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Integration of AI into Customer Service: A Taxonomy to Inform Design Decisions

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INTEGRATION OF AI INTO CUSTOMER SERVICE: A TAXONOMY TO INFORM DESIGN DECISIONS

Research Paper

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Abstract

Artificial Intelligence (AI) is increasingly deployed in customer service for various service delivery tasks. Research and practice alike have extensively dealt with the use, benefits, and effects of AI solutions in customer service contexts. Nevertheless, knowledge on AI integration is dispersed and unsystematized. This paper addresses this gap by presenting a taxonomy to inform design decisions for the integration of AI into customer service with five meta-dimensions, 12 dimensions, and 32 characteristics. Through a rigorous and systematic development process comprising multiple iterations and evaluation episodes, state-of-the-art AI solutions from practice and the current state of knowledge from research were systematized to classify AI use cases. Thus, we contribute with systemized design knowledge to, both, the theoretical knowledge base as well as to practice for application. Eventually, we disclose future research avenues addressing certain meta-dimensions as well as the extension of the taxonomy itself.

Keywords: Artificial Intelligence, Customer Service, AI Integration.

1 Introduction

Customer service is currently undergoing a radical transformation driven by the integration of machine learning (ML), natural language processing (NLP), and related technologies, which are often subsumed under the term artificial intelligence (AI). In line with Gartner's prediction that 15 % of customer service interactions will be handled through AI by 2021 (Gartner, 2019), the successive application of AI is currently revolutionizing customer service toward the service encounter 2.0 (Larivière et al., 2017). Due to their advancing capabilities to autonomously handle inquiries, AI-enabled technologies, such as conversational agents (CAs), are implemented in various business contexts (e.g., finance, e-commerce, IT support) to elevate the efficiency and cost-effectiveness of text-based service delivery (Dwivedi et al., 2021; Gartner, 2019; Sarker, 2021; Xu et al., 2020). Thereby, organizations are able to enhance the availability and accessibility of their service provision as well as to reduce service employees' (SEs) workload, who can focus on more complex requests. Accordingly, AI progressively substitutes tasks of frontstage SEs, such as responding to customers' requests (Huang and Rust, 2018; Davenport et al., 2020). Related research, inter alia, involves the advancement of autonomous service delivery by focusing on customers' experience with AI addressing the representation and behavior of CAs, e.g., assigning social cues and ensuring competence levels (Gnewuch et al., 2017; Adam et al., 2020).

However, despite technological advancements, AI is still far away from fully substituting human intelligence beyond narrow domains (Dellermann et al., 2019). This means that AI can so far reliably handle simple requests for which unique relationships between the problem and solution have been established through training. For more complex requests with a distinct problem but multiple solutions, AI still regularly provides unsuitable answers (Krogh, 2018; Levy, 2018). Therefore, AI and human intelligence should be combined to allow SEs and AI to work side-by-side and foster their collaborative interplay (Wilson and Daugherty, 2018; Wirtz et al., 2018). In this vein, AI-based customer service solutions can support organizational service delivery by displaying answers to SEs to facilitate their inquiry processing. Additionally, AI can recognize intentions and emotions of the inquirer via natural language understanding leading to improved value co-creation during customer-SE interaction (Canhoto and Clear, 2020; Bassano et al., 2020; Sujata et al., 2019). Moreover, SEs can complement AI in various ways, e.g., through training, explaining, and sustaining (Keyser et al., 2019; Dellermann et al., 2019).

To realize efficient service delivery involving SEs and AI, a systematic orchestration of their capabilities and weaknesses is required (Paluch and Wirtz, 2020). Hence, the adoption of AI in customer service demands the differentiation between the roles of SEs and AI and the determination of the interaction with each other and the customer (Larivière et al., 2017; Robinson et al., 2020). Despite the increased interest in research and practice to deploy ML-based AI technology for online customer service, insights on how to integrate it into organizations are scarce (Benbya et al., 2021). Related to this, there is a lack of knowledge in research regarding the interrelationships between SE, customer, and AI within a socio-technical system of an organization's customer service (Bock et al., 2020). This includes the embedding in organizational work and process structures as well as the forms of interaction between SE, customer, and AI (Bock et al., 2020; Keyser et al., 2019). To address these knowledge gaps and provide systemized knowledge about the integration of AI for text-based customer service, the following research question is addressed: *How can conceptual and empirical knowledge on the integration of AI in customer service be classified to provide design decision guidance?*

