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Generative AI in Customer Support Services: A Framework for Augmenting the Routines of Frontline Service Employees

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Abstract

Customer support service employees are facing an increased workload, while artificial intelligence (AI) appears to possess the potential to change the way we work. With the advent of modern types of generative AI, new opportunities to augment frontline service employees have emerged. However, little is known about how to integrate generative AI in customer support service organizations and purposefully change service employee work routines. Following multi-method qualitative research, we performed a literature review, conducted workshops, and interviewed IT support agents, managers, and AI experts. Thereby, we examine AI augmentation for frontline service employees in the context of IT support to carve out where and how GenAI can be leveraged to develop more efficient and higher-quality customer support. Our resulting framework reveals that especially adapting solutions and retaining knowledge is subject to a high degree of AI augmentation.

Keywords: Generative AI, augmentation, artificial intelligence, customer service, large language models

1. Introduction

With the advent of generative AI (GenAI), the possibility to implement augmentation seems to be auspicious (Brynjolfsson et al., 2023). GenAI has been subject to contemporary discussions in the field of education (Lim et al., 2023) and innovation management (Bouschery et al., 2023). Yet, its potential and approaches to augment customer support services remain unexplored in research and practice. The high potential of AI, in general, is extensively being discussed in the customer service literature, where Larivière et al. (2017) framed the concept of service encounter 2.0, De Keyser et al. (2019) developed typical archetypes for technology infusion in frontline services, and Huang and Rust (2018) discussed the role of AI in service comprehensively.

Despite its high promises in research, AI-augmentation research still falls behind in terms of systematic approaches that allow the most advantageous combination of human abilities and GenAI technologies and their interactions (Bucher et al., 2022; Carroll, 2021). The lack of knowledge on a systematic approach to GenAI in customer support service limits the possibilities of GenAI as an augmentation of FSE in terms of increasing efficiency, service quality, customer experience, and reducing costs (Bonetti et al., 2022; Davenport et al., 2020). Therefore, this research aims to conceptualize AI augmentation in customer support services routines and derive a routine-based framework for GenAI augmentation. To the best of our knowledge, our research is one of the first to incorporate the perspectives of customer support service experts on the role of GenAI (Brynjolfsson et al., 2023). Thus, we raise the following research questions: **(RQ1)** How can AI augmentation of FSE in customer support services be conceptualized in general? (**RQ2)** How can GenAI augment the routines of FSE in customer support services?

To answer our RQ, we pursued a multi-method approach (Cyr et al., 2009; Remus & Wiener, 2010): We examine the current literature on AI augmentation in customer service by performing a systematic literature review. Additionally, we conducted 11 semi-structured interviews to identify the particular potential of GenAI in customer support services and discussed with experts within two workshops.

2. Related Work

2.1. Generative AI and Large Language Models

In recent times, there has been significant attention on large language models (LLMs) that are generative and transformer-based. These models are specifically fine-tuned for tasks such as text summarization, classification, sentiment analysis, and many more. LLMs, also known as GenAI, not only have the ability to predict but also generate text. This delineates GenAI from discriminative predictive AI. Notable LLMs like GPT3.5 and LLaMA are well-suited for general questions and open-domain question-answering (Petroni et al., 2019). It can also be utilized as a means of data augmentation (Bayer et al., 2023).

GenAI systems are programmed by so-called prompts (White et al., 2023). These are instructions on what the system should generate. For example, text-to-image generation systems can generate creative pictures based on short textual descriptions (Oppenlaender, 2022). Large language models such as OpenAI's GPT4.0 can create poems or songs from short descriptions (Haleem et al., 2022). Creating and optimizing prompts to generate the most qualitative results is referred to as prompt engineering which is an emerging field of information systems research. The first studies have shown the efficiency of prompt engineering (Liu & Chilton, 2022). OpenAI provided its users with a list of prompt templates that should help formulate effective prompts. By employing such formulas, the results of the LLM can be modified for diverse downstream tasks.

