5-11-2023

May the Guide Be With You: CA-facilitated Information Elicitation to Prevent Service Failure

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Research Paper

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Abstract

Companies automate the delivery of their online services by deploying artificial intelligence-based conversational agents (CAs). However, contemporary CAs still struggle to reliably answer the full range of requests from support seekers. To avoid service failure, service delivery activities of CAs and service employees should be interconnected by a handover of requests. This form of hybrid service delivery requires support seekers to disclose relevant information so that CAs can relay them to service employees prior to an imminent failure. By integrating and extending design knowledge from two DSR projects, we derive four design principles (DPs) to prepare handovers. These DPs guided the implementation of a service script in a CA prototype to facilitate the elicitation of information from support seekers. Based on two evaluation episodes, we show that support seekers feel supported by the CA in disclosing information which results in elaborate input for subsequent processing by service employees after handover.

Keywords: Hybrid Service Delivery, Conversational Agent, Handover, Facilitation.

1 Introduction

Organizations are increasingly leveraging the capabilities of artificial intelligence (AI) to automate business operation processes (e.g., candidate selection, financial fraud detection, and prevention) (Ghosh et al., 2019). With its evolving technological foundations, such as machine learning (ML), AI technology is increasingly able to autonomously perform cognitive tasks in knowledge and service work that demand information processing capabilities (e.g., deductive analytical behavior) (Huang and Rust, 2021). Thereby, the application of AI offers companies the potential to increase their business value (Coombs et al., 2020; Lacity and Willcocks, 2021).

Due to its data richness, especially online service delivery represents a prominent application context for AI. With a continuously growing volume of requests, organizations are exploiting the current capabilities of AI to deliver faster and more efficient service within or across company boundaries to support seekers such as customers or employees (Larivière et al., 2017; Davenport and Ronanki, 2018). This trend of AI-based request handling is predicted to grow to a 95% share by 2025 (Servion, 2018). Seeking to provide elevated service quality for support seekers in these encounters (Mero, 2018), companies are transforming their text-based online service delivery. Therefore, they are adopting AI-based self-service technology that is capable of individualizing service interactions (Larivière et al., 2017). In this context, conversational agents (CAs) have gained popularity, as they allow a human-like, intuitive, and personalized dialog-based interaction with support seekers. Hence, CAs are frequently implemented to automate the processing of knowledge-intensive service requests across various work contexts (e.g., customer service, IT support) that have previously been performed by service employees. Thereby, companies can offer service at any time to quickly resolve support seekers' requests (Thorne, 2017; Fiore et al., 2019; Verhagen et al., 2014).

Nevertheless, AI-based CAs are still far away from achieving human intelligence which causes difficulties in processing complex requests and leads to the provision of unsuitable information (Statista, 2019; Li et al., 2020). Due to these service failures, companies are unable to deliver desired outcomes (Smith et al., 1999). Consequently, support seekers' satisfaction with the service delivery process and acceptance of a CA can get jeopardized. As Seeger and Heinzl (2021) reported, there is a high prevalence of these CA failures in practice which is reflected in a vast number of white papers on the internet addressing this issue and its consequences for companies (Bowers, 2019; Walby, 2022). To alleviate these negative effects and perpetuate CA acceptance among support seekers, initial research is investigating service recovery strategies. One research stream addresses automated conversational repair approaches by focusing on different forms of recovery through interaction between CA and support seeker (Reinkemeier and Gnewuch, 2022; Følstad and Taylor, 2020). These repair attempts include CA actions such as conveying messages that prepare users for failure, prompting users to paraphrase their input or select from provided options to continue the dialog (Weiler et al., 2022; Benner et al., 2021).

In addition to these automated approaches, service recovery strategies are needed that include fallbacks to service employees. Thereby, service failure can be prevented if CA-controlled repair attempts have repeatedly failed (Schuetzler et al., 2021; Benner et al., 2021; Poser et al., 2021). This requires the redesign of service processes to integrate existing work practices of CAs and service employees (Vassilakopoulou et al., 2022; Poser and Bittner, 2021). For continued request processing, either connected or disconnected service process steps can be established. For this purpose, handovers are used where requests of support seekers are relayed from the CA to the service employee for further processing. With connected processes, a request can be immediately handed over to the service employee and seamlessly handled (i.e., by entering the same chat). Disconnected processes imply a time delay in request processing by the service employee (i.e., request sent as a ticket) (Poser et al., 2022c). However, for any service recovery that involves the handover of a request to the service employee, suitable information needs to be available. Until now, however, there is a knowledge gap on how to ensure the elicitation of elaborate information to prepare a potential handover to service employees (Poser et al., 2022a; Poser et al., 2021). To do so, on the one hand, support seekers should be supported in providing relevant and detailed input during encounters. On the other hand, the collected information should meet the requirements of service employees to assist them during request processing after the handover. To address these aspects, the capabilities of CAs can be used to provide structural guidance and assist seekers in a flexible and human-like dialog. By providing an engaging interaction with on-demand support and feedback, service seekers' problems (e.g., comprehension questions) can be reduced and the documentation of information can be improved. For the creation of this dialog, we utilize service scripts that define procedures and activities for specific situations during customer encounters (Kirsch, 1996; Sands et al., 2021). Furthermore, we draw on the concept of facilitation to structure the dyadic interaction with CAs for this well-defined and repetitive task (Tavanapour et al., 2019; Clawson et al., 1993). Thereby, we aim to create a service script for CAs that allows the elicitation of information required by service employees to process requests after handover. Accordingly, we pose the following two-part research question: *How should a CA be designed to (I) assist support seekers in disclosing information (II) that can help service employees in processing requests after handover?*

To address this research question in the context of text-based online service delivery, we investigate intra-company IT support as a prominent internal work context for companies to pilot AI-based technology. Following the design science research (DSR) approach (Hevner et al., 2004), we present prescriptive design knowledge to structure the interaction between support seeker and CA to prepare potential handovers. Therefore, we draw on existing design knowledge from the knowledge base and complement it with problem-motivated design aspects derived from the application domain. The remainder of the paper proceeds as follows. In Section 2, we present related work on AI-based online service delivery, IT support, and CAs. Next, we delineate our research approach in Section 3. Subsequently, we identify objectives of a solution in Section 4, derive the design in Section 5, and demonstrate and evaluate the design in Section 6. We finish our paper with a discussion and conclusion in Sections 7 and 8.

