FROM PRACTICE TO SCIENCE: SOCIAL REACTIONS CAUSED BY CONVERSATIONAL AGENTS — A LITERATURE REVIEW FOR RESEARCHERS AND PRACTITIONERS

Sophie Hundertmark[1], Hans-Georg Fill[2] and Edy Portmann[2]
[1]Lucerne University of Applied Sciences and Arts, 6343 Rotkreuz, Switzerland
[2]University of Fribourg 1700 Fribourg, Switzerland

ABSTRACT

The number of publications focussing on the design of Conversational Agents (CA) has been continuously growing. However, from a research perspective, a review of the existing publications that visualizes both design elements and effects on user behavior is still missing but needed to reach an overall understanding of the connections and dependencies of researched design elements. From a company's perspective, practitioners are forced to first decide on certain design elements and then to optimize these according to their goals, due of the actual state of research. To close this gap, we conducted a systematic literature review and developed a conceptual model that links different design cues with social signals and social reactions. On the one hand our model helps researches to get a better understanding of the influence of several design cues of CAs. On the other hand, our model helps practitioners to design conversational agents according to their companies' goals.

KEYWORDS

Chatbots, Conversational Agents, Social Cues, Systematic Literature Review, Conversational AI

1. INTRODUCTION

Recently, influenced by the technological and scientific advances in the fields of artificial intelligence (AI) and by the growing acceptance of non-human communication partners, the number of companies using chatbots or conversational agents (CAs) to automate their customer touchpoints has grown (Maedche, 2019). In general, AI-based CAs have become a dominant service interface between providers and users (McLean, 2019). These CAs are designed with the intention of supporting users in their everyday lives as intelligent personal assistants (Di Prospero, 2017). Chatbots simulate human communication and can better take on human characteristics compared to other software-based programs (Dale, 2016) (Hilderbrand, 2021). To improve this type of communication technology, companies invest a large amount of effort in the technical development of CAs (Maedche, 2019). In parallel, an increasing number of scientists have focussed on the human perception of different chatbot design elements, also known as social cues and user interaction outcomes (Zierau, N. 2020). In the research fields of information systems (ISs) and human–computer interaction (HCI), the number of publications focussing on the design of CAs has been continuously growing. However, to our knowledge, there is no holistic scientific review or framework that considers chatbot design cues and user perceptions or behaviour outcomes and the relationship among them. From a research perspective, a review of the existing experiments and publications that visualises both design elements and effects on user behaviour and even uncovers the possible contradictions is still missing but needed to reach an overall understanding of the connections and dependencies of researched design elements. From a company's perspective, it is recommended to first define the goals of the chatbot before implementing specific design elements (Hilderbrand, 2021). However, because of the actual state of research, practitioners are forced to first decide on certain design elements and test them in daily businesses and then to optimise these according to their goals. We want to close the research gap and at the same time facilitate the work of practitioners. Therefore, we aim to answer the following research question:

How must conversational agents be designed to trigger certain user reactions and thus achieve the goals of the companies using conversational agents?

We start with information on the conceptual background of conversational agents and social reactions. Thereafter, a systematic literature review (SLR) informed by the work of Webster (2002) and vom Brocke et al. (2015) is conducted, and a taxonomy is developed, applied, and evaluated following Nickerson et al. (2013). Finally, based on the taxonomy we develop a model to show the dependencies between cues of CA, signals on the user's side and reactions on the user's side triggered by the CA.

2. CONCEPTUAL BACKGROUND

2.1 Chatbots and Conversational Agents

Chatbots or CAs are software-based systems that use natural language to simulate a human conversation (Bittner E, 2019). Using these chatbots, users can exchange information (Diederich S, 2019) or access data and services just by using natural language (Følstad A, 2019). Although the naming of these software-based systems is under constant discussion (e.g. CA, chatbot, chatterbot or digital assistant), the main purpose remains the same, that is, to have a non-human system chatting with a human to achieve some purpose (e.g. retrieval of information, use of a service) (Dale, 2016). The first chatbot, called ELIZA, was developed in 1966 by Joseph Weizenbaum as a text-based computer program that 'makes natural language conversation with a computer possible' (Weizenbaum, 1966). In the 1980s, text-based chatbots were extended by voice-based dialogue systems and embodied CAs (McTear, 2016).