We develop a taxonomy to inform design decisions by adopting the perspective of a single AI use case, which is analyzed or planned for implementation. Thereby, we aim to contribute to, both, the theoretical knowledge base as well as to practice for application with systemized knowledge from research and commercial solutions. Regarding theory, we provide relevant characteristics to be considered when investigating AI in different stages of the customer service process. Considering practical and managerial implications for IT management and development, businesses can advance their existing customer service delivery or implement novel interaction types aligned to the dimensions and characteristics of the taxonomy. To address the research question, the paper is structured as follows: First, we give an overview of related work about customer service and AI. After that, we introduce our research approach including the taxonomy development process. We then present an evaluation of our taxonomy prior to completion followed by the description of the final taxonomy organized and aligned to each meta-dimension. Next, we report on the ex-post evaluation of our taxonomy. We close the paper with a discussion and conclusion.

2 Related Work: Customer Service and AI

Service represents an elementary category of industrialized economies and is defined as the "application of competences (knowledge and skills) by one entity for the benefit of another" (Sampson and Froehle, 2006; Maglio and Spohrer, 2008; Vargo et al., 2008, p. 145). A relevant field of service represents companies' customer service offerings in various industries, which typically refer to intangible service delivery directed toward people (e.g., consultancy) or objects (e.g., post-sales service for primary products) (Wirtz et al., 2018). To fulfill customers' needs and demands, this form of service delivery is prevailingly characterized by knowledge intensity and customization, which requires active participation of and input by customers during service provision (Maglio and Spohrer, 2008). As companies strive to deliver high quality service to satisfy customers, a complex set of service processes needs to be orchestrated that spans the complementary service environments frontstage (external) and backstage (internal) (Sampson and Froehle, 2006). In the frontstage, service encounters with customers take place to co-create service. The backstage covers processes that do not directly involve customers and are therefore invisible to them (Glushko and Tabas, 2008; Bock et al., 2020).

To increase service quality and customer satisfaction, research has focused on factors that increase the efficiency and effectiveness in these service environments (Brady et al., 2002; Bitner et al., 2000). In this context, investigations emerged that, inter alia, examine the utilization of technology to create innovative ways of providing, accessing, and manipulating information in the front- and backstage (Amorim et al., 2019). Accordingly, the accessibility and availability of service have been addressed with technology-based self-service concepts such as knowledge portals on websites (e.g., Scherer et al., 2015; Meuter et al., 2000). Furthermore, access to and reuse of knowledge in accordance with customers' inquiries has been improved for SEs, e.g., with repositories (Kankanhalli et al., 2011). In this way, research has accounted for the time-critical, complex, and knowledge-dependent nature of service delivery in customer service contexts (Froehle and Roth, 2004). As an extension of these technology-focused research efforts, recent endeavors focus on the role of AI in customer service (Bock et al., 2020). With its capacity to process and learn based on data, AI is capable of inferring solutions to problems, decision options, or executing actions (Campbell et al., 2020; Raj and Seamans, 2019; Davenport et al., 2020). Hence, the utilization of current narrow AI that bases on ML algorithms is considered to revolutionize service delivery by efficiently and cost-effectively automating service encounters and tasks (Huang and Rust, 2018; Østerlund et al., 2021). This transforms information-rich online customer service since AI is capable of partially substituting or augmenting service activities. To account for this, Ostrom et al. (2019) and Keyser et al. (2019) introduced infusion archetypes for frontstage service delivery involving the entities AI, customer, and SE: AI either *substitutes* SEs by autonomously performing customer encounters or *augments* SEs by supporting them invisibly or visibly to customers through providing relevant information synchronous to the customer interaction. In these settings, customers and SEs encounter AI in the form of an AI-enabled agent and/or embedded AI. The former is a virtually represented agent that facilitates human-like interaction via natural language (e.g., CA), whereas the latter is integrated into platforms or applications without virtual identity (e.g., ticket tool) (Glikson and Woolley, 2020). AI-enabled agents, such as CAs, have been predominantly developed and investigated to substitute mechanical and analytical tasks that require rule-based, systematic, and consistent processing involving data and information (Huang and Rust, 2018; Janssen et al., 2020). Therefore, CA designs focus on interaction and technical capabilities to process customers' inquiries by answering questions or solving problems (Gnewuch et al., 2017; Følstad and Skjuve, 2019; Luger and Sellen, 2016). For the backstage, embedded AI is capable of delivering insights about past inquiries and/or historical customer data to support SEs (Graef et al., 2020; Cheung et al., 2003). Complementing these studies, initial research considers the interconnection of front- and backstage processes and tasks with seamless handovers from CAs to SEs to avoid failure in AI-performed service encounters (Wintersberger et al., 2020; Poser et al., 2021).