2 Research Background

2.1 AI-based Online Service Delivery

Companies are progressively delivering intangible services online to meet support seekers' increased demands for convenient and fast resolution of requests that concern their needs (e.g., consultancy) or state of objects (e.g., product troubleshooting). To do so, online channels are used to offer support seekers support through self-service (e.g., web portals) or service employees (e.g., chat, email). This allows companies to effectively deliver information-rich and time-critical service with a utilitarian and relational nature (Froehle, 2006; Barrett et al., 2015). With the objective of enhancing the accessibility of these online-based service offerings and simultaneously ensuring operational efficiency and satisfactory service experience, AI-based self-service solutions are increasingly deployed (Huang and Rust, 2021). Offering the potential to create value in service environments, AI is defined as the ability of systems to interpret data input, execute actions, make decisions, and learn (Manser Payne et al., 2021; Haenlein and Kaplan, 2019; Bock et al., 2020). For online service delivery, AI appears predominantly in two forms: AI-based agents (e.g., CAs) are represented with a virtual identity and allow interaction via natural language; embedded AI is integrated into systems or applications with different interfaces (Glikson and Woolley, 2020; Poser et al., 2022c).

Recently, research has shown that the range of service tasks that can be executed by AI has expanded as its capabilities have evolved (Huang and Rust, 2018). More specifically, insights from research and practice demonstrate that AI is currently capable of autonomously processing homogeneous, repetitive, well-defined, and knowledge-intensive requests in encounters with support seekers (Zierau et al., 2020; Coombs et al., 2020). However, contemporary AI is so far unable to handle non-routine requests that require experimentation and intuitive processing (Schuetzler et al., 2021). To leverage the potential of AI-generated value, different deployment scenarios for online encounters with support seekers have been proposed and studied. On the one hand, AI-performed encounters refer to AI autonomously co-creating service with support seekers. On the other hand, AI can augment encounters between support seeker and service employee visibly or invisibly (Ostrom et al., 2019; Keyser et al., 2019). In this vein, the design of CAs' representation and interaction with support seekers has been extensively studied to positively affect the service experience (Zierau et al., 2020). To augment service employees during encounters with support seekers, initial research focuses on dashboards (Dubey et al., 2020) or CAs (Gao and Jiang, 2021).

As online service tasks are interdependent and AI still regularly fails in processing complex requests, hybrid forms of service delivery involving both AI and service employees are increasingly explored (Ostrom et al., 2019). As a result, new tasks arise for service employees to deliver service, such as monitoring and rectifying AI failure (Coombs et al., 2020). So far, however, there is a lack of knowledge about the interrelationships between service employee, support seeker, and AI as well as about the division and linkage of (sub-)tasks between service employee and AI allowing hybrid service delivery (Bock et al., 2020).

2.2 IT Support and AI

A prevalent work context for deploying AI-based online service delivery is IT support. This intangible service includes maintenance, problem-solving, and consulting on IT products (hard- and software) that were sold to external customers or are deployed in an organization (Shaw et al., 2002; Poser and Bittner, 2021). Accordingly, service offerings are directed toward internal or external support seekers. In this context, service employees are responsible for providing immediate, efficient, and high-quality support to support seekers, ensuring error-free use of IT products (González et al., 2005). Thus, questions are answered, assistance is provided with the installation of soft-and hardware, and problems are solved. In order to handle the varying degrees of complexity and problems, the IT support process is organized hierarchically (Marrone and Kolbe, 2011). In first-level support, requests or problems are accepted via various communication channels with the aim of finding solutions quickly. If the request cannot be resolved, a ticket will be created and escalated to a higher support level. Second-level support then provides direct support or offers solution approaches for more complex requests or problems. Third-level support handles tickets that require an individual solution through customizing the IT product or service (Simoudis, 1992).

The number of requests and their diversity in content is increasing in IT support, causing high demands on service employees (Poser and Bittner, 2021). Hence, to ensure timely and efficient restoration of IT operations, AI-based systems are investigated and used to automate or augment (sub-)tasks for service delivery (Crowston and Bolici, 2019). For instance, CAs can tackle the large volume of requests in first-level support as a self-service channel for support seekers (Fiore et al., 2019; Schmidt et al., 2021). In this context, research shows that CAs can answer FAQs and autonomously solve a restricted set of problems of support seekers (Meyer von Wolff et al., 2020; Vinyals and Le, 2015). In addition, embedded AI applications are studied to support service employees by providing suitable knowledge during request processing (e.g., Graef et al., 2021). However, as of yet, AI has often been deployed and studied as a stand-alone solution solving only a subset of issues. The interconnectedness between AI and service employees to achieve a purposeful integration of AI across service delivery activities has not yet been addressed. Furthermore, the perspective of service employees in AI-based service delivery has not been considered much (Poser and Bittner, 2021).

