAs and users.

The **Input Interaction** dimension describes how users can make inputs. Common input interactions take place via *text* or *voice* (Chan & Tsai, 2019; Nomura et al., 2020). An example of interaction with *buttons* is the chatbot presented by Maniou and Veglis for news dissemination in crises, which allows navigation using various button menus (Maniou & Veglis, 2020). Other systems can process *multimedia* input, for example a chatbot to collect information from volunteers and citizens, with the submission of images being one use case (Konstantoudakis et al., 2023).

The **Output Interaction** dimension specifies how output is transmitted to the user. Three types represent the output of *text*, *voice* or *multimedia* (Lai et al., 2020; Rodsawang et al., 2020; Yoneoka et al., 2020). A final type is the output of *facial expressions,* such as the intelligent embodied CA called AINI as a front-end interface for a crisis communication network portal (Goh et al., 2006).

The **Integration** dimension plays a crucial role in the embedding and deployment of CA systems, as it considers the different platforms and environments. These systems can be integrated in a variety of ways to ensure an optimal user experience. Examples of integration possibilities include implementation in *messenger platforms* to enable seamless interaction via messaging services (Konstantoudakis et al., 2023). Alternatively, a CA can be natively integrated into specific applications or operating systems to ensure deeper integration. Use via phone calls enables broader accessibility, while integration into smart home systems enables interaction in the context of the home environment (Lai et al., 2020; Sermet & Demir, 2018). In addition, integration into augmented reality platforms offers an immersive and enhanced level of interaction for users (Sermet & Demir, 2018).

The **Human in the Loop** dimension describes the possibility and mechanisms for human operators to intervene in the process. The *forwarding to a hotline* represents an identified mechanism that can be found in a voice Bot, for example. This partially automated the medical history processes for a hospital during the Covid-19 pandemic. As soon as it detected symptoms that indicated a disease, it forwarded the patient to a human operator (Lai et al., 2020). The *content customization prompt* was identified in an employee training application. The flow of conversation focuses on material created by a supervisor and can be interrupted if it is unclear. In such cases, a message is automatically sent to the supervisor, who is given the opportunity to revise the learning material (Syed et al., 2020). However, most approaches provide *no specific functionality*.

Category: Social Aspects

As described above, social response theory plays an important role in the design of CA. Dimensions of this category describe which general features CAs support in order to imitate human-like behavior.

The dimension **Role Model** classifies the existing systems based on the roles they take on towards the user. A CA in the role of a *facilitator* acts as a link between different parties to transmit information or facilitate communication (C.-H. Tsai et al., 2023). In the role of a *peer,* the CA interacts with the user on an equal footing without assuming a superior position. The interaction takes place in a cooperative and supportive manner, with the agent acting as a partner (Jiang et al., 2022). A conversational agent in the role of an *expert* imparts specialized knowledge and provides in-depth information on a specific topic (Goh et al., 2006)

The **Relationship Length** dimension concerns the duration and development of the interaction between the user and the CA, with different systems taking different approaches to the design of this relationship. An example of *short-term relationships* is a chatbot for medical history taking in a hospital presented by (Rodsawang et al., 2020). In contrast, Jiang et al. provide an example of a conversational agent that establishes a *long-term relationship.* They describe the use of the REPLIKA service during the Covid-19 pandemic which is intended to provide users with a supportive and empathetic conversation partner (Jiang et al., 2022).

Another dimension is the CA's ability to recognize, interpret and respond appropriately to **Social Cues**. These include facial expressions, gestures and tone of voice, which play a key role in creating an authentic and human-like interaction. An example of *present* social signals in this context is the output of facial expressions into a chatbot that can respond to user emotions (Goh et al., 2006). In contrast, these social signals are *not present* in other CAs (M.-H. Tsai et al., 2019).

CONCLUSION

In this paper, the research in progress and first results towards a taxonomy for conversational agents in disaster management was presented. The taxonomy was developed on the basis of an established methodology using an extensive, systematically compiled knowledge base. After two methodological iterations, a taxonomy consisting of 13 dimensions and 42 characteristics was created. The derived dimensions address both core features of the CAs and organizational aspects such as purpose and user groups, as well as domain-specific characteristics. This general orientation makes it possible to classify all domain-specific approaches and serve different purposes. The taxonomy can be used to help practitioners differentiate between suitable solutions for their purposes and to get an overview of what features they can or cannot expect from current IT systems. The examples given in the explanation of the dimensions can also provide inspiration for the use of CAs in disaster management. On the other hand, the taxonomy can also support scientists in the classification of research artifacts in the form of software demonstrators and application concepts. In addition, the taxonomy also represents an analysis of the current state of the art and shows which aspects of CAs for disaster management have so far been addressed to a greater or lesser extent by research. Although the analysis of the state of the art is not the focus of the paper, some trends can already be identified based on the frequency of the dimensions addressed. Most of the conversational agents examined serve to inform users and are generally designed for pandemics offering text-based interaction. The target group is usually the general population and subgroups of this population, with disaster managers being a secondary target. An interesting observation is that, in contrast to applications in the commercial sector only a few exceptions rely on human-in-the-loop functionalities. Even though research has shown that implementing human-in-the-loop functionalities in CAs can benefit users, task workers, and system performance (Reitmeier et al., 2020).

