# “May I Help You?”: Exploring the Effect of Individuals’ Self-Efficacy on the Use of Conversational Agents

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# "May I Help You?": Exploring the Effect of Individuals' Self-Efficacy on the Use of Conversational Agents

*Short Paper*

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## Abstract

*Conversational agents (CAs) increasingly permeate our lives and offer us assistance for a myriad of tasks. Despite promising measurable benefits, CA use remains below expectations. To complement prior technology-focused research, this study takes a user-centric perspective and explores an individual's characteristics and dispositions as a factor influencing CA use. In particular, we investigate how individuals' self-efficacy, i.e., their belief in their own skills and abilities, affects their decision to seek assistance from a CA. We present the research model and study design for a laboratory experiment. In the experiment, participants complete two tasks embedded in realistic scenarios including websites with integrated CAs – that they might use for assistance. Initial results confirm the influence of individuals' self-efficacy beliefs on their decision to use CAs. By taking a human-centric perspective and observing actual behavior, we expect to contribute to CA research by exploring a factor likely to drive CA use.*

**Keywords:** Self-efficacy, Conversational agent use, Human behavior, User-centric, Laboratory experiment

## Introduction

Conversational agents (CAs) as a novel instance of user assistance systems increasingly permeate our professional and private lives and offer us assistance for a myriad of tasks (Maedche et al. 2019). Although they do not yet meet all expectations (e.g., regarding their capabilities) (Fotheringham and Wiles 2022), they still provide a range of advantages (Grudin and Jacques 2019): In private contexts, CAs can make users' lives easier, for example by presenting the latest weather forecast, reminding them of appointments, or playing users' favorite music (Gnewuch et al. 2017). Similarly, in professional contexts, CAs can assist employees in decision-making or even take over complete tasks from them (Maedche et al. 2019), thus enabling measurable benefits (Pfeuffer et al. 2019) such as increased productivity and efficiency (Brandtzaeg and Følstad 2017; Pfeuffer et al. 2019). However, although users do confirm that using CAs makes their everyday lives easier and more convenient (NIM 2019), user acceptance is still limited and, thus, CA usage still does not meet expectations (Ben Mimoun et al. 2012). This may point to significant

unrealized potential (Grudin and Jacques 2019). Hence, it is essential to understand what factors exert an influence on whether people use CAs (Pfeuffer et al. 2019).

As a literature review by Riefle and Benz (2021) shows, extant research on CA use predominantly (79% of investigated papers) takes a technology-focused perspective, focusing on technical aspects such as advancing natural language processing capabilities (Gnewuch et al. 2017) or exploring the influence of (anthropomorphic) design features on users (Rietz et al. 2019). However, the influence of human factors on individuals' decision to use CAs as assistance systems is not yet well understood (Riefle and Benz 2021). This paper seeks to address this gap by putting the users and their individual characteristics in the center of attention for explaining CA usage. In particular, we explore individual's assessment of their own skills and abilities, i.e., their belief in performing a task better or faster on their own, resulting in them not seeing any need to use a CA. In a study testing a chatbot prototype as support for software engineers, Okanović et al. (2020) notice that experienced software engineers, who need to run a system test, self-assess their own skills and abilities as so high that they do not expect any performance improvement from CA assistance. They believed to be more qualified to perform the task and would perform better *without* this assistance. However, given that people tend to overestimate their own skills and abilities (Vetter et al. 2011), completing the task *with* the assistance of a CA may likely be beneficial (Bansal et al. 2021; Hemmer et al. 2022; Schemmer et al. 2022). To understand how individuals' evaluation of their own skills and abilities influences their use of CAs, we draw on the concept of self-efficacy – defined as individuals' belief in their capacity to accomplish a task and achieve their desired goals (Bandura 1978).

The relevance of individuals' self-efficacy beliefs for task completion and the decision to seek assistance (e.g., from a CA) is further substantiated by extant research, identifying self-efficacy as an important factor influencing individuals' behavior (e.g., Bandura 1978; Cleavenger et al. 2007). Yet, empirical research on the influence of self-efficacy (as a user trait) on the use of CAs is still missing, which is why we intend to answer the following research question:

*RQ: How does an individual's self-efficacy influence the use of conversational agents?*

This short paper presents the research design we apply to address this question. We measure the influence of self-efficacy on CA usage by conducting a laboratory experiment, in which we observe participants' actual behavior regarding CA use. In the experiment, participants (n=194) complete two tasks that are embedded in realistic scenarios including websites with integrated CAs – that they might use for assistance. We measure participants' self-efficacy by means of questionnaires, expose them to two different tasks and observe their usage of a CA option. Thereby we expect to show the influence of individuals' self-efficacy beliefs on their decision to use CAs as assistance system. By concentrating on the user perspective, we will complement prior research by exploring a factor likely to explain CA use. This enables a more comprehensive view on factors influencing CA use, which may eventually inform the individualized design and facilitate successful CA acceptance and use.
The remainder of this paper is structured as follows: Section 2 outlines the self-efficacy theory including prior studies examining self-efficacy as a determinant of human behavior and provides a brief overview of the background on CAs. In Section 3, we derive our research model and hypotheses, while Section 4 presents the design of the empirical study and initial results. Section 5 concludes by giving an outlook on the expected contributions and the next steps.