2.3 Conversational Agents

CAs represent AI-based agents and are defined as software systems that interact with users via natural language (Diederich et al., 2022; Bittner et al., 2019). Depending on the interaction mode (text vs. speech) and appearance (virtual identity vs. no identity), different terms such as chatbot, cognitive assistant, virtual or personal assistant are used to refer to CAs (Gnewuch et al., 2017). Due to their ability to communicate in a human-like manner and conduct personalized interactions, CAs are used in various domains for service-related tasks (e.g., finance, education, customer service, IT support) (Keyser et al., 2019). Their intuitive use facilitates unobstructed interaction and elevates the accessibility of online service offerings (Adam et al., 2021a). As CAs are capable to capture and retrieve knowledge as well as execute or trigger actions in systems, they are frequently used for automated, text-based self-service encounters with support seekers (Meyer von Wolff et al., 2019). In order to improve the adoption, use, and usability of CAs, different aspects have been investigated in research (Lewandowski et al., 2023). One stream of research examines the influence of social cues in terms of representational features (e.g., gender) and interaction style (e.g., message length, service scripts) on users (Sheehan et al., 2020; Sands et al., 2021). Another stream addresses technical characteristics to sustain error-free usage (natural language processing (NLP) engine, response latency) (Edirisooriya et al., 2019; Hu et al., 2018).

Despite the advances in ML and NLP, CAs still cause conversational breakdowns (Benner et al., 2021). To prevent these CA failures, research endeavors explore repair strategies and their effects on support seekers (Huang and Dootson, 2022). In this context, approaches of automated CA-initiated repair strategies are pursued that incorporate, among others, the detection of the error type and the application of suitable actions (Reinkemeier and Gnewuch, 2022). In addition, hybrid repair strategies with fallback to service employees are investigated. For this purpose, handover scenarios are considered in which CAs relay requests to service employees when previous automated CA-initiated attempts have failed. For these service recovery strategies, requests from support seekers are handed over and either resolved directly or delayed. In previous research, the perspective of support seekers during handover (Wintersberger et al., 2020), the procedural flow and the information categories required for service employees have been examined (Poser et al., 2021; Poser et al., 2022a). So far, however, there is a lack of knowledge on how CAs can gather relevant information in the interaction with support seekers to prepare a handover and thereby support service employees' subsequent request processing.

For the design of CA-guided service encounters, service scripts have been introduced to define CAs' activities and their sequence for different interaction scenarios (Sands et al., 2021). Hence, service scripts can be used to define the behavior of CAs for the elicitation of information. To define these activities, the concept of facilitation can be applied, which focuses on supporting individuals to achieve a task goal through interventions in a structured process (Clawson and Bostrom, 1996; Clawson et al., 1993). In the established facilitation framework of Bostrom et al. (1993), the activities for automated facilitation refer to (1) process and (2) relationship aspects to sustain (3) task achievement. Previous research has examined CA facilitators in various contexts. The results illustrate that CAs are capable of guiding individuals through a task process (Tavanapour et al., 2019), prompting for input or reformulation of input (Louvet et al., 2017), and providing task-related support (Wang et al., 2007). Accordingly, the concept of facilitation could be used to engage support seekers in a process of information elicitation to prepare a handover to service employees and thereby address the described research gap.

3 Research Approach

In this paper, we adopt the DSR paradigm to produce a solution for a prevalent real-world problem in online service contexts that are characterized by a lacking interconnectedness of activities performed by AI-based CAs and service employees (Hevner et al., 2004). To derive a CA design that sustains hybrid service delivery via handovers, we use the interior mode of DSR (Adam et al., 2021b). Accordingly, we create and evaluate prescriptive design knowledge and demonstrate a designed CA artifact.

To overcome the commonly limited reusability of design knowledge and minimize its monolithic structure, we create and evolve design knowledge across two DSR projects (see Figure 1) (vom Brocke et al., 2020; Baskerville and Pries-Heje, 2019). Initialized by the identification of a shared problem, we aim to produce suitable design knowledge that, due to its projectability, is applicable to a class of problems for related application domains. More precisely, we derive design principles (DPs) by iteratively performing design cycles across two projects to enable consecutive task processing involving the handover from a CA to an employee in semi-automated task settings. By accommodating for CAs' bounded capabilities, we aim to ensure that their preceding activities support subsequent human task accomplishment. The solution development revolves around a human-centered documentation process of user input (e.g., concern, problem, feedback) by a CA to support users and enable employees to finish a task after handover.

