Towards designing an AI-based conversational agent for on-the-job training of customer support novices

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Abstract. Due to the high drop-out rates in IT support desks, efficient onboarding of novices becomes a relevant and recurring challenge. Especially in the case of IT support, solving technical issues and service requests while the conversation with the customer is still ongoing imposes high demands on novice support agents. As artificial intelligence (AI) can already classify service requests and help find solutions, AI-based augmentation holds great potential for improving the onboarding phase and reducing time-to-performance. For this reason, we propose an AI-based conversational (co-)agent during the onboarding phase of customer support novices to reduce the time spent on service tasks and enable on-the-job training. Following action design research, we aim to develop an instantiation of an AI-based co-agent to reduce the job demand for the service center agent novices and augment problem-solving capabilities by considering cognitive load. The co-agent will be implemented with one development partner and evaluated with two different case partner organizations. In this research-in-progress project, we developed a low-fidelity prototype and derived a tentative architecture that allows for a generalized development of such conversational agents in customer service organizations.

Keywords: Conversational AI agents · Customer service · Onboarding · Action design research.

1 Introduction

New entrants to customer service are expected to solve problems after a short period of formal training. Through formal training, novices are qualified to handle most support requests they have learned during their upfront onboarding phase without customer contact. However, in case of new problems, novices are forced to invest much time in solving them or forward the case to a colleague [30]. Consequently, the overall service performance of the incoming requests for the same few problems is affected. In general, the time-to-performance of call center agents takes more than six months [1] due to the high cognitive load [7] initially experienced by novices. As a result, the novices often need more support during real-time customer (support) conversations highlighting the comparatively low effectiveness of the formal upfront training. Particularly since the turnover rate is up to 70% for new employees in customer support service [23]. In order not to overwhelm novice employees, the quality of onboarding is crucial and plays a decisive role in employee retention [32]. This prevents a high resignation level and a low first-call resolution among the novices. To avoid a higher average training time, it would be useful to assist the novices [25]. Therefore, an on-the-job AI assistant enables the novices to improve their problem-handling, while the initial training time does not need to be extended [19].

There is a growing body of research on AI-based augmentation in the frontline and customer service. The changed environment in frontline service, primarily due to the influence of new and intelligent technologies, represents the core of several studies on a general basis [26, 9, 17]. In particular, AI-driven approaches, such as the regulation of collaborative AI [14] or AI-assisted interpersonal emotion regulation [12], dominate research in this area. Beyond the purely technical perspective of using AI-based augmentation, human collaboration with technologies like AI [24] is also an evolving area of research. Whether investigating the use of employee-facing conversational agents in online customer service [36] or specifying the role of AI bots in teams [4, 2], the focus is on human-machine collaboration. Besides the mentioned research, there are still important questions unanswered. That is, while research already aimed at providing initial insights about the impact and potentials of AI coaches [18, 11], we observed a lack of research on the application and design of employee-facing AI-based bots [36] to support [10] novice employees during their onboarding. Consequently, we formulate the following research question: *How can we design an AI-based conversational agent for the onboarding phase of service center novices that improves both learning and task performance?*

The remaining paper is structured as follows: Within the second section, we propose our planned research approach according to the action design research (ADR) methodology by Sein et al. [31]. The third Section describes the design and development of our artifact. Lastly, we conclude and propose a future research agenda in Section 4.

2 Research Approach

According to Sein et al. [31], our research follows ADR, an appropriate methodology for practice-oriented problems with a high degree of direct industrial contact. Action Research [3] serves as the foundation for ADR, but unlike Action Research, which primarily seeks to transform an organization and address its issues, ADR focuses on the iterative design of an artifact and the theory associated with it [13, 21]. ADR is a design-oriented method; hence there should be practice-inspired research and a theory-guided artifact that emerges through an iterative process with significant organizational influence. Along with the research progress, we aim to derive artifacts developed with organizational partners and gain knowledge from the interventions as well as from the reflection and learning phase to solve the underlying challenge. The core tasks are building the artifact, intervening with the corporate partners, and evaluating in an iterative process. All steps, key elements, and methods of our ADR process according to the chosen framework of Sein et al. [31] are described in detail in chapter 3.