2.2. Organizational Routines

Organizational routines can be referred to as an agreement about how to do work. Routines represent behavioral patterns of actions performed multiple times to achieve a certain goal (Pentland & Hærem, 2015). While prior research has emphasized the stability of routines comparable to habits, the research on routine dynamics also concerns the change of organizational routines over time. According to this stream of literature (Dittrich & Seidl, 2018; Feldman et al., 2016; Goh & Pentland, 2019), endogenous as well as exogenous factors can induce a change in routines (Goh & Pentland, 2019). Technologies represent one of the fundamental exogenous factors of routines (Pentland et al., 2011). For instance, Berente et al. (2016) showed that infusing technology can result in new patterns performed by workers.

Within the field of IT service management, Pentland (1992) was the first to analyze the activities of call center agents and derived organizational moves as the underlying units of routines that were performed by the FSE. In this research, we make use of the class of "give away", which comprises moves like assign, refer, transfer, and escalate. Das (2003) extended this view on technical support service work by investigating "problem-solving" routines.

3. Research Approach

As Figure 1 illustrates, our research design consists of multiple steps including a systematic literature review, multiple expert interviews, and workshops.

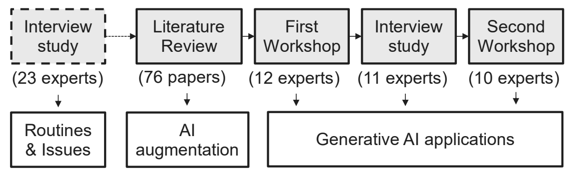

Figure 1: Multi-method research approach

3.1. Systematic Literature Review

We conducted a systematic literature review on AI applications in service research following vom Brocke et al. (2015) and Webster and Watson (2002). The analysis aimed at reviewing existing perceptions and implementations of AI augmentation concerning different forms of augmentation and different degrees of AI infusion. The search queries were adjusted according to the database-specific restrictions. The general query can be presented as follows: *"artificial intelligence" AND ("augment*" OR "ai-supported" OR ai-enabled" OR "ai-mediated" OR "ai-assisted" OR "human-ai collaboration") AND "service*"*. After preparing the search query, outlets were selected. Due to the interdisciplinary character of human-ai interaction in CS, high-quality journals and proceedings of information systems (IS), human-computer interaction (HCI), service, and management served as a foundation for the database search. The selection of research fields aligns with prior literature reviews on conversational agents (CA) and human-ai interaction (Elshan et al., 2022; Rzepka & Berger, 2018; Zierau et al., 2020).

Given the recent increase in AI systems (Rzepka & Berger, 2018) and to incorporate state-of-the-art AI and research, as for the period, 2017-2022 was applied as a hard-coded filter. The query-based search resulted in 652 hits in total. Thereof, 160 papers were further processed based on an initial title screening. After a subsequent abstract screening, 98 papers were transferred to the reading stage, after which, 47 papers were finally included based on specific inclusion and exclusion criteria. Afterward, a forward and backward search was conducted to cover any ignored papers and hence to ensure completeness. In sum, 76 papers were finally analyzed by applying qualitative coding with MAXQDA.

3.2. Interview Study and Workshops

We conducted a qualitative interview study (Mayring, 2004) to identify the potential of GenAI in customer support services and specify AI augmentation of customer support service routines. Based on expert experience we aim to outline applications of GenAI along the derived customer service routines and elaborate on how challenges can be addressed by employing state-of-the-art artificial intelligence including GenAI and large language models in particular.

Table I. Expert interviews

ID	Role	Experience	Company
E1	Data scientist	Programming	Tech-Startup
E2	Data scientist	Programming	Tech-Startup
E3	Support agent	ITSM	Manufacturing
E4	Data Scientist	Programming	Research
E5	Manager	ITSM, AI-PM (AI product manager)	IT provider
E6	Manager	ITSM, AI-PM	IT provider
E7	Suport Agent	ITSM,	IT provider
E8	GenAI expert	AI-PM	CAI provider
E9	Expert	ITSM	Research
E10	Expert	NLP, LLMs	Research
E11	Expert	AI-PM	Research

In addition, we conducted two workshops including support agents, managers, and work councils from three different pilot partners as well as experts in the field of ITSM and AI. The workshops allowed for discussions and interaction between multiple stakeholders. The first workshop took place before the interview session to introduce GenAI and explain the functionalities of large language models. That way, the participants, as well as the interview partners had a fundamental understanding of the capabilities of GenAI. Additionally, the experts were asked to elaborate on use cases for GenAI along the IT support process and test different prompts in ChatGPT immediately. Within the second workshop, the goal was to look at the step of documentation that was emphasized during the interviews. Therefore, the participants elaborated on the challenges and derived applications of GenAI in more detail.