2.2 Conversational Agents as Non-Human Social Actors

CAs using natural language can express human-like behaviour, which makes conversations feel like a chat with a real human (Gnewuch U. M., 2017). Nass et al. (1994) developed a paradigm called 'Computers Are Social Actors' (CASA) (Nass, 1994). According to this paradigm, users ignore the fact that the CA cannot have any human features during a conversation with a CA (Nass C. M., 2020). Rather, they direct their attention to the social cues applied by the chatbot to assign a social entity to it. This causes the users to attribute familiar stereotypes to chatbots and automatically apply social rules, expectations and scripts known from inter-personal communication when communicating with CAs (Nass C. M., 2020). Using social cues, chatbots can trigger responses from humans, regardless of how rudimentary those cues are (Moon, 2000).

2.3 Social Cues, Social Signals, and Social Reactions

This work is based on a construct of social cues, social signals, and social reactions according to Feine J. et al. (2019). In their research, they argue that a signal evolves from cues when they are created to have a communicative meaning, or the receiver attributes an informative meaning to them. Therefore, they defined a cue of a CA as any design feature of a chatbot salient to the user that presents a source of information (e.g. nodding) (Feine, 2019). This means that cues are antecedents of signals and comprise all the perceptible design features of a CA. Consequently, cues can evolve into a social signal through the attribution of socialness towards a CA (Smith, 2003). This attribution of a social signal is the result of the user's conscious or sub-conscious interpretation of the cues, which finally triggers a social reaction from the user (Nass C. M., 2020).

3. EXISTING RESEARCH

Analysing existing research reviews and classifications in the field of CAs, it seems that most of them focus on design cues to analyse their outcomes regarding users' feelings and behaviour. For instance, Zierau (2020) conducted an SLR aimed at developing a taxonomy that classifies CA characteristics into three major categories: functional, mechanical and human cues. Their work provides deeper insights into service designs with CAs and to support them in systematising and synthesising research on the effects of specific CA characteristics from a user experience perspective (Zierau, 2020). However, they did not distinguish between social signals and social cues. Feine et al. (2019) developed a taxonomy on social cues while structuring cues in four segments: verbal, visual, auditory and invisible. However, although their taxonomy is very detailed and considers many different social cues, there are no explanations for the consequences when applying certain design elements. Rapp et al. (2021) discussed the main factors influencing the interaction between humans and chatbots. However, they did not develop any framework or visualisation for their findings. Janssen et al. (2020) introduced a taxonomy of design elements for a domain-specific chatbot structure to differentiate and categorise domain-specific chatbots according to archetypal qualities that guide practitioners when making design-related decisions. Although they considered a huge number of design elements, they did not mention any dependencies between design elements and user behaviour.

In summary, to our knowledge, no review or taxonomy development established over the last few years has placed user behaviour first or analysed how it can be influenced using different CA design elements or social cues.

4. METHODOLOGY

A combination of different research methods was chosen to answer the research question. The work begins with a systematic literature review (SLR) according to Webster (2002) and vom Brocke et al. (2015). Based on the SLR, which is shown in Table 1, three taxonomies are then developed, using the methods based on Nickerson et al. (2013).

Table 1. Overview of the Systematic Literature Review (SLR)

Step	Research Approach	Outcome
1st Step	Keyword Research: Libraries: - IEEE Library - AIS Library - ACM Portal - Science Direct - Emerald	1893 papers in total: - ACM: 697 - AIS: 140 - Emerald: 12 - IEEE: 796 - Science Direct: 248
2nd Step	Results screening: Exclusion criterions are: - Research does not include an experiment neither and procedure of A-B testing - Research does not consider social cues and their effect on user`s reactions - Research that does not focus on text-based chatbots - Research that is not written in English language	49 papers in total: - ACM: 3 - AIS: 12 - Emerald: 1 - IEEE: 13 - Science Direct: 2
3rd Step	Additional search methods: - Backward search - Forward search - Snowballing approach	69 papers in total: - ACM: 4 - AIS: 21 - Emerald 1 - IEEE 20 - Science Direct 2

4.1 Phase 1: Literature Review

To find relevant literature as a basis for the analysis of the dependencies between social cues, social signals and social reactions, an SLR was conducted between March and May 2021. In their methodology, vom Brocke et al. (2015) suggest a definition of the scope to clarify and determine the basic features of a literature search before the actual work is conducted. Therefore, a sequential search process has been chosen. This means that the whole search process followed pre-defined steps. To reach a high level of transparency in this literature review, the main methodical search steps are described as follows.