3 Design and Development

In order to structure this study, we present the steps of our ADR process and explain key preliminary results and the planned moves in each phase for continuing the research.

3.1 Problem Formulation and Theoretical Foundation

To overcome low first-call resolution rates, long response times, and a high fluctuation rate among the novices, our main goal in this study is to assist the customer service novice during their onboarding process. Therefore, we identified the opportunity to support the customer service agents with an AI-based on-the-job training conversational co-agent. Along with the organizational partners, we decided to implement the project within an in-house IT support manufacturing company and of a software vendor as a subclass of customer service.

In the development of an AI-based agent, some influencing design concepts (theory-guided artifacts) should be considered at all stages of the ADR process to bridge the gap between theory and practice. In the context of this research, optimizing learning performance is a sub-goal to improve the onboarding process. Learning performance should be significantly improved by minimizing the cognitive load, including the use of simple language and supporting the natural way of communicating with the co-agent [35]. This can be achieved by presenting material clearly and providing opportunities for the novices to engage with it and actively apply their knowledge to overcome overreliance or so-called automation bias [6]. By considering the principles of cognitive load theory [7], the co-agent should induce learning experiences that are more effective for novices and, at the same time, improve task performance [5]. Therefore the theory can be used in conjunction with the co-agent to improve user interface design in terms of content presentation and recommendation adaptation. For example, the co-agent can convey information concisely and clearly, and break difficult activities into smaller, more manageable parts. Another principle of cognitive load theory is that learners have various background knowledge and expertise and that this variety can affect how much cognitive effort is required to accomplish a task [16]. For this reason, the co-agent can be designed to adapt to the novice's knowledge and expertise, for example, by providing more or less detailed explanations as needed. Overall, the theory provides a theoretical framework for understanding how the human brain processes information and how AI-based conversational agents can be designed to minimize the novice cognitive load. The idea behind the theory of cognitive fit in human-computer interaction is that a user interface should be created with the user's cognitive processes in mind. This means that tasks should be executed compatible with the novice's mental model of the information and the task [27]. This includes using natural language processing techniques to understand the input of the novice agent and respond in a way that is easy for the novice to understand [33]. In terms of technical support theory, the concept of organizing moves [8, 22] is applied to the design and management of IT support routines so that customer support can improve the efficiency and effectiveness of their work and better meet the needs of the customer. The routines provide a structure for learning goals and tasks and a foundation for the (co-)agent journey. When planning and organizing moves with an AI-based conversational agent, it is important to know the goals of the move as well as the capabilities and limitations of the AI agent. In addition, we the theory will guide the development of the augmentation capabilities along the ADR project. Thereby, it allows for the targeted evaluation of each of the AI-based augmentation capabilities and, moreover, enables us to observe changes in the workplace and effectiveness of on-the-training in customer service. This includes defining exactly what tasks the co-agent can perform, such as helping with difficult customer problems or recommending an escalation of a problem. In addition, detailed rules and procedures must be established to monitor the co-agent's performance and resolve any problems or issues that may arise.

Other essential aspects of problem formulation are ensuring long-term organizational commitments and defining roles and responsibilities. The project consists of a composition of four parties. The research group takes care of the process design and architecture of the agent, as well as the theoretical background. A provider of conversational AI systems will support developing the conversational co-agent, and two case study partners are willing to implement and roll out a prototype in the organization and provide opportunities for interviews, focus groups, and observations as part of the pilot instantiation.