4. AI-based Routine Augmentation

The literature on AI in customer services showed that augmentation forms a triad of human-ai interaction spanning the customer, the support agent, and the AI. Given the archetype conceptualization of (De Keyser et al., 2019) and our results of the literature review, we outline a triad that in which AI is integrated into the routines of FSE in five different ways. According to Leonardi (2011) we adopt a perspective of flexible routines and flexible technologies, where FSE doe not only consult technology in a unidirectional way but rather interact bidirectional and adapt the use of technology flexibly. Relating to Murray et al. (2021) our results show different types and degrees of AI augmentation – indicated by the bar in Figure 2. In the following the five overarching modifications of routines through AI are elaborated.

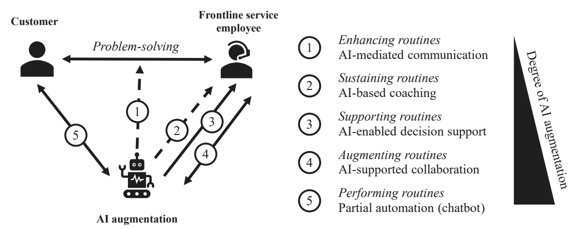

Figure 2: AI augmentation

Enhancing: AI-mediated communication (AI-MC) extends the field of computer-mediated communication by influencing human-to-human communication through AI (Hancock et al., 2020; Hohenstein & Jung, 2020). In terms of customer support services, AI-MC can be applied to enhance the communication between employees and customers to improve the quality of employees' communication (and skills) and thereby increasing customer satisfaction (Robertson et al., 2021; Seeber et al., 2020). Additionally, aspects of collaborative writing can be applied to improve text writing (Wiethof et al., 2020). Collaborative writing can enhance the readability and comprehensibility of written emails and ticket documentation.

Sustaining: A promising use case for augmenting FSE can be AI coaches that support workers in learning new skills and improving their customer communication as part of on-the-job training (Luo et al., 2021). Examples from education and research underline this potential: CAs are already used as learning companions (Chhibber & Law, 2019). Still, AI coaching is a less established field of augmentation research.

Supporting: AI-enabled decision support is an emerging area of research, showing great promise. It refers to the provision of advice to decision-makers that enhance decision outcomes (Jussupow et al., 2021). Decision augmentation is gaining great momentum for instance in healthcare services (Braun et al., 2022; Cai et al., 2019; Calisto et al., 2022; Hemmer et al., 2022). However, there is a large potential for improving customer support service routines by supporting employees in categorizing inquiries or assessing customer sentiment for example. Thus, AI augmentation is going to impact the decision-making routines by providing recommendations (Reinhard, Li, Dickhaut, Reh, et al.).

Augmenting: The mechanisms of augmenting routines (Murray et al., 2021) can have multiple manifestations – reaching from Q&A tools to search engines. In that sense, AI acts as a teammate, where it can serve as a facilitator, leader, or team member (Bao et al., 2020; Bittner et al., 2019). The triad of employee, customer, and AI can be interpreted as a team. For example, AI can act as a teammate for FSE when searching for solutions or creating chatbot content. Accordingly, many researchers describe the combination of humans and machines as a hybrid service team, where AI transforms from being a tool to being a teammate (Cabitza et al., 2021; Schelble et al., 2022; Wiethof et al., 2020). Thus, laying the focus on the exchange of information and skills to perform better together.

Performing: In a broader sense of AI augmentation, GenAI is meant to relieve FSE from a high workload and monotone and mundane tasks (Cabitza et al., 2021). Hereby, chatbots are applied to provide customers with self-service encounters (Wiethof & Bittner, 2022). As such certain routines and parts of routines on the task level will be translated into automatable pieces and will be replaced by AI (Robinson et al., 2020). Overall, the literature argues that mechanical tasks are most likely to be replaced, while intuitive and empathetic tasks will still be performed by FSE (Huang & Rust, 2022). The perspective of AI augmentation in the sense of performing routines is expected to imply new routines of managing and maintaining self-service systems including the curation of data for example. In addition, a customer service chatbot could also be utilized to support FSE as the research of (Vassilakopoulou et al., 2022) has revealed.