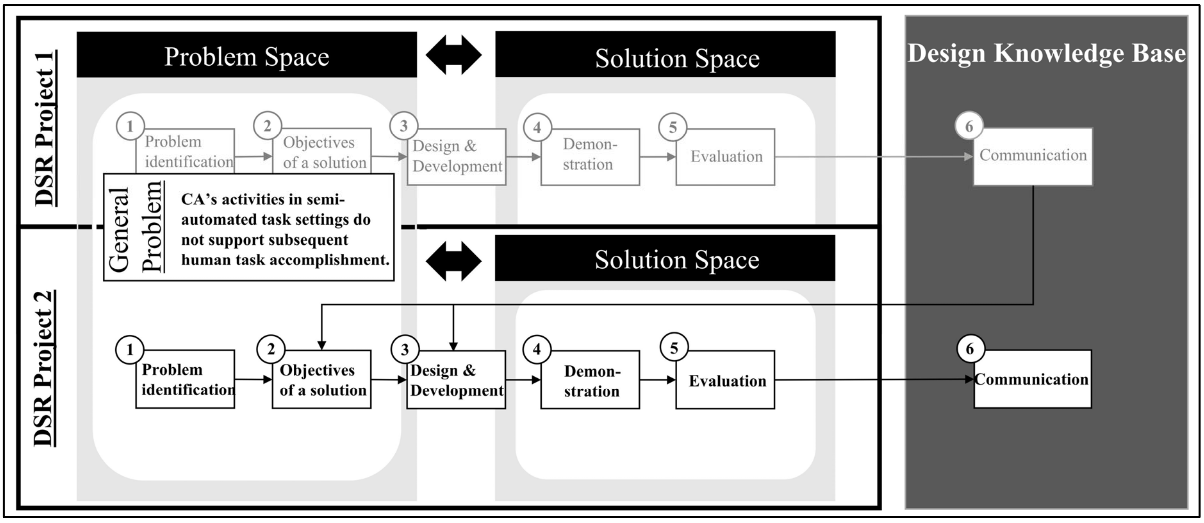

Figure 1. Interconnection of DSR projects structured with DSRM.

For the DSR project covered in this paper, we initialized the six-step DSR method (DSRM) by Peffers et al. (2007), to address missing CA's activities and handovers of information to support service employees' subsequent task accomplishment in IT support (**Problem Identification**). In search for **Objectives of a Solution**, we identified a preceding DSR project that addressed a related problem. In *DSR Project 1*, we generated design knowledge to support users in providing elaborate and detailed input through a CA facilitator in the context of crowdsourcing (Poser et al., 2022b). The evaluation of this design knowledge indicated that the quality of information handed over to employees sustained their subsequent task processing. As the DPs from *DSR Project 1* are characterized by a high projectability with moderate abstractness and high concept density (Wache et al., 2022), we considered them to inform the solution development in *DSR Project 2*. To ensure their fitness, we derived practice-oriented meta-requirements (MRs) from the application domain IT support. Therefore, we conducted semi-structured interviews with six experts (E1-6; gender: three female, three male; work experience: 1-20 year(s); fields of expertise: first-level, second-level IT support, quality assurance, development) from IT support to gain insights into the (1) nature of information in service tickets and (2) problems support seekers face during submission of requests. Based on verbatim transcripts, we performed a qualitative content analysis following Mayring (2015) that delivered issues to formulate MRs defining characteristics of a CA capable to elicit relevant information from support seekers (see Section 4). For the analysis, in the first step, the research team inductively developed code categories. Based on 30% of the verbatim transcripts, these categories were defined, subsumed, and grouped into main categories. In the second step, the remaining transcripts were analyzed and adjustments were made to code categories. In this open coding process, the researchers generated categories that were continuously harmonized to avoid researcher bias (e.g., confirmation bias). As a result, 5 main categories and 12 sub-categories emerged. For **Design and Development**, we enriched the existing DPs from the previous DSR project with the newly derived MRs in order to define a final set of DPs. Based on these updated DPs, we specified design features (DFs) to guide the development of a CA prototype, which was created with Botpress[1]. To construct this prototype, we created a training dataset based on a ticket sample drawn from the pool of a cooperating organization that processes IT support tickets in the field of public transportation (see Section 5). Subsequently, as a **Demonstration**, the CA was tested by 15 participants in a user test (see Section 6.1). To evaluate the applicability and feasibility of the design knowledge as well as the effects of the CA on support seekers, a quantitative questionnaire was administered to the participants. First, the instantiated DPs were assessed with five items (e.g., "How helpful are the guidance and suggestions of the CA?"). Second, 18 standardized items were included from the scale 'user satisfaction with question answering systems' by Ong et al. (2009) comprising subscales on ease of use, usefulness, service quality, and information quality. All items were rated with a 5-point Likert scale. In the **Evaluation**, we examined the effectiveness of the CA by analyzing the elicited information after the handover. For this purpose, four experts (E1-4) from the second step (Objectives of a Solution) individually reviewed information from current tickets and information elicited by the CA. To evaluate the level of detail, completeness, comprehensibility, specificity, and processability, experts were interviewed. We used the verbatim transcripts to perform a qualitative content analysis (Mayring, 2015) (see Section 6.2). According to a deductive procedure, we formed three ordinal categories (quality, meaningfulness, and processability/processing) and two nominal categories (advantages/disadvantages and improvements in quality) based on the question categories from the interview guideline. **Communication** will be completed with the publication of this paper.

4 Objectives of a Solution

To derive a solution and basic goals for the design, MRs were defined by incorporating the perspectives of service employees and prospective support seekers to identify relevant design aspects for the CA, prevent existing challenges, and ensure the elicitation of relevant information. Based on adverse

[1] https://botpress.com/download

characteristics of information of current tickets that refer to incorrect or incomprehensible as well as missing information, information elicitation by a CA should be determined.

Tickets are often not complete and lack details: “Not enough information is available in a well-prepared form” (*E4*). In addition, the required information about the problem description is missing (e.g., an error message). “In some cases, the description is only two lines of text” (*E2*). (**Issue1.1**). Moreover, associated data that helps service employees to grasp the underlying issue of the request (e.g., screenshots or personal data of the support seeker) is often unavailable. As a result, “90% of the tickets are incomplete” (*E5*) (**Issue1.2**). These shortcomings in content, incorrect, or missing information occur “because customers can write freely” (*E1*). Support seekers “often do not adhere to predefined guidelines, do it the way they think it should be done” (*E2*). Therefore, a guiding structure incorporating requests for required information would be useful (**MR1.1**). In addition, obligatory information for request processing should be defined because “tickets are better with mandatory fields” (*E5*) and the submission of requests without this information should not be accepted (**MR1.2**).

MR1: The CA should point users to mandatory fields and record the input.