The overall focus of these previous studies predominantly lies on the development of stand-alone solutions for AI-performed service encounters in the frontstage. In addition, so far, there is limited knowledge about the role, activities, and integration of AI in the backstage. In principle, systematic knowledge with a holistic perspective on the integration of AI into customer service covering front- and backstage is until now scarce (Bock et al., 2020).

3 Research Approach

This paper aims to shed light on relevant design decisions for the integration of AI into the front- and/or backstage of customer service contexts by identifying and systematizing integration characteristics. For this purpose, dimensions related to service processes and the interaction between AI and humans (SEs and customers) are explored. As this still represents a nascent phenomenon, for which existing knowledge has not yet been structured and organized, a classification of associated concepts can help to consolidate understanding and further sense-making in this complex domain. For this endeavor, taxonomies are a suitable method, as they ascertainably present relationships, commonalities, and differences of concepts (Kundisch et al., 2021; Nickerson et al., 2013; Bailey, 1994). Following Kundisch et al. (2021), we rely on the Design Science Research (DSR) paradigm by adopting a build-evaluate pattern to construct and assess our taxonomy (Hevner et al., 2004; Sonnenberg and vom Brocke, 2012). Accordingly, our research approach comprises two consecutive process phases: (1) development and (2) evaluation (see Figure 1).

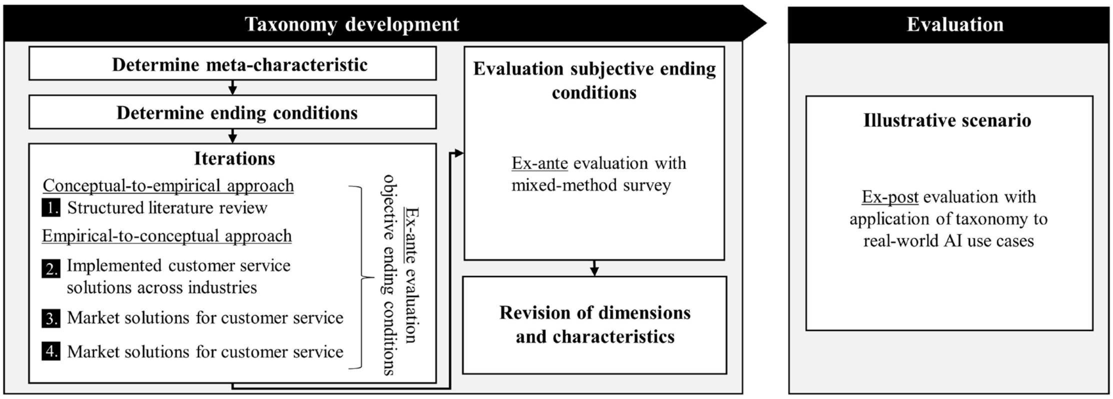

Figure 1. Research phases.