As customers, agents, and AI are forming a triadic relationship, our results indicate that conversational agents that incorporate multiple AI capabilities facing employees and customers can constitute AI augmentation. Up to the first four degrees of AI augmentation, the conversational agent acts as a "hidden assistant" or "whisper assistant", listening to the conversation and "whispering" recommendations and giving advice in real-time (Reinhard et al., 2023).

5. Routine-Based Framework for AI Augmentation

Based on 23 expert interviews with frontline support agents from prior research within the larger research project (Schmidt et al., 2022), we identified employee-related, pressing issues, and mapped those with routines of technical IT support workers along the customer service process (Figure 3). Following the data structure by (Gioia et al., 2013), we systematized the most crucial issues and further approached experts during 11 subsequent interviews and two workshops to discuss the potential of GenAI.

5.1 Assign

The routine of assigning problems comprises creating the ticket, retrieving missing information, and categorizing it accordingly. Based on these sub-tasks, the experts came up with multiple forms of GenAI application to relieve FSE. First, the initial contact could be performed by a *chatbot* that tries to answer simple questions such as FAQs (E1). By fine-tuning pre-trained large language models with enterprise data from software documentation, solved tickets, and knowledge base articles, the capabilities of chatbots in answering recurrent questions are promising. If the problem cannot be handled by the bot, the chatbot subsequently takes care of documenting the request. A ChatGPT-like tool could help to *perform queries* and improve the quality of the incoming problem descriptions (E1, E7). The first workshop confirmed that perception by emphasizing the capability of GenAI to check for missing information in the problem description. Participants expected that the AI could contact customers automatically to complete the descriptions. In addition to categorizing an incoming ticket according to its content, FSEs typically are asked to assign a priority and other categorizations such as severity. However, experts argue that neither the customer himself nor the chatbot should be approached to predict prioritization (E1, E6).

5.2 Refer and Transfer

The documented ticket then must be referred to and transferred to a dedicated department with expert knowledge of the given problem. This step is summarized as *ticket routing* – often called *triage* - (E2, E7), which represents a classical deterministic problem. While standard machine learning approaches can reliably predict multiple classes, utilizing the embeddings of large language models provide new capabilities for training classifiers. In workshop one, a participant said that the GenAI extracted well-suited keywords (E4). Therefore, transformer models can be utilized to revise categories to produce better-distinguished categories. This could be for example different software products or modules. Still, the interviewees expect the AI learns from the existing database of tickets and the knowledge of different routing decisions and routing errors (E7). In addition, GenAI can be applied to develop *skill profiles* based on the solved tickets of the experts and train a model on classifying an incoming ticket (E2, E4, E10). GenAI and especially large language models are supposed to understand the variety of tickets and topics an expert solves much better. Especially, its capability in identifying keywords for tagging different problems can be utilized to enable a *matching* between issues and experts (E1). Interviewee E7 states: *"So far, we have also had a lot of people who have been contacted personally, so that you really just have to look for experts and that has been difficult, and we still have challenges in one place or another*". Additionally, GenAI has a large potential in *clustering* tickets according to different categories and in developing trees of categories (E2).

5.3 Escalate

In case the ticket can neither be solved by the customer himself with the help of a chatbot or first-level support, the tickets need to be escalated to the next higher level. The routine of escalating a ticket is challenged with insufficient documentation of when to escalate and whether an agent has the permissions and rights to fulfill service requests (E2). An AI augmentation tool should help the FSE to know what the customer can solve, what the FSE can solve by himself, or what needs to be escalated. Expert 3 emphasized: "*I would go back a step … first I have to be able to assess whether I can solve it or not? …the recommendation: Hey, you can`t solve this ticket!"* As in many other cases, the potential depends on the type of customer support. The FSE can also be augmented in *requesting additional information and data* that is required to solve the ticket on the higher support levels (E2, E3, E7). With the information, the second-level support should be able to directly solve the problem or perform a service request (E2). However, it is important to not annoy the customer and request too much information (E3). And finally, similar to routine "assign", a *ticket summarization* with the most important information the second-level support should focus on, could be provided (E7).