# Theoretical Background

In this section, we outline the self-efficacy theory, that explains the link between individuals' beliefs in their own capabilities and subsequent behavior. Furthermore, we provide the foundations on CAs as an instance of user assistance system.

## *Self-Efficacy as Determinant of Human Behavior*

Bandura's (1978) self-efficacy theory is one of the dominant theories explaining human behavior (Tamilmani et al. 2020). Originally stemming from social psychology, self-efficacy theory has been adopted in various fields of research, including management science, education, health care sciences, and IS (Rieder and Rhyn 2020; Tamilmani et al. 2020). At its core, self-efficacy theory expresses that individuals' behavior

is considerably influenced by their own belief in their skills and abilities, i.e. their perceived capacity to perform the actions required to achieve desired goals (Bandura 1978). People who believe they are capable of performing some action not only undertake that action, but also perform it confidently and persist in face of obstacles (Bandura 1982). In fact, crucial for their behavior is not what they are objectively capable of, but what they believe they can do (Bandura 1997; Hsu and Chiu 2004). The stronger individuals' belief in their skills and abilities – i.e. the higher their self-efficacy – the more likely they are to perform an action and persist until they succeed (Bandura 1978, 1982): A student with a high level of self-efficacy trying to embrace arithmetic concepts will continue studying even if she has difficulties with some exercises. In contrast, individuals with a low level of self-efficacy will likely give up trying to achieve the desired goals, e.g., mastering mathematics, when challenges arise (Bandura 1978, 1982).

Self-efficacy can be distinguished in *general self-efficacy,* which is a broad and stable trait independent of certain activity domains, and *task-specific self-efficacy*, which is specific to a task or context (Bandura 1997; Luszczynska et al. 2005). Thus, besides a fundamental belief in their capacity to generally achieve desired goals (varying in strength from person to person), there is also a task-specific facet of self-efficacy: While an individual may have a high level of self-efficacy with respect to analyzing large amounts of data, she may still show a low level of self-efficacy when it comes to presenting the results from the analysis. This is due to the fact that both tasks require different, specific skills and abilities that individuals may or may not believe they possess. Hence, their behavior and persistence in performing these tasks will likely be different.

The influence of self-efficacy beliefs on individual behavior has been demonstrated in several studies across domains (Rieder et al. 2021): In IS, self-efficacy is predominantly studied with regard to individuals' belief in their ability to use technology such as a computer (Compeau and Higgins 1995). Researchers find an indirect influence of individuals' perceived capacity to operate a technology on their intention to use this technology, which is mediated by its perceived ease of use (e.g., Cheng 2011). Looking at other disciplines, self-efficacy is further studied in the context of personal health, education, or work. For example, Strecher et al. (1986) find self-efficacy to be strongly related to health behavior change and maintenance, while Stajkovic and Luthans (1998) highlight the impact of self-efficacy on work performance. Similarly, Multon et al. (1991) report significant relationships between individuals' self-efficacy beliefs and academic performance and persistence. Against this background, Kitsantas and Chow (2007) reveal significant correlations between students' self-efficacy beliefs and their help-seeking behavior from peers and instructors. This finding is especially interesting with regard to our study interests as we seek to understand individuals' use of CAs as assistance systems, which – to the best of our knowledge – has not been examined before.