3.2 Building, Intervention, and Evaluation

The iterative phase of "Building, Intervention, and Evaluation" (BIE) takes place in two different IT support organizations in order to better generalize the findings and later show their relevance for different types of IT support services. As such, we refer to a two-stage design and development phase. At first, the ADR team implements a text-based co-agent for in-house IT support employees in a manufacturing company. The second case refers to software-specific IT support of a small software vendor, where the text-based co-agent from the first case is adapted and extended. The final solution can support new agents during chats. In sum, both cases comprise four design cycles, illustrated in Figure 1.

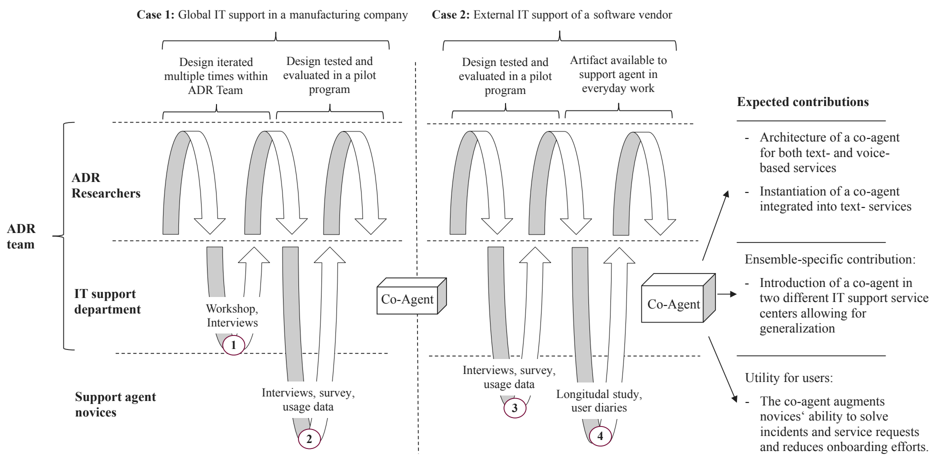

Fig. 1. ADR cycles (adapted from [31])

Cycle 1. Initially, we developed a low-fidelity prototype as a clickable mockup of the co-agent. We demonstrated the tool and the agent journey within the ADR team in front of 12 workshop participants, including IT support managers and agents. Then we divided the participants into two focus groups. Each focus group was asked to discuss about the general use cases for a co-agent in their organization, the potential for augmenting the onboarding phase, the augmentation interface and user experience as well as additional configuration levels. In conclusion, the participants argued for a high potential of the presented use cases within the low-fidelity prototype. The participants stated that support agents should still have direct access to ticket search engines in order to add specific details that were not mentioned in the course of the conversation. "If no solutions are suggested by the Whisper Assistant, could the Whisper Assistant itself suggest which information it is missing to find a solution?" the first group summarized. Most of the discussion was based on documenting the tickets. A semi-automated process should be where the support agent and co-agent aggregate the relevant data according to the second focus group: "The user should select or highlight the important content that goes into the documentation". Therefore, an upload function should be provided to collect error messages and logfiles, or customer data should be connected automatically. Regarding the augmentation interface, the group concluded that the recommendations should be easily transferred to the chat and at the same time revised efficiently. Based on the workshop evaluating the applicability and design, we finally derived a conceptual alpha version that is being transferred into the second cycle. The tentative agent journey and the clickable mockup are depicted in Figure 2.

Cycle 2. We then plan to develop a high-fidelity prototype for a chat-based co-agent. The prototype will be piloted within a global IT support unit and be integrated into messaging software. We plan to evaluate the prototype by means of interviews with customer service novices during their onboarding phase. More-