5.4 Locate

To solve an incoming request, agents search for several different sources such as the world wide web, knowledge bases, existing ticket databases, and software documentation (E2). Despite merely integrating databases and providing interactive search engines (E7), locating the right solutions and suitable information remains a challenge for most cases (E3). Experts in the field hope to utilize embeddings – the learned representations of the tickets – to improve existing search engines and ticket matching systems (E3, E4). With this, GenAI and large language models are expected to provide FSE with *solution recommendations* in real-time and in a more intuitive way according to the first workshop. The FSE is then asked to review the recommendations and select the one that fits the best. Often multiple similar tickets could fit into a given query. FSE face the challenge of having very specific requests that are only insufficiently documented. The quality of the recommendations will mainly depend upon how the internal databases are incorporated into the pre-trained large language model to answer domain-specific requests and prevent hallucinations (E4). Again, *ticket summarization* reveals a large potential to improve solution search because summarized tickets allow agents to decide more efficiently whether a solution might fit (E3, E7). In contrast to many quite short and scarcely documented tickets, a lot of tickets show a quite long history with a lot of unnecessary information. Thus, GenAI-based summarization can put the focus on the relevant details instead of screening the whole ticket. For example, expert 3 stated: *"So, it's very, very exciting, especially what you're saying about the tickets always being helpful in the search because they're too long or poorly documented."*

5.5 Adapt

After locating a suitable or more than one suitable solution description, the FSE adapt the located solutions and customize them to the given customer specifications and the underlying case. Here, the language capabilities of large language models can play out. First, given the problem description and the located solution, GenAI could produce a proposal for a solution. One instantiation could be *email writing support* that considers the given input and builds upon predefined templates. As E7 emphasized: "*I took some sample tickets from us and simply changed the ticket description … And then an email was sent directly to the customer, without me having asked for it. Even* *though I can't technically assess whether everything in there is correct, I thought it sounded very good"*.

Second, from a *collaborative writing* perspective, AI can help FSE at adapting to the style of the corresponding customer as well as the agent himself (E2, E10). Third, *machine translation* of tickets and emails saves agents time and relieves them from mundane tasks (E6, E7, E10). This application is also empowering agents to act multi-lingual on a text-based level. Fourth, given the knowledge and the customer profiles, *customization* can be performed by considering the expertise, the language of the customer (E2, E3), and its customer sentiment (E1). This allows for distinguishing between customer documentation respectively communication and technical documentation of the solution by incorporating different degrees of detail. However, the language model should not emphasize irrelevant information and digress (E1). Such an approach can finally improve the communication and collaboration between first-level support and second-level support (E3): "*…so it always depends, but now let's say we don't necessarily provide the customer with all the information in the last detail, just as much as is interesting for him, then I could also understand that we make it a bit more technical for the solution documentation"*.

5.6 Generate

The discussions on generating completely new solutions were strongly related to the routine of adapting existing solutions. The experts within the workshop argued that GenAI can support agents to create readable solutions considering its content, form, and structure. However, the capability of solving a new problem lies within the responsibilities of the FSE. Still, the GenAI can *generate text* from provided bullet points or short sentences that the large language model extends and explains (E4). Thus, experts suggest providing the GenAI system instructions and a structure (E7). In addition, it can help to generate a meaningful *short description or title* for the issue (E4). In summary, despite its generative character state-of-the-art AI is not being proposed to help agents to create solutions from scratch.

5.7 Retain

In contrast, to "generate", the routine of retaining knowledge inhibits more potential of AI augmentation. The current issue lies within the reluctance of FSE to document their steps and their knowledge during or after fixing the issue (E3). The workshop revealed that there is a lack of motivation, time, and structures respectively templates. The goal is to socialize knowledge by transforming knowledge at the individual level to the collective level. Leonardi (2007) showed that when a knowledge management technology constrained computer technicians' ability to learn from coworkers, they changed their documentation routine. First, retaining knowledge can be augmented with GenAI by providing the system with all available data points including emails, chats, agent documentation, and transcribed calls, and summarizing useful ticket documentation (workshop