Step 1 - Keyword search: Keyword search was performed on the relevant libraries for IS and HCI research: IEEE Library, AIS Library, ACM Portal, Science Direct and Emerald. To ensure that the right keywords and suitable libraries were used, knowledge exchange with other researchers from the field of chatbots and IS research was performed and their input was directly integrated. Finally, the focus was placed on the keywords 'conversational agent', 'chatbot' and 'chat bot'. All variations of the keywords (singular or plural, hyphenated or not hyphenated) used in the title or abstract were considered. Additionally, the search process focussed only on papers published in the last 10 years (2011 to May 2021).

Step 2 - Paper selection: All search results were screened according to pre-defined exclusion criteria. These exclusion criteria were as follows: the study does not include an experiment or a procedure for A-B testing, the study does not consider social cues and their effect on users' reactions, the study does not focus on text-based chatbots or the study is not written in English. Additionally, duplicates were removed. To find the dependencies among cues, signals and reactions, it is necessary to explore the causal connections between the three. However, not many methods suggest causality as conclusively as experiments do (Webster M. S., 2014). Experimental methods involve a systematic manipulation of independent variables while measuring the target behaviour to determine whether a relationship exists between the variables manipulated and behaviour (Sturmey, 2020). After this second step, a total of 49 papers were included in the literature research.

Step 3 - Additional research: With the papers selected from the previous step, backward and forward search were performed, and a snowball search approach was applied. Since most of the papers that remained after the previous step were published in the last one or two years, there was only a very small amount of literature that was added by the forward search. In sum, after the third step, 20 more research items were added.

Step 4 - Paper analysis: A total of 69 relevant papers were analysed in an iterative process. The main goal of this analysis was to obtain a list of master codes and master code descriptions. The relevant master codes focussed on the attributes of social cues, social signals and social reactions.

4.2 Phase 2: Taxonomy Development

In the fields of IS and HCI, the taxonomy development according to Nickerson et al. (2013) is widely used, therefore it was used as a basis for our taxonomy too. Nickerson et al. (2013) invented a step-by-step method for developing taxonomies while ensuring the completeness of the identified dimensions and characteristics of an object.

The first step is to focus on the taxonomy of social reactions, starting with defining the meta-characteristic as a basis for the classification of social reactions (Nickerson, 2013). It was decided to use any social reaction influenced by a CA as meta-characteristic. Next, in line with Nickerson et al. (2013), subjective and objective ending conditions that determine the termination of the taxonomy development process were defined:

1. At least one service cue is classified under every characteristic of every dimension.
2. No new dimension or characteristic has been added in the last iteration.
3. Every dimension and every characteristic in its dimension is unique and is not repeated.
4. Every known service cue is classified in the taxonomy.

In the iterative process of empirical-to-conceptual and conceptual-to-empirical approaches, a taxonomy of social reactions was developed. Second and third, two taxonomies for social signals and social cues were developed and social signals respectively cues were defined as meta-characteristics. Then, the same process as for social reactions was applied, and the same ending conditions were defined. Since it is possible to refer to the same paper analysis, development was restarted with the empirical-to-conceptual approach, followed by a combination of iterations of empirical-to-conceptual and conceptual-to-empirical approaches. An overview of all the papers considered and the taxonomies can be found in the appendix[1].