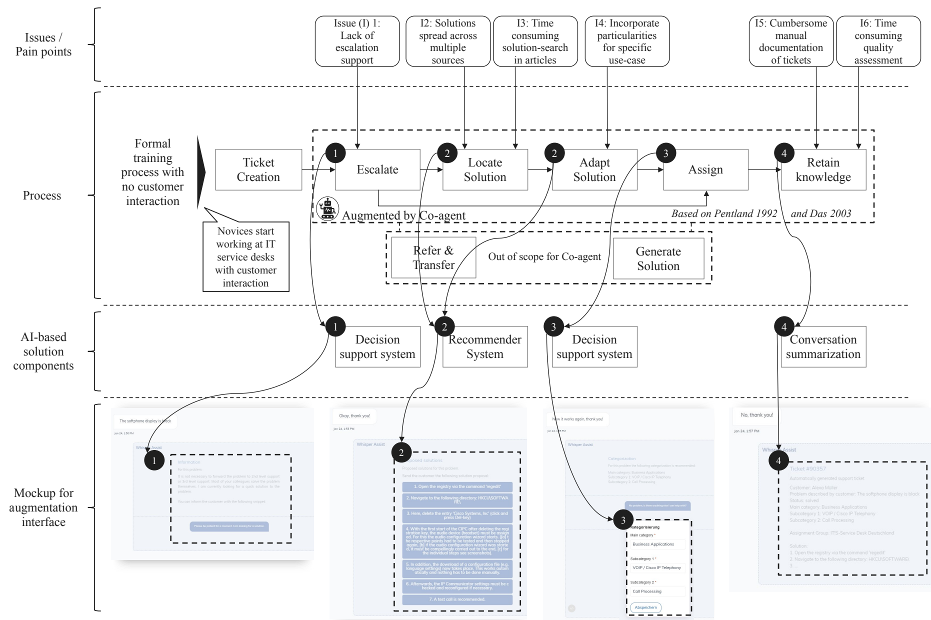

Fig. 2. Tentative agent journey after the introduction of the co-agent based on [22] and [8] and mockup for the augmentation interface

over, we will conduct a survey to get more feedback on functionality, usability, and the impact on learning and performance. For the evaluation, we plan to use qualitative [34] and quantitative [15] evaluation metrics. Finally, usage data will complement the evaluation and provide insights on performance metrics similar to the evaluation of classical chatbots [29, 20]. However, the key construct will be cognitive load, which is planned to evaluate qualitatively according to Sweller [35], and the corresponding learning performance and task performance [5]. After the second cycle, we expect to have generated a reference architecture that can be utilized by other IT support organizations and extended to assist hotline employees.

Cycle 3. To integrate into our second case company, the text-based co-agent architecture must be adjusted and evaluated within an initial BIE cycle similar to cycle 2. We apply the existing knowledge bases and set of solved tickets to train the co-agent's AI capabilities. This cycle ensures that different service centers can rely on the derived design knowledge to augment novice support agents.

Cycle 4. Finally, we plan to carry out a long-term study to better understand the impact of such a co-agent on the onboarding process. Based on user diaries in terms of a long-term study, insights into building expertise will be analyzed [28].

3.3 Reflection and Formulization of Learning

We, as the researchers, reflected on the design and development phase during multiple workshops. This allowed us to reconfigure the theoretical background and the underlying theories for designing a co-agent, focusing on the interaction between humans and the co-agent. Moreover, we plan retrospectives to evaluate the architecture development and the design process.

Key preliminary outcomes of the phase of formalization of learning are the agent journey, a clickable mockup, and a tentative reference architecture for co-agents for customer service employee onboarding. The architecture (Figure 3) can be broken down into four main components. The first is the communication interface. The co-agent's functionalities should be integrated with dedicated service chat tools, chatbots, or as in the first case, into internal communication tools. An underlying conversational AI processes the natural language of the conversation, recognizes customers' and agents' intents, and requests certain augmentation capabilities. The AI-based augmentation capabilities then aim at supporting typical technical support routines [8, 22], while the subsequent augmentation interface considers cognitive load and cognitive fit to maximize task and learning performance. In later cycles, the architecture will be instantiated and adjusted iteratively. Our research will be focused on the two most influential components: the domain-specific layer and the human-AI interaction layer. According to the evaluation workshop, the focus should be placed on problem-solving and documenting features.