Since the research is still in progress not all steps in the underlying methodological approach of Nickerson et al (2013) have been executed yet. An important future step is the evaluation of the results. Nickerson et al. suggest having potential users evaluate the usefulness of the artifact. In the present scenario, disaster managers should be consulted to determine the extent to which the presented taxonomy aids them in choosing the appropriate CA for their specific use case. Similarly, the subjective termination criteria could not be considered and not all objective ending conditions could be met after the last iteration (Nickerson et al., 2013), so that further iterations will be necessary in future steps. The underlying knowledge base could be expanded for this purpose. With the selected search string, only CAs that were built specifically for disaster management applications can be identified. An extension of the search string could include other, domain-unspecific applications based on their potential use in disaster situations. The inclusion of solutions in practical use that have not yet been scientifically documented is also conceivable. In these ways, we want to further develop the taxonomy, which already offers decision-making and orientation aids for practitioners and scientists in its current state, into a valid and well-founded tool in the future.

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REFERENCES

Ahmady, S. E., & Uchida, O. (2020). Telegram-based chatbot application for foreign people in Japan to share disaster-related information in real-time. *2020 5th International Conference on Computer and Communication Systems (ICCCS)*, 177-181. https://ieeexplore.ieee.org/abstract/document/9118510/

Albris, K. (2018). The switchboard mechanism: How social media connected citizens during the 2013 floods in Dresden. *Journal of Contingencies and Crisis Management*, *26*(3), 350-357. https://doi.org/10.1111/1468-5973.12201

Balderas, A., García-Mena, R. F., Huerta, M., Mora, N., & Dodero, J. M. (2023). Chatbot for communicating with university students in emergency situation. *Heliyon*, *9*(9). https://www.cell.com/heliyon/pdf/S2405-8440(23)06725-7.pdf

Bing is now the default search for ChatGPT - The Verge. (n.d.). Retrieved January 8, 2024, from https://www.theverge.com/2023/5/23/23733189/chatgpt-bing-microsoft-default-search-openai-build

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

Brandtzaeg, P. B., & Følstad, A. (2017). Why people use chatbots. In I. Kompatsiaris, J. Cave, A. Satsiou, G. Carle, A. Passani, E. Kontopoulos, S. Diplaris, & D. McMillan (Eds.), *Internet Science* (Vol. 10673, pp. 377-392). Springer International Publishing. https://doi.org/10.1007/978-3-319-70284-1_30

Brave, S., Nass, C., & Hutchinson, K. (2005). Computers that care: investigating the effects of orientation of emotion exhibited by an embodied computer agent. *International journal of human-computer studies*, *62*(2), 161-178.

Chan, H.-Y., & Tsai, M.-H. (2019). Question-answering dialog system for emergency operations. *International Journal of Disaster Risk Reduction*, *41*, 101313.

Chattaraman, V., Kwon, W.-S., Gilbert, J. E., & Ross, K. (2019). Should AI-Based, conversational digital assistants employ social- or task-oriented interaction style? A task-competence and reciprocity perspective for older adults. *Computers in Human Behavior*, *90*, 315-330. https://doi.org/10.1016/j.chb.2018.08.048

Cooper, H. M. (1988). Organizing knowledge syntheses: A taxonomy of literature reviews. *Knowledge in Society*, *1*(1), 104. https://doi.org/10.1007/BF03177550

Dastin, Jeffrey: *Microsoft unveils AI office Copilot in fast-moving race with Google* In: *Reuters*, 16.03.2023. Retrieved 14. 02.2024.

Feine, J., Gnewuch, U., Morana, S., & Maedche, A. (2019). A taxonomy of social cues for conversational agents. *International Journal of Human-Computer Studies*, *132*, 138-161.

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*.

Gnewuch, U., Morana, S., & Maedche, A. (2017). *Towards Designing Cooperative and Social Conversational Agents for Customer Service*. Proceedings of the Thirty Eight International Conference of Information Systems (ICIS 2017).