[1]https://drive.google.com/file/d/1dxzgsj-N0EodNlpbfHBVuxNBskwzAmO8/view?usp=sharing

4.3 Phase 3: Taxonomy Evaluation

After all the ending conditions were met, the iterative process of taxonomy development was complete (Nickerson, 2013). Over several iterations, three taxonomies were developed for social reactions, social signals, and social cues. According to Nickerson et al., (2013) to ensure that the new taxonomy is of a high quality, it should be assessed against the following five criteria: conciseness, robustness, comprehensibility, extendibility, and explanatory power. This study follows the procedure of Zierau (2020), who conducted semi-structured interviews with experts. Most of our experts were researchers from the relevant research field. Additionally, three practitioners were asked who are familiar with chatbots for more than three years. The following are the main points that were discussed during the interviews:

- Conciseness generally refers to the number of dimensions, which should cover the phenomenon sufficiently and at the same time should not overwhelm the reader (Zierau, 2020).
- Robustness means that, based on the dimensions and characteristics, it can be differentiated between objects of interest (Zierau, 2020).
- Comprehensiveness describes the ability of a taxonomy to classify all the objects of a phenomenon of interest (Zierau, 2020).
- Extendibility refers to the ability of a taxonomy to include new dimensions and characteristics (Zierau, 2020).
- Explanatory power refers to the ability of a taxonomy to highlight the inter-relationships between different elements and characteristics transparently and, thus, to uncover previously unknown aspects of a phenomenon (Zierau, 2020).

All in all, the expert interviews were highly positive, and most criteria were almost met. Those that were not met were adapted according to the experts' feedback.

4.4 Phase 4: Taxonomy Application

In the last step, all taxonomies were applied to analyse the selected literature, starting with analysing the dependencies between social reactions and social signals, followed by the analysis of social signals and their influence on social cues. The goal of this phase was to develop guidelines for practitioners and researchers on which social cues and signals must be created to trigger the desired social reactions with CAs. In the end, these guidelines will be visualised in a framework showing all the dependencies between the different factors. The results of this last phase can be found in the online appendix[1].

5. UNDERSTANDING THE TRIGGERS FOR SOCIAL REACTIONS

5.1 Combining the Taxonomies

During the taxonomy development, five independent categories of social reactions were found: satisfaction, trust, behaviour, sales and brand (connectivity)-related. For social signals, only four independent categories were found: utility, doubt, emotion and relationship-related. For social cues we defined the categories quality-related cues, language-oriented cues, cues influencing message intensity and cues explaining the chatbot itself, human-like cues, user-centred cues, cues dealing with failure and cues influencing the bot's character. Answering the research question, the dependencies between social reactions and social signals were first analyzed. Subsequently, the dependencies between social signals and social cues were evaluated. The previously defined taxonomies served as the basis for the analysis of the dependencies. In a third step, the dependencies between reactions, signals and cues were combined.

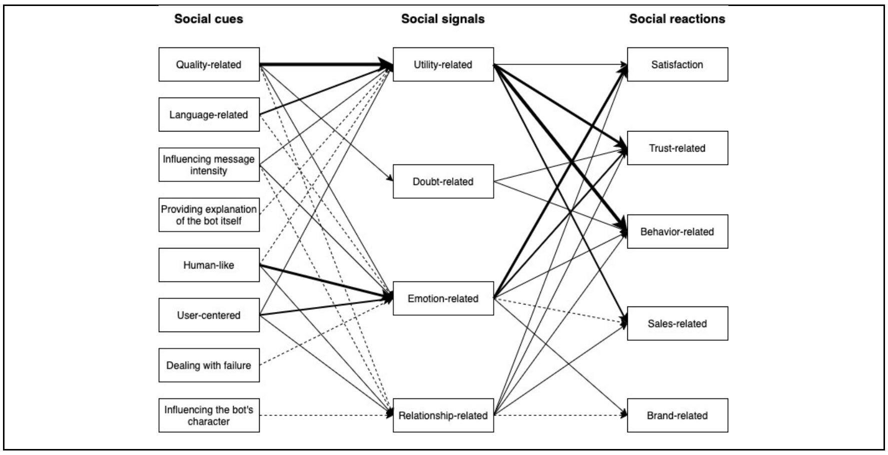

Figure 1. Conceptual model for cues, signals and reactions

Figure 1 shows the conceptual model that links social reactions, social signals and social cues. We see that the reaction satisfaction is mainly influenced by emotion-related signals. These are triggered mainly by human-like and user-centred cues. Trust-related and behaviour-related reactions are mainly triggered by quality-related cues, which cause utility-related signals. Sales-related reactions are consequences of utility-related signals and relationship-related signals. Whereas brand-related reactions are mainly triggered by human-like and user-centred cues.