As support seekers supply insufficient or incomplete content in their requests, service employees are required “[…] to repeatedly ask for information” (*E2*), which is time-consuming (**Issue2.1**). “Asking again - one to three times on average - because of incomprehensible information is most time-consuming” (*E6*). Explaining to support seekers what information is needed demands a high level of communication effort for service employees. During these contacts, service employees have to “[…] pose specific questions to get what you need” (*E2*). Apart from the time invested in communicating with support seekers, additional workload is caused by “correcting tickets which involves multiple feedback iterations” (*E4*) (**Issue2.2**) and requires changes in ticket documentation. In this context, “ticket correction is not complicated, just time-consuming” (*E2*) (**Issue2.3**). Additionally complicating the ticket processing is delayed response times of support seekers. This results in “additional work time between 5 and 30 minutes, up to hours or days” (*E6*), which can hinder the final closure of tickets for a long time (**Issue2.4**). As shortcomings in content or missing information arise because support seekers “sometimes do not realize the importance of information items” (*E4*) or “forget to follow guidelines” (*E3*), support seekers should be supported in submitting complete and comprehensive input. This requires a standardized process comprising a “concrete list of questions” (*E2*) (**MR2.1**). support seekers should understand that it is necessary to follow the process. “If customers are guided step by step, you get what you need” (*E1*) (**MR2.2**).

MR2: The CA should present and guide through a followable process by asking relevant questions step by step.

Furthermore, support seekers have difficulties summarizing appropriate content due to comprehension problems or lack of knowledge: support seekers “[...] write what they know” (*E6*) (**Issue3.1**). Accordingly, support seekers regularly - despite specifications of desired content - do not know what is needed or are not aware of the importance of certain information (e.g., content is generic). Hence, for service employees “it is usually not clear what is meant” (*E2*) (**Issue3.2**). In addition, some support seekers formulate multiple concerns into one request at the same time (**Issue3.3**). Overall, the quality of the provided information depends on the experience of the support seekers. Individuals “with whom you have a lot of contact create better tickets” (*E1*) than those with whom IT support rarely has contact. Hence, during information disclosure, the theme of a request should be identified to guide support seekers through a specific process, as “well-directed questions make it easier for individuals” (*E1*) (**MR3.1**). In addition to specific questions in the process, assistance should be offered when support seekers do not know what is required or have questions (e.g., explanation of prompted information items). Accordingly, to prevent support seekers from feeling helpless, suggestions should be made for specific questions (**MR3.2**).

MR3: The CA should understand and categorize requests to ask appropriate questions and provide explanations and suggestions when users have difficulties in understanding.

Generally, support seekers experience distress before submitting a request and wish for an individualized and appeasing interaction. Therefore, a CA should give support seekers the feeling that he or she is being helped. More specifically, "individuals need to feel that their request is being taken care of" (*E6*) (**MR4.1**). In addition, the CA should conduct a personal, friendly, and intuitive interaction with support seekers (e.g., provide button-based response options). In doing so, the CA should be empathetic and support seekers "should not feel dumb" (*E4*) (**MR4.2**).

MR4: The CA should conduct a friendly, intuitive, and empathetic interaction with users.

5 Design and Development

In this section, we present DPs of the type form and function from two DSR projects. In addition, we illustrate and describe the instantiation of the DPs with a situated implementation in form of a technical prototype.

5.1 Design Principles

We utilize the facilitation framework of Bostrom et al. (1993) to categorize CA capabilities and activities according to aspects of process, task, and relationship. In the first DSR project, we created four DPs (DP1.1-1.4) to design CAs that are able to guide users through a process to disclose information in a structured way (Poser et al., 2022b). To complement this design knowledge, we defined two additional DPs (DP2.1-2.2) based on the practice-oriented MRs from the second DSR project. Finally, following a supportive approach, we integrated an (re)defined the DPs (see Figure 2).

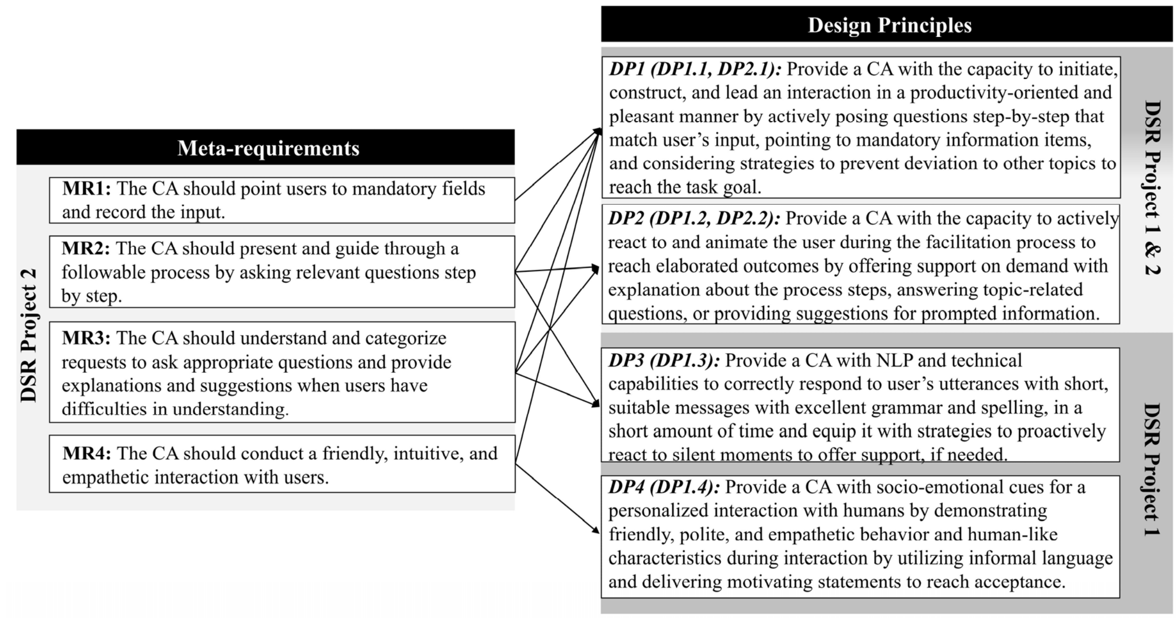

Figure 2. MRs from the current DSR project and DPs from both projects.