Goh, O. S., Fung, C. C., Wong, K. W., & Depickere, A. (2006). An embodied conversational agent for intelligent web interaction on pandemic crisis communication. *2006 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology Workshops*, 397-400. https://ieeexplore.ieee.org/abstract/document/4053278/

Infographic: Threads Shoots Past One Million User Mark at Lightning Speed. (2023). Statista Daily Data. https://www.statista.com/chart/29174/time-to-one-million-users

Jang, H., & Lee, S. (2023). Introducing the Co-oriented Scansis (CoS) model: A case of chatbot, Lee-Luda. *Public Relations Review*, *49*(4), 102360. https://doi.org/10.1016/j.pubrev.2023.102360

Janssen, A., Passlick, J., Rodríguez Cardona, D., & Breitner, M. H. (2020). Virtual Assistance in Any Context. *Business & Information Systems Engineering*, *62*(3), 211-225. https://doi.org/10.1007/s12599-020-00644-1

Jiang, Q., Zhang, Y., & Pian, W. (2022). Chatbot as an emergency exist: Mediated empathy for resilience via human-AI interaction during the COVID-19 pandemic. *Information Processing & Management*, *59*(6), 103074.

Johnson, K. (2018). Facebook Messenger passes 300,000 bots. *VentureBeat*. https://venturebeat.com/ai/facebook-messenger-passes-300000-bots/

Konstantoudakis, K., Christaki, K., Sainidis, D., Babic, I., Kogias, D. G., Inglese, G., Bruno, L., Giunta, G., Patrikakis, C. Z., Balet, O., Rossi, C., Dimou, A., & Daras, P. (2023). Common Operational Picture and Interconnected Tools for Disaster Response: The FASTER Toolkit. In H. J. Scholl, E. E. Holdeman, & F. K. Boersma (Eds.), *Disaster Management and Information Technology: Professional Response and Recovery Management in the Age of Disasters* (pp. 83-110). Springer International Publishing. https://doi.org/10.1007/978-3-031-20939-0_6

Lai, L., Wittbold, K. A., Dadabhoy, F. Z., Sato, R., Landman, A. B., Schwamm, L. H., He, S., Patel, R., Wei, N., Zuccotti, G., Lennes, I. T., Medina, D., Sequist, T. D., Bomba, G., Keschner, Y. G., & Zhang, H. (Mark). (2020). Digital triage: Novel strategies for population health management in response to the COVID-19 pandemic. *Healthcare*, *8*(4), 100493. https://doi.org/10.1016/j.hjdsi.2020.100493

Maniou, T. A., & Veglis, A. (2020). Employing a chatbot for news dissemination during crisis: Design, implementation and evaluation. *Future Internet*, *12*(7), 109.

Marradi, A. (1990). Classification, typology, taxonomy. *Quality and Quantity*, *24*(2). https://doi.org/10.1007/BF00209548

Nass, C., & Moon, Y. (2000). Machines and Mindlessness: Social Responses to Computers. *Journal of Social Issues*, *56*(1), 81-103. https://doi.org/10.1111/0022-4537.00153

Nickerson, R. C., Varshney, U., & Muntermann, J. (2013). A method for taxonomy development and its application in information systems. *European Journal of Information Systems*, *22*(3), 336-359. https://doi.org/10.1057/ejis.2012.26

Nißen, M., Selimi, D., Janssen, A., Cardona, D. R., Breitner, M. H., Kowatsch, T., & von Wangenheim, F. (2022). See you soon again, chatbot? A design taxonomy to characterize user-chatbot relationships with different time horizons. *Computers in Human Behavior*, *127*, 107043.

Nomura, S., Yoneoka, D., Shi, S., Tanoue, Y., Kawashima, T., Eguchi, A., Matsuura, K., Makiyama, K., Ejima, K., Taniguchi, T., Sakamoto, H., Kunishima, H., Gilmour, S., Nishiura, H., & Miyata, H. (2020). An assessment of self-reported COVID-19 related symptoms of 227,898 users of a social networking service in Japan: Has the regional risk changed after the declaration of the state of emergency? *The Lancet Regional Health - Western Pacific*, *1*, 100011. https://doi.org/10.1016/j.lanwpc.2020.100011

Reeves, B., & Nass, C. I. (1996). *The media equation: How people treat computers, television, and new media like real people and places*. Center for the Study of Language and Information, Cambridge University Press.

Reitmaier, T., Robinson, S., Pearson, J., Kalarikalayil Raju, D., Jones, M. (2020). An Honest Conversation: Transparently Combining Machine and Human Speech Assistance in Public Spaces. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (pp. 1-12).