### *Conversational Agents as User Assistance Systems*

User assistance systems (UAS) assist users with performing their tasks (Maedche et al. 2016). In contrast to more basic UAS such as digital versions of handbooks, CAs are a novel instance of UAS that is enabled by artificial intelligence and associated with advanced interaction capabilities. These capabilities allow them to sense and adapt to their environment and thus to react to users' current context and needs (Maedche et al. 2016). CAs are defined as software-based systems that interact with the user in natural language (McTear et al. 2016). According to their primary mode of communication, they are distinguished into text-based CAs, called chatbots, and voice-based CAs, often referred to as intelligent agents or personal assistants (McTear et al. 2016). Due to technological advancements in machine learning and natural language processing, CAs have improved considerably over the last decades and are becoming increasingly popular in research and practice (Gnewuch et al. 2017). Today, CAs offer assistance in a wide range of domains, typically applied in messaging applications, on websites, or in the case of intelligent agents, embedded in physical devices (Maedche et al. 2019; McTear et al. 2016): In customer service, chatbots may provide prompt answers to users' questions (Gnewuch et al. 2017; Riefle et al. 2022); in healthcare, special CAs can assist physicians in disease diagnosis or support patients during treatment and recovery (McTear et al. 2016; Meier et al. 2019). Similarly, in private life, CAs such as Apple's Siri or Amazon's Alexa become personal assistants that simplify the tasks of setting reminders, scheduling meetings, or checking news and weather forecasts (Gnewuch et al. 2017). Nevertheless, users' acceptance and use of CAs remains limited (Grudin and Jacques 2019), urging researchers to investigate possible reasons in order to address and eventually overcome identified acceptance barriers (Laumer et al. 2019).

Extant research on the acceptance and use of CAs explores a range of influencing factors ranging from the benefits offered by CAs to technical design features: Brandtzaeg and Følstad (2017) and Laumer et al. (2019) highlight expected benefits such as increased productivity and performance as key motivational factors for using CAs; whereas other researchers such as Rietz et al. (2019) and Sheehan et al. (2020) focus on technical design features, finding that anthropomorphic cues are an important determinant of CA use. Sheehan et al. (2020) further point out the significant moderating effect of user characteristics on the relationship between anthropomorphism and use. Hence, the need to also understand the users and their individual characteristics becomes evident (Følstad and Brandtzaeg 2017; Pfeuffer et al. 2019).

Summing up, theory and prior empirical investigations emphasize self-efficacy as a significant determinant of individual behavior. Furthermore, self-efficacy captures individuals' beliefs in their own skills and abilities, which makes it an interesting concept with regard to the investigation of user assistance systems such as CAs – especially since self-efficacy has been found to be highly correlated with seeking assistance (e.g., Kitsantas and Chow 2007). For that purpose, we present a research design to empirically examine the relationship of individuals' self-efficacy and their use of CAs as assistance system.

## Research Model

We examine the influence of different levels of self-efficacy on individuals' use of CAs. The dependent variable in our research model is the individual's decision to use the CA, influenced by the independent variable of self-efficacy which is composed of general and task-specific self-efficacy (Bandura 1997). As an individual trait, self-efficacy impacts individuals' thoughts and actions (Bandura 1982) – in our case this is reflected in their perceived need for assistance to complete a task and thus in their use of the CA.

General self-efficacy is a fundamental and stable trait inherent in all individuals (Bandura 1982) determining how they assess their competence, how much effort they invest in activities, and how they deal with adversities (Bandura 1978, 1982). Individuals with a high level of general self-efficacy believe they have the required skills and abilities to deal with a variety of tasks irrespective of particular domains or their objective competence (Bandura 1978, 1982; Luszczynska et al. 2005). They generally are confident to achieve their goals and to execute the necessary actions to attain these goals, even if obstacles arise (Bandura 1978, 1982; Luszczynska et al. 2005). Therefore, they may not feel a need for assistance (Bandura 1982; Cleavenger et al. 2007) like the one obtainable from a CA. Thus, we hypothesize:

*H1: General self-efficacy negatively influences CA use.*

Individuals' task-specific self-efficacy should be considered when one is interested in individuals' behavior concerning certain tasks in specific domains (Bandura 1997; Hsu and Chiu 2004). This is relevant, for instance, for the design of domain-specific CAs. Given that CAs are designed for intuitive user interaction (McTear et al. 2016), we reckon that it is not so much the individuals' perceived competence in using the CA that is decisive for using the assistance system. Rather, it is their perceived skills and abilities in solving the actual task at hand, that determines whether they will resort to an assistance system. In fact, people performing a particular task rely on their assessment of their own abilities and their willingness to persist when deciding to seek support (Kitsantas and Chow 2007). For example, physicians who could seek the assistance of a CA in diagnosing a patient, will do so when they believe that using the CA will improve their performance, i.e., make the diagnosis faster and/or more accurate (Laranjo et al. 2018). Similarly, customers searching online for information on a product might consider whether they will be able to find the information on their own and whether it might be faster and more convenient to use the CA provided on a website (Gnewuch et al. 2017). Hence, in the specific task at hand, when individuals think they have reached their competence limit or seeking assistance will improve their performance, that is, when they have a low level of task-specific self-efficacy, we expect them to use CAs. Vice versa, when individuals have a high level of task-specific self-efficacy and thus believe they can complete the task on their own, they rather do not seek the assistance of a CA and hence refrain from using it. We accordingly hypothesize:

*H2: Task-specific self-efficacy negatively influences CA use.*

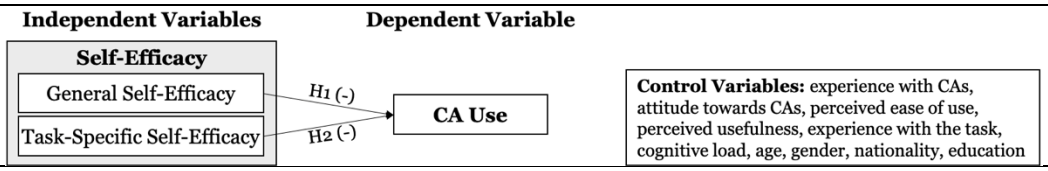


**Figure 1. Research Model**

Figure 1 depicts our research model. As control variables we use age, gender, education, experience with the task, cognitive load, prior experience with CAs, perceived ease of use of CAs, perceived usefulness of CAs, and attitude towards CAs. These variables were chosen based upon their use in previous studies and their potential for impacting study results (Bakke and Henry 2015). By additionally controlling for these factors, we are able to test alternative explanations for CA use. For example, by measuring experience with CAs and perceived ease of use we account for the alternative explanation that an individual's experience and perceived competence in operating CAs might lead to increased use. However, given that research considers CAs as intuitive to use and finds users to easily understand how to use them, we decide to not include individuals' competence in using CAs as independent variable in our study (McTear et al. 2016; Shevat 2017).

# Design of Empirical Study

To understand the influence of self-efficacy on individuals' CA use and to test our research model, we conducted a lab experiment. This allowed us to ensure high internal validity and replicability, while still targeting a large and diverse sample (Karahanna et al. 2018).

## *Participants and Procedure*

The experiment was conducted at an experimental laboratory in Germany. In total, 194 participants (29% female, average age = 23.2, range 18-41 years) completed the study, of which 180 datasets were valid. The sample received a monetary—in part performance-based—compensation for their participation (Kvaløy et al. 2015). Participants could earn a bonus payment (ca. 40% of maximum total payment) for completing the tasks correctly, thus fulfilling the requirements of an incentive-compatible experiment.

We tested our research model applying a within-subject design, in which each participant was exposed to two different task contexts. To achieve generalizable results regarding the influence of individuals' self-efficacy beliefs on their CA use, we observed participants' *actual behavior* in typical task contexts. While general self-efficacy can be assumed to naturally be present in varying levels in the population (Bandura 1997; Luszczynska et al. 2005), in order to evoke different levels of task-specific self-efficacy in individuals, we varied the task context regarding the task type and complexity (Bandura 1982; Hu et al. 2010). Therefore, we used realistic scenarios including real-world resembling websites with integrated chatbots in which the two tasks had to be performed. While participants completed the two tasks, we tracked their behavior, in particular, whether they used the CA for assistance. One task was a simple information search task (Campbell 1988) that asked participants to retrieve information on the candidate who won the previous mayoral elections. Participants were directed to a website presenting them a variety of newspaper articles on a range of global, regional, and local topics. They could either identify the relevant article and extract the required information on their own or seek assistance from the provided chatbot. In contrast, the second task was a financial decision task of increased complexity as it entailed outcome multiplicity, which is an objective task complexity attribute according to Campbell (1988). Participants were asked to choose the financial product with the highest return. Therefore, a bank website provided the participants with information on the financial products (i.e., time deposits) as well as the required formulas for calculations and background information on time deposits. They could then either use this information to decide on the best product on their own or ask the chatbot for assistance. For both tasks, participants were requested to provide their answer in order to continue the experiment, yet there was no time limit for task completion.

All participants completed both tasks, yet the order was randomized (i.e., counterbalanced) to minimize carry-over effects: When starting the experiment, the first screen explained the experiment procedure and incentivized participants as described by Kvaløy et al. (2015). Next, participants were presented with the first task, before continuing to the fictitious website to complete it. After completing the task, participants filled out a short questionnaire collecting data on their task-specific self-efficacy as well as the prior

experience with the task, and cognitive load (as control variables). These steps were equivalent for the second task. During task completion, data on participants' behavior with regards to the CA was collected, i.e., we tracked whether individuals used the chatbot to complete the task. Finally, participants completed an overall questionnaire collecting data on individuals' general self-efficacy, demographics (i.e., age, gender, education), prior experience with CAs, perceived ease of use, perceived usefulness, and attitude towards CAs (as control variables). A free-text question also asked them to indicate why they have (not) used the CAs to solve the tasks. Figure 2 summarizes the experimental procedure.