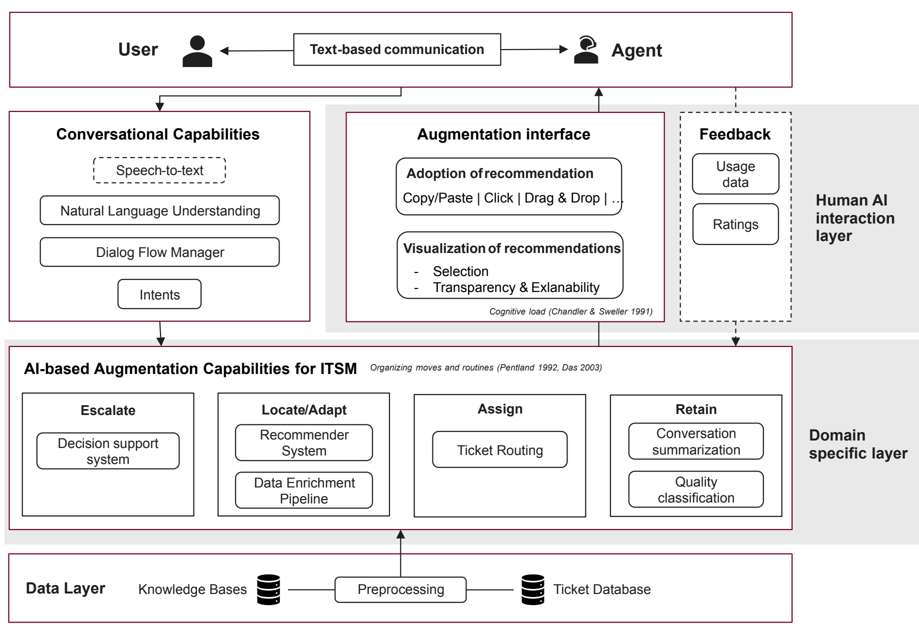

Fig. 3. Preliminary co-agent reference architecture for service employee augmentation

4 Conclusion and Further Research

This research-in-progress paper provides the technical and conceptual basis for our planned research by stating the problem space (overwhelmed customer support agent novices), selecting a research method (ADR), and providing initial hypotheses for artifacts as solution types via an instantiation of a co-agent in four BIE cycles in two cases (with a project partner for each case). The first BIE cycle has already been performed, and a preliminary agent journey, a low-fidelity prototype, and a tentative reference architecture have been presented. In further research, we aim to incorporate organizational context and evaluate the derived artifacts with two project partners by conducting cycles two to four, as shown in Figure 1.

We expect to contribute to the research on conversational agents and AI-based augmentation in the field of support services (e.g., [9, 17, 26]) by providing an architecture as a solution artifact. Additionally, we aim to contribute to the literature by applying insights regarding AI coaching and learning (e.g., [18, 11]) to the onboarding phase as experienced by customer support novices. Furthermore, we differentiate from [36] by integrating the co-agent into the conversation and focusing on the use of such an co-agent for the onboarding. In constrast to prior research, we examine the use of a co-gent within the realm of technical customer support - a field that is characterized by a higher level of complexity and higher degree of expert knowledge. In terms of practical implications, we expect to provide practitioners with guidance on developing and introducing co-agents in their service centers efficiently. This includes the technical aspects of such systems and organizational implications, such as suggestions for modified formal training during the onboarding of new human support agents to familiarize them with the co-agent. In addition, we expect to empirically demonstrate the benefit of augmentation in terms of more convenient help, resulting in higher satisfaction. Further expected outcomes are the instantiation of two high-fidelity prototypes, an updated architecture, and a long-term evaluation at support agents' workplaces.

Following the levels of generalization suggested in Sein et al. [31], our architecture as a solution artifact could be developed into a class of solutions and thus be made industry agnostic and transferable to other domains in customer service. Our research would also contribute to designing and developing complex AI-based augmentation landscapes for service employees. Future research could derive design principles from the expected research outcomes to share more generalized knowledge and consider call center agents as the target group by designing voice-based real-time support during onboarding.

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