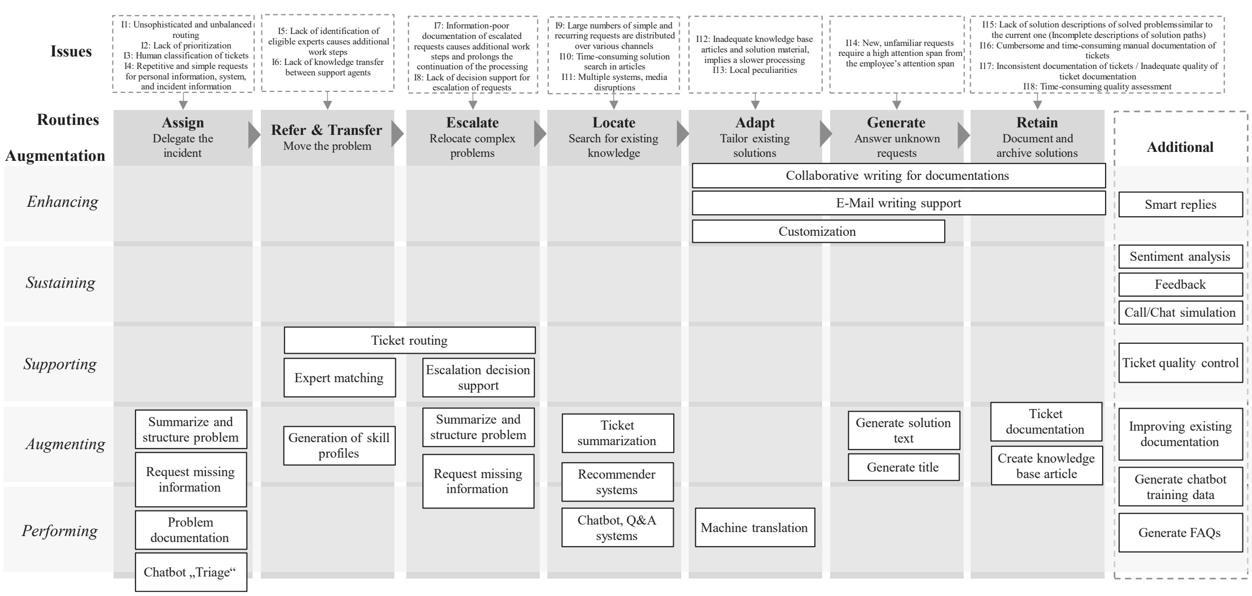

Figure 3: Routine-based AI augmentation framework for customer support services.

2). Second, GenAI could be utilized to *improve existing documentation* (workshop 1). The AI should identify low-quality tickets deterministically and suggest improvements (Reinhard, Li, Dickhaut, Peters, & Leimeister). Correspondingly the AI should ask the agent to document and add missing information (E2). Third, many customer support service organizations maintain knowledge bases to transfer knowledge from an individual to a collective level. Thus, given a predefined structure, agents could be augmented in created *knowledge base articles* from the dialogues (workshop 1) (E2, E3). In general, the generative aspects can be used to maintain any kind of knowledge repository, for instance, FAQs, product documentation, and the mentioned knowledge base articles. Regarding the creation of knowledge base articles, expert 3 mentioned: "*Yes, the editorial effort is quite high. So, when something new comes in or a change is made, our knowledge managers look at it, does it fit, etc. Everything is structured. Inside it's understandable and so on, it also works - the AI can definitely support that.*". The routine "retain" is also positively influenced by AI applications presented in "adapt". *Machine translation*, *collaborative writing*, and *generating text* from bullet points contribute to supporting and augmenting the routine of retaining knowledge. To overcome the mentioned challenges, AI augmentation tools should provide meaning and enable transparency as well as traceability. According to the second workshop, the documentation work should be made visible and underline the potential of relieving FSE from repetitive tasks. Additionally, such systems can induce a sense of ownership by incorporating a scoring model and by highlighting good documentation. Even gamification could be combined with the capabilities of GenAI.