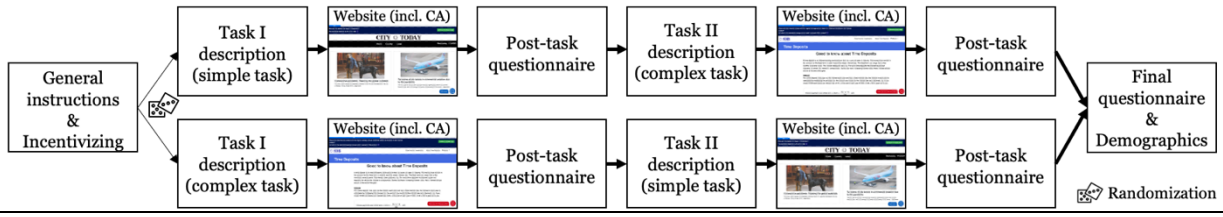


**Figure 2. Experimental Procedure**

## *Measurement of Variables*

We measured the dependent variable, i.e., whether individuals use the CA, by tracking participants' actions on the fictitious websites. Therefore, we model CA use as a dichotomous variable (yes/no) which takes the value 'yes' as soon as participants send a message to the chatbot. All questionnaire measures in this study are drawn from existing studies and adapted to the context of the experiment and CA use. For measuring general self-efficacy we refer to the 10-item scale by Schwarzer and Jerusalem (1995) as it has proven to be applicable across domains, cultures, and languages (Luszczynska et al. 2005). Task-specific self-efficacy was measured using 7-item scales based on Hsu and Chiu (2004), which we adapted to our specific tasks according to the formulation recommendations by Schwarzer and Fuchs (1996). Typical items for the self-efficacy scales are "I am confident that I can ...(perform something), even if ... (barrier)." (Schwarzer and Fuchs 1996, p. 170), which were measured on a seven-point Likert-type scale ranging from 'absolutely untrue' to 'absolutely true'.

For the measurement of control variables, we used established seven-point Likert-type scales anchored from 'strongly disagree' to 'strongly agree': After each task, prior task experience, cognitive load, and perceived task complexity were measured using two items based on Dishaw and Strong (1999), one item based on Paas et al. (1994), and four items based on Maynard and Hakel (1997). At the end of the experiment, we measured individuals' general attitude towards CAs using six items based on Dishaw and Strong (1999), perceived ease of use of CAs using four items based on Davis et al. (1989), perceived usefulness of CAs using four items based on Bhattacherjee (2001), and prior experience with CAs with one self-reported item as do Hackbarth et al. (2003).

## *Initial Analysis Results*

As a first step, we analyze the mandatory free-text answers on why the participants have (not) used the CAs for task completion applying common methods of qualitative content analysis (Mayring 2015). This analysis confirms the hypothesized influence of individuals' self-efficacy beliefs on their decision to use the CA: 19 participants indicate that they thought they were faster doing it on their own: E.g., "I felt like I could gather the information quicker myself." This may be attributed to the fact that they evaluate their own skills as so high, that they do not expect any improvement from CA assistance. In contrast, 21 participants declared the CA helped them solve the tasks more efficiently and conveniently: "...because it was the easiest and most effective way to complete the tasks." Participants' answers show that they found the CA to speed up their task completion – especially in task contexts where they "lacked experience".

In addition, 27 individuals state that they did not feel the need to seek assistance: "I think I can rely on my own skills", "...because I didn't feel like I needed help." They stated to be "confident enough" to possess the abilities to solve the tasks on their own. Furthermore, another 5 used the CA to verify their own results: "I used the chatbot to check my results". This indicates that they do think they could complete the tasks alone but were not completely confident after all. Finally, 15 participants expressed that they lacked the skills to solve the tasks without assistance: "I felt overwhelmed", "I felt confident finding information on the

websites but not confident enough using formulas". Especially the last quote is interesting, as it emphasizes the task-dependent influence of self-efficacy, that has been outlined in Section 2. While this participant considers her abilities to be sufficient to solve information search tasks, she felt the need for assistance when making a financial decision.

## Conclusion and Expected Contribution

In this paper, we present a research model and study design to examine the influence of individuals' self-efficacy beliefs on their use of CAs for task assistance. By applying a lab experiment and using realistic task scenarios including fictitious websites with integrated chatbots, we observed participants' actual usage behavior. This allows us to provide more reliable empirical evidence on the relationship of individuals' self-efficacy and CA use than just measuring individuals' behavioral intention. So far, we have conducted the experiment to collect the data. Furthermore, an initial analysis of the free-text answers on why the participants have (not) used the CAs for task completion indicate the influence of individuals' self-efficacy beliefs on their decision to use the CA.