Process and task. Facilitative activities related to process and task are intended to inform and instruct individuals about the task. For this purpose, the CA should be able to initiate a dialog, explain the task at hand with its relevant steps, and guide support seekers through the process in a productivity-oriented fashion to elicit relevant information by asking questions (**DP1.1**). To be able to record different types of information, the CA should be able to guide through different processes based on users' input, pose matching questions, and point out mandatory information items (**DP2.1**). During this process, the CA should respond to the support seeker, motivate him or her, offer help with process steps, answer input-related questions, and provide explanations (**DP1.2)** as well as suggestions for prompted information to receive detailed and elaborate input (**DP2.2**). In general, for the CA to be able to guide the support seeker through a process to elicit information, the support seeker's intentions should be correctly recognized and responded to quickly with predefined messages (**DP1.3**).

Relationship. Creating a pleasant atmosphere during the process of information elicitation is important. In this regard, support seekers should feel that they are taken seriously. Therefore, the CA should offer personalized and friendly interactions and provide socio-emotional support (**DP1.4**).

5.2 Instantiation

The CA prototype was created using Botpress and made accessible for evaluation via a website embedded in a chat window. We used the Botpress NLP engine to train the ML model with information from existing tickets. For the evaluation of the instantiated design, the inclusion of tickets was limited to error messages for three common thematic categories extracted from a representative sample of tickets from the collaborating organization's ticket pool. The development of the CA prototype entailed the definition of a service script to outline the basic conversation flow during information elicitation (see Figure 3). To define the activities of the CA, we used the Botpress dialog manager. Furthermore, we defined the representation and interaction style with dialog texts (see Figure 3 for dialog snippets). To guide the development of the prototype, based on the DPs we derived the following DFs.

To proactively initiate the elicitation of information, the CA offers user buttons to determine the superordinate category of support seekers' requests and subsequently pose questions (**DF1**: *DP1, DP2*). To inform users about relevant and required information, the CA describes items before prompting the support seeker to disclose them and displays a summary of documented input before handing it over to the service employee (**DF2**: *DP1, DP2*). An appropriate subcategory is recognized based on user input and a corresponding dialog is triggered and suitable questions are posed (**DF3**: *DP3, DP1*). During information elicitation, the CA should proactively offer and provide examples of what appropriate information looks like for the requested information items (**DF4**: *DP2*). To create a pleasant user experience, the CA should be represented by an avatar and address users directly in a friendly and respectable way (**DF5**: *DP4*).

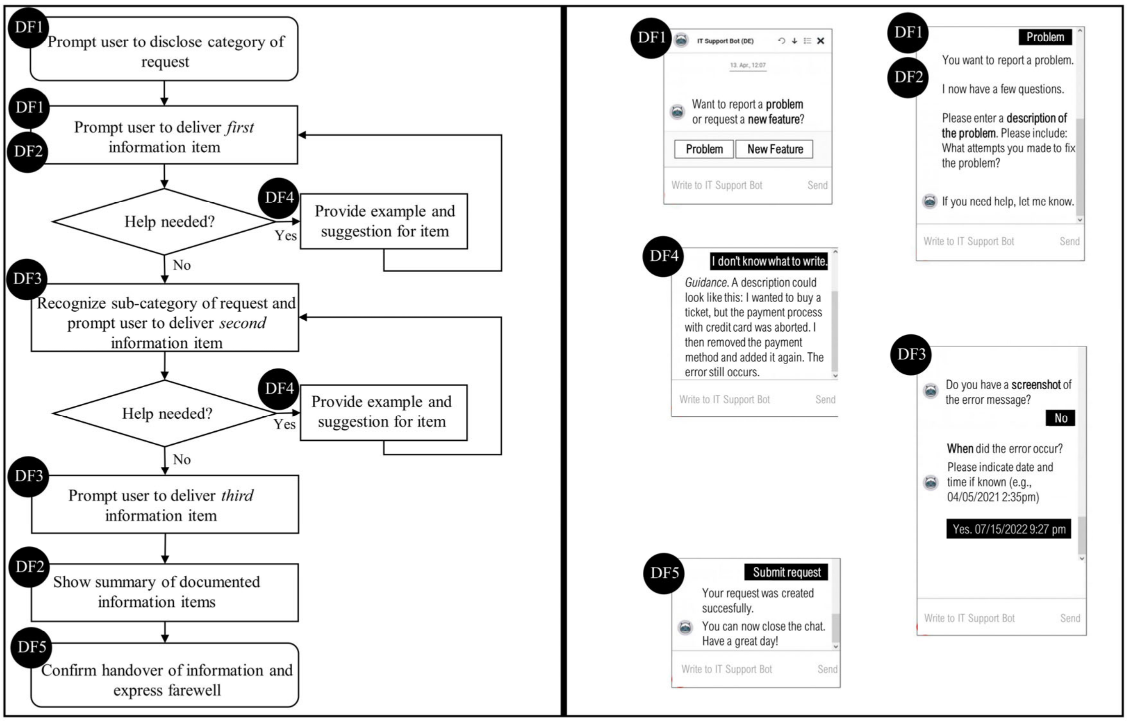

Figure 3. Service script (left) and exemplary snippets (right – translated into English) of the information elicitation with corresponding DFs.