Rodsawang, C., Thongkliang, P., Intawong, T., Sonong, A., Thitiwatthana, Y., & Chottanapund, S. (2020). Designing a competent chatbot to counter the COVID-19 pandemic and empower risk communication in an emergency response system. *OSIR Journal*, *13*(2). http://www.osirjournal.net/index.php/osir/article/view/193

Ruoff, M., Gnewuch, U., Maedche, A., & Scheibehenne, B. (2023). Designing conversational dashboards for effective use in crisis response. *Journal of the Association for Information Systems*, *24*(6), 1500-1526.

Steven I. Ross, Fernando Martinez, Stephanie Houde, Michael Muller, and Justin D. Weisz. (2023). The Programmer's Assistant: Conversational Interaction with a Large Language Model for Software Development. In 28th International Conference on Intelligent User Interfaces (IUI '23), March 27–31, 2023, Sydney, NSW, Australia. ACM, New York, NY, USA, 24 pages. https://doi.org/10.1145/3581641.3584037

Sarbay, İ., Berikol, G. B., & Özturan, İ. U. (2023). Performance of emergency triage prediction of an open access natural language processing based chatbot application (ChatGPT): A preliminary, scenario-based cross-sectional study. *Turkish Journal of Emergency Medicine*, *23*(3), 156.

Sermet, Y., & Demir, I. (2018). An intelligent system on knowledge generation and communication about flooding. *Environmental Modeling & Software*, *108*, 51-60. https://doi.org/10.1016/j.envsoft.2018.06.003

Stieglitz, S., Hofeditz, L., Brünker, F., Ehnis, C., Mirbabaie, M., & Ross, B. (2022). Design principles for conversational agents to support Emergency Management Agencies. *International Journal of Information Management*, *63*, 102469. https://doi.org/10.1016/j.ijinfomgt.2021.102469

Syed, H. A., Schorch, M., & Pipek, V. (2020). Disaster learning aid: A chatbot centric approach for improved organizational disaster resilience. *Information Systems for Crisis Response and Management Conference; Virginia Tech: Blacksburg, VA, USA*, 448-457. https://kontikat.de/wpcontent/uploads/2021/07/Syed_Schorch_Pipek_2020_DisasterAid_ISCRAM2020.pdf

Tsai, C.-H., Rayi, P., Kadire, S., Wang, Y.-F., Krafka, S., Zendejas, E., & Chen, Y.-C. (2023). Co-Design Disaster Management Chatbot with Indigenous Communities. *20th International Conference on Information Systems for Crisis Response and Management (ISCRAM)*, *2023*, 1. https://digitalcommons.unomaha.edu/isqafacpub/126/

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

vom Brocke, J., Simons, A., Niehaves, B., Riemer, K., Plattfaut, R., & Cleven, A. (2009). Reconstructing the Giant: On the Importance of Rigour in Documenting the Literature Search Process. *ECIS 2009 Proceedings*. 161. https://aisel.aisnet.org/ecis2009/161

vom Brocke, J., Maaß, W., Buxmann, P., Maedche, A., Leimeister, J. M., & Pecht, G. (2018). Future Work and Enterprise Systems. *Business & Information Systems Engineering*, *60*(4), 357-366. https://doi.org/10.1007/s12599-018-0544-2

Wambsganss, T., Höch, A., Zierau, N., & Söllne, M. (2021). Ethical Design of Conversational Agents: Towards Principles for a Value-Sensitive Design. *Wirtschaftsinformatik 2021 Proceedings.* https://aisel.aisnet.org/wi2021/ZMethods/Track01/2

Weber, F., Wambsganss, T., Rüttimann, D., & Söllner, M. (2021). Pedagogical agents for interactive learning: A taxonomy of conversational agents in education. In *Forty-Second International Conference on Information Systems. Austin, Texas* (pp. 1-17).

Weise, K., Metz, C., Grant, N., & Isaac, M. (2023). Inside the A.I. Arms Race That Changed Silicon Valley Forever. *The New York Times.* https://www.nytimes.com/2023/12/05/technology/ai-chatgpt-google-meta.html

Weizenbaum, J. (1966). ELIZA-a computer program for the study of natural language communication between man and machine. *Communications of the ACM*, *9*(1), 36-45. https://doi.org/10.1145/365153.365168

Yoneoka, D., Tanoue, Y., Kawashima, T., Nomura, S., Shi, S., Eguchi, A., Ejima, K., Taniguchi, T., Sakamoto, H., Kunishima, H., Gilmour, S., Nishiura, H., & Miyata, H. (2020). Large-scale epidemiological monitoring of the COVID-19 epidemic in Tokyo. *The Lancet Regional Health - Western Pacific*, *3*, 100016. https://doi.org/10.1016/j.lanwpc.2020.100016