Next, we will analyze the full dataset using structural equation modeling to test our hypotheses. By doing so, we expect to contribute to research and practice alike. Our findings will shed light on the multi-faceted field of CA acceptance and use by contributing to a better understanding of the influencing factors of individual CA use. In particular, our study will be the first to empirically investigate the effect of self-efficacy on CA use and, hence, will contribute to CA research by providing insights into a previously unexplored factor influencing CA use. In addition, our study puts the individual user in the center of attention, which sets it apart from existing research that mainly focuses on the technology (Riefle and Benz 2021). By concentrating on technically improving CA capabilities and testing different design features, the human aspect in user-system-interaction often remains under-researched, which is where our study comes in in order to contribute to a more comprehensive view on CA use. Only when the influencing factors on CA use are known, designers are enabled to develop and implement better assistance systems. For instance, when designers know that the targeted users are characterized by a high level of self-efficacy, they can design the assistance system such that it does not undermine their sense of competence. These considerations about the role of self-efficacy and other influencing factors on CA use may ultimately inform the process of how new (assistance) systems are introduced in companies. Overall, this study further reiterates the overarching importance of human factors for successful CA acceptance and use.

## References

Bakke, S., and Henry, R. 2015. "Unraveling the Mystery of New Technology Use: An Investigation into the Interplay of Desire for Control, Computer Self-Efficacy, and Personal Innovativeness," AIS Transactions on Human-Computer Interaction (7:4), pp. 270–293.

Bandura, A. 1978. "Self-Efficacy: Toward a Unifying Theory of Behavioral Change," Advances in Behaviour Research and Therapy (1:4), pp. 139–161.

Bandura, A. 1982. "Self-Efficacy Mechanism in Human Agency," American Psychologist (37:2), pp. 122–147.

Bandura, A. 1997. Self-Efficacy: The Exercise of Control, New York: W.H. Freeman and Company.

Bansal, G., Tongshuang, W. U., Zhou, J., Raymond, F. O. K., Nushi, B., Kamar, E., Ribeiro, M. T., and Weld, D. S. 2021. "Does the Whole Exceed Its Parts? The Effect of AI Explanations on Complementary Team Performance," in Conference on Human Factors in Computing Systems (CHI), Yokohama, Japan, pp. 1–16.

Bhattacherjee, A. 2001. "Understanding Information Systems Continuance: An Expectation-Confirmation Model," MIS Quarterly (25:3), pp. 351–370.

Brandtzaeg, P. B., and Følstad, A. 2017. "Why People Use Chatbots," in 4th International Conference of Internet Science (INSCI), I. Kompatsiaris, J. Cave, A. Satsiou, G. Carle, A. Passani, E. Kontopoulos, S. Diplaris, and D. McMillan (eds.), Thessaloniki, Greece, pp. 377–392.

Campbell, D. J. 1988. "Task Complexity: A Review and Analysis," Academy of Management Review (13:1), pp. 40–52.

Cheng, Y.-M. 2011. "Antecedents and Consequences of E-Learning Acceptance," Information Systems Journal (21:3), pp. 269–299.

Cleavenger, D., Gardner, W. L., and Mhatre, K. 2007. "Help-Seeking: Testing the Effects of Task Interdependence and Normativeness on Employees' Propensity to Seek Help," Journal of Business and Psychology (21:3), pp. 331–359.

Compeau, D. R., and Higgins, C. A. 1995. "Computer Self-Efficacy: Development of a Measure and Initial Test," MIS Quarterly (19:2), pp. 189–210.

Davis, F. D., Bagozzi, R. P., and Warshaw, P. R. . 1989. "User Acceptance of Computer Technology: A Comparison of Two Theoretical Models," Management Science (35:8), pp. 982–1003.

Dishaw, M. T., and Strong, D. M. 1999. "Extending the Technology Acceptance Model with Task-Technology Fit Constructs," Information and Management (36:1), pp. 9–21.

Følstad, A., and Brandtzaeg, P. B. 2017. "Chatbots and the New World of HCI," Interactions (24:4), pp. 38–42.

Fotheringham, D., and Wiles, M. A. 2022. "The Effect of Implementing Chatbot Customer Service on Stock Returns: An Event Study Analysis," Journal of the Academy of Marketing Science, Journal of the Academy of Marketing Science.

Gnewuch, U., Morana, S., Adam, M., and Maedche, A. 2017. "Towards Designing Cooperative and Social Conversational Agents for Customer Service," in Thirty Eighth International Conference on Information Systems (ICIS), Y. J. Kim, R. Agarwal, and J. K. Lee (eds.), Seoul, South Korea, pp. 1–13.