6 Demonstration and Evaluation

This section presents two evaluation episodes to assess the instantiated design knowledge and support seekers' satisfaction with the CA. In addition, the suitability of information that was elicited with the help of the CA for subsequent processing by service employees is determined.

6.1 Demonstration

As part of the demonstration, we evaluated the materialized DPs and performed a user test to assess support seekers' experience with the CA during the process of information elicitation. To do so, 15 individuals, consisting of service employees from the collaborating organization and potential support seekers, each submitted a request and disclosed information using the implemented CA. This user test was based on a simulation, as participants submitted a request after they were given detailed background information on various regularly submitted errors. To perform the user test, participants were given access to the web-based CA. The ticket submission process could be started by the participants themselves. After submission, participants were asked to complete a quantitative questionnaire.

To gain insights into the implementation of the DPs, five questions were answered and received good to excellent ratings. This result illustrates the successful instantiation, applicability, and feasibility of the DPs. More specifically, the elicitation of information to submit a request was rated as satisfactory (M = 4.40, Mdn = 5.00, SD = 0.71). Participants perceived the offered assistance and proposed suggestions for information items by the CA as supportive (M = 4.00, Mdn = 4.00 SD = 0.89). During the interaction, participants felt well informed to enter the information requested (M = 4.47, Mdn = 5.00, SD = 0.71). In addition, the CA was rated as respectful in personality (M = 4.47, Mdn = 5.00 SD = 0.71) with an appropriate level of direct and personal interaction (M =4.20, Mdn = 4.00, SD = 0.74).

Complementing these findings, results from the user satisfaction questionnaire indicate that participants were generally satisfied with the CA-guided information elicitation process (see Table 1). The *ease of use* and *usefulness* ratings imply that the CA was user-friendly and has the potential to increase the effectiveness and productivity of submitting a request. The information presented during the interaction (*information quality*) was rated as relevant, and understandable but not tailored to the individual user. In addition, the CA was rated to provide a high quality of service, as it operates reliably and quickly.

Scale	No. of items	Mean (Median)	SD
Ease of use	5	4.36 (5.00)	0.23
Usefulness	5	4.20 (4.00)	0.07
Service quality	4	4.40 (5.00)	0.12
Information quality	4	4.35 (5.00)	0.31

Table 1. User satisfaction results.

6.2 Evaluation

For the evaluation, we examined the information generated by participants in the previous evaluation episode (see Section 6.1) during the CA-facilitated elicitation process to verify the effectiveness of the CA prototype. For this purpose, four experts each reviewed information from current tickets and compared it with information elicited by the CA for the same request category.

The *level of detail* of information obtained by the CA during the process "is more detailed, as it checks whether everything has been entered" (*E1*). Relevant information is attained through proactive prompts by the CA which sustains the "immediate recognition of the issue the user is facing" (*E2*). In addition, the "level of detail is optimized by omitting unimportant elements" (*E4*). In terms of *completeness*, the obligation to provide information results in a higher volume of information that is required by service employees than in current tickets: "the user cannot get around it and has to provide the information via the CA, so it is definitely more complete" (*E1*). As a result, "you have a better understanding of the request […]" (*E3*). Moreover, "by specifying what kind of information we need via the CA, users provide us with more or almost all information we need" (*E2*). The *comprehensibility* of the information is "[...] higher compared to current tickets" (*E3*) and "[…] you see directly: this is the problem, this is what happened" (*E2*). A request-based collection of information leads to thematically related items, which sustains service employees' recognition of requests. In this context, the information handed over by the CA support service employees, for example, "the categorization in the title is very good in content" (*E3*). "If you hold individuals by the hand and tell them I want to know this and that, then information is directly more comprehensible for us" (*E1*). In general, there is an improvement in terms of clarity and quality of information elicited by the CA as support seekers have to understand step by step in the process what their request is about. Regarding *specificity*, the information obtained by the CA covers the relevant items. The proposed help and suggestions reduce ambiguity in the content. "It's the specificity that's helpful because users have to keep input short. Of course, they can write extensive texts, but very few people will do that with a CA" (*E2*).

The characteristics of information obtained by the CA have an impact on their subsequent processing by service employees. "At best, you have all information at a glance and can start right away" (*E1*). The processing improves because the "[…] overview and categorization are clearer and predominantly relevant information reduced to the most important items can be identified more quickly" (*E4*). Overall, "the work is more on the user to tell us what the problem is, not on us to figure it out" (*E2*). This can shorten the processing time, as "the user enters everything via the CA, ideally, it all fits and you have the information and start working" (*E2*) - this reduces feedback loops. The handover to service employees "[…] speeds up the entire workflow considerably, which can save employees' time" (*E2*) as information is categorized with a title and description.

Despite these positive aspects in terms of information characteristics, there is potential for improvement. The degree of granularity for the information elicitation depends on the abilities and practice of support seekers to enter input. Therefore, after roll-out, the CA should prompt support seekers for various information items to ensure coverage of required information. During operation, information categories can be reduced as support seekers become more experienced in using the CA. Moreover, information about support seekers' hard- and software that can be retrieved automatically should be improved.