Experts realized within the workshop, and they confirmed that intuition that large language models are well suited for tasks where form and formalities are important. That is the case for retaining knowledge, given the fact that tickets and solutions should be articulated and structured to support knowledge transfer. Expert 1 stated that the strength of these models lies within their capability to formulate text: "*So, language has two perspectives, and I would say that is a little bit of form and content… ChatGPT is simply very good in terms of form, that is to say, it depicts words and forms, structures meaningful sentences, does not have any spelling mistakes in it and simply suggests a great deal of competence, whereas you really hardly notice that there is not a person sitting there*"

Accordingly high is the number of applications that can be conceptualized with regards to GenAI. GenAI could especially help employees with literacy weaknesses and technology-focused employees with documenting their work and communicating with customers in a highly qualified fashion (E3). Bridging the gap between technical documentation and customer communication.

6. Discussion and Conclusion

As a result of the literature and the empirical investigations, the concept of AI augmentation encompasses varying degrees of human and AI agency involved in the execution of routines depending on the type of routine and the underlying task itself. In the case of enhancing routines, FSE can rather accept or reject smart replies or suggestions for improvement in collaborative writing. While in the case of performing routines, the human roles will change to curating data and supervising bots. Our results suggest that the responsibilities and routines of FSE will change with increasing the degree of AI infusion. For example, taking over and recovering service breakdowns and generating solutions for new problems or adjusting solutions for existing problems due to changes in IT systems will become the key role of FSE. As research shows, high-quality support does not use AI to replace human support agents, it rather provides opportunities to leverage the full potential of human agency. Our paper further strengthens this argument.

The proposed framework of AI augmentation outlines a multi-functional conversational agent that acts as a co-worker towards the FSE by "listening" to the customer communication, taking over simple and repetitive tasks as well as "whispering" different recommendations and collaborating within certain routines. The overview of the applications of GenAI shows that the generative characteristics of large language models will impact a lot of existing use cases of AI augmentation in customer service but also enable new forms of augmentation. The results furthermore reveal that GenAI affects the use cases of deterministic AI, for example, classification problems for assigning, referring, or escalating problems. Generating high-quality documentation of tickets including escalation decisions and complete problem and solution descriptions is going to fuel classification problems.

The study consolidates the prior research on organizing routines by Pentland (1992) and Das (2003) and complements the important task of retaining knowledge (Argote et al., 2003) within a framework for AI augmentation. The systematization of routines in customer support services can guide other studies in identifying valuable and promising fields of GenAI use in customer services and thereby extends prior research on AI in customer services (De

Keyser et al., 2019; Huang & Rust, 2022; Larivière et al., 2017). By bridging the gap between organizational routine research and human-ai collaboration, this study shows different types of AI augmentation of routines and exhibits to which degree AI is impacting these routines (Murray et al., 2021). In addition, the conceptualization of AI augmentation (Raisch & Krakowski, 2021) in customer support services aggregates the existing literature and provides a new understanding of employee-centric applications of AI at the workplace. Overall, we contribute a perspective of AI augmentation as a mechanism for developing employee-centered AI tools, showing that the infusion of GenAI can reach enhancing up to performing routines (Murray et al., 2021).

Regarding practical contributions, the framework can guide customer support service organizations in deriving and analyzing the potentials of GenAI along their support routines. The framework as well as the conceptualization of AI augmentation as a conversational agent provides a blueprint for relieving and empowering FSE while simultaneously improving the service quality and performance. Given the routine-based approach practitioners are enabled to focus on flexible moves and tasks instead of designing static to-be processes. Concerning the degree of augmentation, different instantiations of human-AI interactions are demanded to ensure the reliability and performance of GenAI systems and to keep FSE engaged and cautious in being augmented by AI. Overall, the resulting framework can be adapted to prepare for the coming age of GenAI.

Several limitations lie within the scope of our research. First, although we experienced saturation in the sample of expert interviews, only a few support agents were involved, and the sample could be extended to consider the variety of applications of GenAI in different industries. Including more FSE can furthermore provide more details and reflections because FSEs are the ones who are especially involved in performing the routines. Second, the conducted research does not consider the emergence of new routines from infusing AI into customer support services. However, prior research has shown (Berente et al., 2016) that the use of technology results in new and additional routines related to the use and exploitation of technology itself. Observing the occurrence of new patterns of action and interactions due to the nature of GenAI should be a matter of future research including perspectives of task delegation, explainability, and human control for example. And lastly, despite letting the workshop participants test prompts, we could not extract knowledge from analyzing the prompts. Such prompt analysis is crucial for building GenAI systems. However, it requires a much larger sample of prompts and feedback regarding the responses.

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