Grudin, J., and Jacques, R. 2019. "Chatbots, Humbots, and the Quest for Artificial General Intelligence," in Conference on Human Factors in Computing Systems (CHI), S. Brewster and G. Fitzpatrick (eds.), Glasgow, pp. 1–11.

Hackbarth, G., Grover, V., and Yi, M. Y. 2003. "Computer Playfulness and Anxiety: Positive and Negative Mediators of the System Experience Effect on Perceived Ease of Use," Information & Management (40:3), pp. 221–232.

Hemmer, P., Schellhammer, S., Vössing, M., Jakubik, J., and Satzger, G. 2022. "Forming Effective Human-AI Teams: Building Machine Learning Models That Complement the Capabilities of Multiple Experts," in 31st International Joint Conference on Artificial Intelligence (IJCAI), pp. 2478–2484.

Hsu, M. H., and Chiu, C. M. 2004. "Internet Self-Efficacy and Electronic Service Acceptance," Decision Support Systems (38:3), pp. 369–381.

Hu, J., Huhmann, B. A., and Hyman, M. R. 2010. "The Relationship between Task Complexity and Information Search: The Role of Self-Efficacy," Psychology & Marketing (30:6), pp. 461–469.

Karahanna, E., Benbasat, I., Bapna, R., and Rai, A. 2018. "Opportunities and Challenges for Different Types of Online Experiments," MIS Quarterly (42:4), iii–x.

Kitsantas, A., and Chow, A. 2007. "College Students' Perceived Threat and Preference for Seeking Help in Traditional, Distributed, and Distance Learning Environments," Computers and Education (48:3), pp. 383–395.

Kvaløy, O., Nieken, P., and Schöttner, A. 2015. "Hidden Benefits of Reward: A Field Experiment on Motivation and Monetary Incentives," European Economic Review (76), pp. 188–199.

Laranjo, L., Dunn, A. G., Tong, H. L., Kocaballi, A. B., Chen, J., Bashir, R., Surian, D., Gallego, B., Magrabi, F., Lau, A. Y. S., and Coiera, E. 2018. "Conversational Agents in Healthcare: A Systematic Review," Journal of the American Medical Informatics Association (25:9), pp. 1248–1258.

Laumer, S., Maier, C., and Gubler, T. F. 2019. "Chatbot Acceptance in Healthcare: Explaining User Adoption of Conversational Agents for Disease Diagnosis," in Twenty-Seventh European Conference on Information Systems (ECIS), J. vom Brocke, S. Gregor, and O. Müller (eds.), Stockholm, pp. 1–18.

Luszczynska, A., Scholz, U., and Schwarzer, R. 2005. "The General Self-Efficacy Scale: Multicultural Validation Studies," Journal of Psychology (139:5), pp. 439–457.

Maedche, A., Legner, C., Benlian, A., Berger, B., Gimpel, H., Hess, T., Hinz, O., Morana, S., and Söllner, M. 2019. "AI-Based Digital Assistants. Opportunities, Threats, and Research Perspectives," Business Information Systems Engineering (61:4), pp. 535–544.

Maedche, A., Morana, S., Schacht, S., Werth, D., and Krumeich, J. 2016. "Advanced User Assistance Systems," Business and Information Systems Engineering (58:5), pp. 367–370.

Maynard, D. C., and Hakel, M. D. 1997. "Effects of Objective and Subjective Task Complexity on Performance," Human Performance (10:4), pp. 303–330.

Mayring, P. 2015. "Qualitative Content Analysis: Theoretical Background and Procedures," in Approaches to Qualitative Research in Mathematics Education, A. Bikner-Ahsbahs, C. Knipping, and N. Presmeg (eds.), pp. 365–380.

McTear, M., Callejas, Z., and Griol, D. 2016. The Conversational Interface: Talking to Smart Devices, Springer.

Meier, P., Beinke, J. H., Fitte, C., Behne, A., and Teuteberg, F. 2019. "FeelFit – Design and Evaluation of a Conversational Agent to Enhance Health Awareness," in Fortieth International Conference on Information Systems (ICIS), H. Krcmar, J. Fedorowicz, W. F. Boh, J. M. Leimeister, and S. Wattal (eds.), Munich, Germany, pp. 1–17.

Ben Mimoun, M. S., Poncin, I., and Garnier, M. 2012. "Case Study-Embodied Virtual Agents: An Analysis on Reasons for Failure," Journal of Retailing and Consumer Services (19:6), Elsevier, pp. 605–612.

Multon, K. D., Brown, S. D., and Lent, R. W. 1991. "Relation of Self-Efficacy Beliefs to Academic Outcomes: A Meta-Analytic Investigation," Journal of Counseling Psychology (38:1), pp. 30–38.