5.2 Evaluation of the Model for Triggering the Desired Social Reactions

This model was built on the findings reached on social reactions, social signals and social cues and their dependencies. For a first validation of this model, four unstructured expert interviews with practitioners who already implement CAs in their companies were conducted. During the interviews, it was found that some companies do not consider social cues at all. They view CAs more as a software project, without considering the right design criteria. However, none of the interviewed persons rejected the model. Some connections were positively confirmed with practical examples, whereas other connections received at least positive approval from the interviewed people.

5.3 Applying the Model for Triggering the Desired Social Reactions

From a company's or practitioner's perspective, the model should be read from right to left. Each company first defines the goals that should be reached with the CA before defining the individual cues (Hilderbrand, 2021). In practice, companies and practitioners first decide which social reactions they want to trigger with the chatbot. Then, they decide which social signals must be evoked to trigger the defined social reactions, according to this model. After that, they find out which social cues their CA must integrate to trigger the needed social signals, according to the taxonomy. From a research perspective, the model may be read from left to right. Usually, research first focusses on specific social cues to analyse the consequences of applying these cues. It may then focus on the triggered social signals and their influence on social reactions.

6. DISCUSSION AND LIMITATIONS

Although this research followed well-established guidelines and relied on other reviews and taxonomy development processes in the fields of IS and HCI, there might be some limitations in our model, which we would like to discuss.

First, the defined search strategy might have missed relevant publications. As with any literature review, the identified and selected publications had an impact on the list of identified triggers and cues and on the developed model. If other literature sources are used and other reactions, signals and cues are considered, the model may change.

Second, although the SLR and taxonomy development are based on known methods in the fields of IS and HCI, namely, Webster (2002), vom Brocke et al. (2015) and Nickerson et al. (2013), the taxonomy development is still influenced by personal perceptions. To address this point, several expert interviews were conducted during the research process and feedback from other researchers was obtained on a regular basis. Consequently, the taxonomy and model were adjusted according to their feedback.

Third, the whole model with its analysed CA features has not been finalised. We believe that, because of technical advancements, more triggers and design elements may need to be added in the future. However, according to the results of the expert interviews, we assume that the model with its taxonomies provides a sufficient state-of-the-art tool for developing high-performance CAs.

7. CONCLUSION AND OUTLOOK

The research question can be answered with the framework that is developed in the course of this work. It should be emphasized that the model can be read from different perspectives, namely on the part of practitioners and researchers. Discussions with experts from companies that are already using chatbots or are at least planning to do so soon have shown that while the current framework is helpful in creating chatbots, further optimization is still needed. Discussions have shown that companies usually pursue several goals with their conversational agent. However, these are weighted differently. Thus, in the long run, it is difficult to apply the model exactly like this. Rather, a system must be developed that can also handle fuzzy values and that can consider the different weightings of the pursued goals. In the development of such a system, the discipline of fuzzy logic can be applied. Fuzzy systems can deal with fuzzy data and are therefore very well suited to form an ontology for the developed framework (Zadeh, 1988). Researchers who apply “fuzziness” not only classify cues, signals and reactions into fixed categories, but also take into account their position within the category (Zadeh, 1988). This would mean that the developed framework does not work exclusively with exact data or goals, but also with the different weighting or prioritization of the individual goals. In this case, reactions are defined as goals. Additionally, we must consider that the assignments between cues, signals, and reactions, only show the dependencies of the individual variables and assign a certain strength to these dependencies. The assignments in the model are therefore not always exact, but rather show which dependencies are stronger and which dependencies are weaker. All this leads to the idea to add a fuzzy system to the developed framework to make the framework applicable to conversational agents. Thus, future research should focus on the question “how fuzzy-logic can help to build a system that first considers individual companies goals which might be a mixture of several users reactions, and second considers various strength of the relationship between reactions, signals and cues”. In the next steps we will develop a fuzzy cognitive map which will first consider the different relationships inside the framework itself. Afterwards, the fact that companies focus on more than one user reaction which are prioritised differently must be added to the new fuzzy system.

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