7 Discussion

Motivated by the current weaknesses of CAs in autonomously delivering service, this study addresses the limited design knowledge to configure fallbacks in the form of handovers from CAs to service employees. More specifically, the current knowledge gap on CA-guided information elicitation during interaction with support seekers is tackled to prevent impending service failures by relaying information to service employees. Accordingly and in line with calls from research, we propose a hybrid service delivery scenario for online services (Coombs et al., 2020; Lacity and Willcocks, 2021). In this regard, a purposeful division and interconnection of service delivery activities between CA and service employee need to be ensured (Benbya et al., 2021). Therefore, we adopted a holistic socio-technical perspective to integrate requirements from the perspective of support seekers and service employees (Makarius et al., 2020). Thereby, we aimed to ensure that support seekers feel supported in providing information during the CA-guided service interaction so that service employees can easily complete the processing of the request after the handover.

Based on two consecutive DSR projects, we present evolved design knowledge in the form of four DPs to design the elicitation of information by CAs. To define the activities of the CA for a service script, we built on the established concept of facilitation that focuses on supporting individuals to achieve a task goal through interventions in a structured process. The user test evaluation has shown that the implementation of the DPs is feasible and leads to satisfactory interactions for support seekers. In particular, the proactively offered support and suggestions for prompted information items (DP2) as well as the friendly and respectful behavior (DP4) were rated positively. These results are substantiated by the finding that the CA has been evaluated as user-friendly and has the potential to increase the effectiveness of a request submission for support seekers. Overall, the evaluation with potential support seekers indicates that information elicitation is useful and DPs are applicable. In addition, the effectiveness of the CA was assessed by service employees, who analyzed the information elicited by the CA. To assess the characteristics of this information, a comparison was performed with information content from current tickets with the same thematic focus. The corresponding results underline the importance of DP1 and DP3, as the facilitating behavior of the CA provides a promising step-by-step approach to collect thematically appropriate information while ensuring mandatory items, leading to higher completeness as well as comprehensibility of CA-elicited information. Furthermore, DP2 yields an increased level of specificity and comprehensibility, as support seekers are better informed about prompted information by the CA via proposed explanations, suggestions, or examples. Equipped with this information after handover, the efficiency of request processing from service employees' point of view could increase and thereby reduce the waiting time for support seekers.

By using and evolving design knowledge from separate but related problem spaces, we provide prescriptive knowledge of the type "exaptation" according to the contribution framework of Gregor and Hevner (2013). With this design knowledge, we offer insights for research and practice on how to strengthen the robustness of CA-based service delivery in IT support in particular and for intangible online services in general. Accordingly, this study contributes to research on CAs, online service delivery, and future work scenarios. The results show that the focus in designing CAs should not only – as in previous research –meet the demands of support seekers but should also meet the requirements of service employees. Thereby, the successful continuation of request processing by service employees after handover can be ensured. Moreover, by linking the activities of the CA and the service employee, possible service failures could be reduced and hybridization of service provision can be achieved. These findings can be used to intensify the investigation of service recoveries via fallbacks to service employees by distinguishing between two handover types, which ensure the direct or delayed continuation of request processing. In our study, we applied the facilitation concept to the context of online service delivery. A novel approach to designing self-service interactions between support seekers and AI-based agents is provided by combining it with service scripts. Overall, the results show that this approach and the implementation of the DPs have the potential to produce improved working conditions for service employees by reducing the number of repetitive requests and providing support with relevant information after the handover from CAs. With the presented results, we contribute to facilitation literature, as we show that the concept can be applied to the online service context. For practice, we provide implementable design knowledge to guide the construction of interaction templates for CAs in the context of online service. In particular, organizations can benefit from the insight that hybridizing service processes via the integration of the activities of CAs and service employees might result in improved service quality.

Despite these valuable contributions, there are a few limitations to consider, which provide avenues for future research. First, the results show that the elicitation of information is satisfactory from the support seekers' point of view and service employees perceive it as supportive to continue request processing. However, to gain insights into the effectiveness of this hybrid work process in the future, the entire workflow should be evaluated in a naturalistic environment. In this context, it should be assessed whether handing over information that was elicited by the CA can reduce the overall number of service failures. In addition, it should be evaluated whether this hybrid online service delivery leads to expected relief for service employees and improved support seeker satisfaction. Second, the implementation of DPs in the CA prototype is limited to the elicitation of information to prepare handover. In future research, it should also be investigated whether the facilitative activities that guide support seekers in providing information can also increase the resolution rate of CAs and thereby avoid handover to service employees. In addition, the influence of support seekers' experience in providing information should be investigated to achieve a balanced granularity in the process of the CAs' information elicitation. In this regard, automated recognition of support seekers' input by the CA could be explored to provide personalized guidance that matches users' experience level. Third, for the study at hand, we considered the online service work context IT support, which has similarities to customer service in the organization of work (Davenport and Ronanki, 2018). To verify the applicability of the DPs to different service domains (e.g., finance, insurance), the design knowledge should be applied, implemented, and evaluated.

8 Conclusion

With this study, we address the current disconnectedness of the activities of CA and service employees during online service encounters with support seekers to enable hybrid service delivery. By evolving design knowledge across two DSR projects, we present DPs to design CAs that are capable of eliciting relevant information while interacting with support seekers. As a result, fallbacks with handovers to service employees can be realized to avert imminent service failures by CAs. The results of the study show that the design of a service script that bases on the concept of facilitation enables CAs to prepare a handover. The guidance with elements of flexibility in terms of on-demand support and feedback helps support seekers in providing relevant information in the elicitation process. By adopting a holistic socio-technical approach, the generated design knowledge meets the demands of support seekers concerning a satisfying interaction with a CA. Moreover, the elicited information supports service employees in continuing the processing of requests after the handover.

Acknowledgment

The research was financed with funding provided by the German Federal Ministry of Education and Research and the European Social Fund under the "Future of work" program (INSTANT, 02L18A111).

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