NIM. 2019. "Alexa, Google Assistant, Siri Und Co: Die Digitalen Mitbewohner Auf Dem Weg Zum Mitentscheider Und Lebensberater." (https://www.nim.org/sites/default/files/medien/359/dokumente/2019_9_nim_pm_smart_speaker_dt-fin.pdf (Accessed 21 Oct 2020)).

Okanović, D., Beck, S., Merz, L., Zorn, C., Merino, L., Van Hoorn, A., and Beck, F. 2020. "Can a Chatbot Support Software Engineers with Load Testing? Approach and Experiences," in International Conference on Performance Engineering (ICPE), Edmonton, AB, pp. 120–129.

Paas, F. G., Van Merriënboer, J. J., and Adam, J. J. 1994. "Measurement of Cognitive Load in Instructional Research," Perceptual and Motor Skills (79:1), pp. 419–430.

Pfeuffer, N., Benlian, A., Gimpel, H., and Hinz, O. 2019. "Anthropomorphic Information Systems," Business Information Systems Engineering (61:4), pp. 523–533.

Rieder, A., Eseryel, U. Y., Lehrer, C., and Jung, R. 2021. "Why Users Comply with Wearables: The Role of Contextual Self-Efficacy in Behavioral Change," International Journal of Human–Computer Interaction (37:3), pp. 281–294.

Rieder, A., and Rhyn, M. 2020. "Situational Self-Efficacy and Behavioral Responses to Wearable Use," in Twenty-Eighth European Conference on Information Systems (ECIS), F. Rowe, R. El Amrani, M. Limayem, S. Newell, N. Pouloudi, E. van Heck, and A. El Quammah (eds.), Marrakesh, pp. 1–11.

Riefle, L., and Benz, C. 2021. "User-Specific Determinants of Conversational Agent Usage: A Review and Potential for Future Research," in 16th International Conference on Wirtschaftsinformatik, Essen, pp. 1–15.

Riefle, L., Brand, A., Mietz, J., Rombach, L., Szekat, C., and Benz, C. 2022. "What Fits Tim Might Not Fit Tom: Exploring the Impact of User Characteristics on Users' Experience with Conversational Interaction Modalities," in 17th International Conference on Wirtschaftsinformatik., pp. 1–9.

Rietz, T., Benke, I., and Maedche, A. 2019. "The Impact of Anthropomorphic and Functional Chatbot Design Features in Enterprise Collaboration Systems on User Acceptance," in 14th International Conference on Wirtschaftsinformatik, T. Ludwig and V. Pipek (eds.), Siegen, pp. 1642–1656.

Schemmer, M., Kühl, N., Benz, C., and Satzger, G. 2022. "On the Influence of Explainable AI on Automation Bias," in Thirtieth European Conference of Information Systems (ECIS), Timişoara, pp. 1–12.

Schwarzer, R., and Fuchs, R. 1996. "Self-Efficacy and Health Behaviours," in Predicting Health Behaviour: Research and Practice with Social Cognition Models, M. Conner and P. Norman (eds.), Buckingham: Open University Press, pp. 163–196.

Schwarzer, R., and Jerusalem, M. 1995. "Generalized Self-Efficacy Scale," in Measures in Health Psychology: A User's Portfolio. Causal and Control Beliefs (1st ed.), J. Weinman, S. Wright, and M. Johnston (eds.), Windsor: NFER-NELSON, pp. 35–37.

Sheehan, B., Jin, H. S., and Gottlieb, U. 2020. "Customer Service Chatbots: Anthropomorphism and Adoption," Journal of Business Research (115), pp. 14–24.

Shevat, A. 2017. Designing Bots: Creating Conversational Experiences, (A. Rufino, ed.), Beijing, Boston, Farnham, Sebastopol, Tokyo: O'Reilly.

Stajkovic, A. D., and Luthans, F. 1998. "Self-Efficacy and Work Performance: A Meta-Analysis," Psychological Bulletin, p. 240.

Strecher, V. J., McEvoy DeVellis, B., Becker, M. H., and Rosenstock, I. M. 1986. "The Role of Self-Efficacy in Achieving Health Behavior Change," Health Education & Behavior (13:1), pp. 73–92.

Tamilmani, K., Rana, N. P., Nunkoo, R., Raghavan, V., and Dwivedi, Y. K. 2020. "Indian Travellers ' Adoption of Airbnb Platform," Information Systems Frontiers, pp. 1–20.

Vetter, J., Benlian, A., and Hess, T. 2011. "Overconfidence in IT Investment Decisions: Why Knowledge Can Be a Boon and Bane at the Same Time," in Thirty Second International Conference on Information Systems (ICIS), D. F. Galletta and T.-P. Liang (eds.), Shanghai, China, pp. 4335–4351.