For the development phase, the rigorous and systematic method of Nickerson et al. (Nickerson et al., 2013) is adopted. In line with DSR, the development and evaluation phases include several evaluation episodes (Venable et al., 2016; Kundisch et al., 2021). During development, formative ex-ante evaluations are performed. On the one hand, the research team assessed objective ending conditions for each development iteration (see Section 4.1). On the other hand, experts from research and practice conducted an evaluation of the subjective ending conditions with a complete version of the taxonomy (see Section 4.2). As part of the summative ex-post evaluation, the adapted, final taxonomy was applied to illustrative scenarios to provide insights on its usability and validity (see Section 6). Thereby, the taxonomy represents a DSR artifact of the type model (Kundisch et al., 2021), providing prescriptive knowledge on how to design (theory for design and action) the integration of AI into customer service from a socio-technical perspective (Gregor and Hevner, 2013; Gregor, 2006).

4 Taxonomy Development

The iterative taxonomy building method according to Nickerson et al. (2013) comprises several steps. The development process starts with the definition of the meta-characteristic to determine the purpose of the taxonomy (Nickerson et al., 2013; Lösser et al., 2019). We define the meta-characteristic as *design decisions for the integration of AI in service delivery processes for customer service* to facilitate researchers and practitioners in their analyses and design undertakings. In this context, design decisions refer to characteristics of service processes, the AI-based technology, and the interaction between humans and AI. The second step includes the definition of ending conditions to determine the requirements to conclude the development process. For the taxonomy development phase, we adopted the objective conditions proposed by Nickerson et al. (2013). In the third step, either an inductive (empirical-to-conceptual) or deductive (conceptual-to-empirical) approach is chosen to initiate the identification of characteristics and dimensions. The application of these approaches can alternate for subsequent iterations. For the conceptual-to-empirical approach, the focus lies on deducing and grouping characteristics into dimensions based on existing scientific knowledge. The empirical-to-conceptual approach involves the utilization of a variety of real-world objects to identify and classify characteristics into dimensions (Nickerson et al., 2013; Lösser et al., 2019). To initiate the development process, we chose the conceptual-to-empirical approach because initial scientific knowledge exists, but is so far unstructured. After each iteration, the assessment of the objective ending conditions by two taxonomy designers was analyzed in terms of their agreement to decide about the continuation of the development. In the following, we describe the four conducted iterations and depict the taxonomy evolution process in Figure 2.

4.1 Taxonomy building process

Iteration 1: For the first iteration, we adopted the conceptual-to-empirical approach to develop a profound understanding of the domain under study. To identify extant and pertinent scientific knowledge in various fields such as service science, human-computer-interaction, and information systems (IS), we conducted a systematic literature review following the guiding principles of Webster and Watson (2002) as well as vom Brocke et al. (2015). For the search process, we chose three domain-relevant IS databases, namely ACM Digital Library, AIS eLibrary, and ScienceDirect, to identify relevant peer-reviewed English publications. The search process was performed with a search string. By executing an initial database search, we identified suitable keywords. Based on these results, we created the following search string: *((“employee*” OR “customer*” OR “user*”) AND (“AI” OR “artificial intelligence”) AND (“service” OR “support”))*. The search delivered 738 hits across databases. In two subsequent screening phases, the fit of the publications to the defined meta-characteristic was independently assessed by two researchers. In the first screening phase, the number of publications was reduced by excluding duplicates and inaccessible articles. Furthermore, we used abstracts, titles, and keywords to exclude publications that did not focus on the service domain. The application of these exclusion criteria yielded 101 publications. During the second screening phase, these publications were subject to an in-depth full-text analysis. 19 articles remained after excluding publications, which focus on (1) robotics (2) pure technological aspects without service application, and (3) business intelligence. To reveal higher-order characteristics and dimensions, these articles were iteratively coded. In an initial round, two researchers inductively created a set of master codes (service domain, involved entities, aspects of human-AI-interaction, and service processes) by independently coding the 19 publications and resolving discrepancies. Based on these codes, characteristics were generated and their labeling continuously harmonized in discussions. Subsequently, these characteristics were individually grouped into dimensions by the researchers. Through constant exchange, divergent assignments were cleared and labels for the dimensions were jointly derived. As a result, the following seven dimensions were added to the taxonomy in the first iteration: *service stages*, *AI role*, *task type*, *knowledge and data insights*, *form of AI appearance*, *AI transparency to customers*, and *data and knowledge processing*.

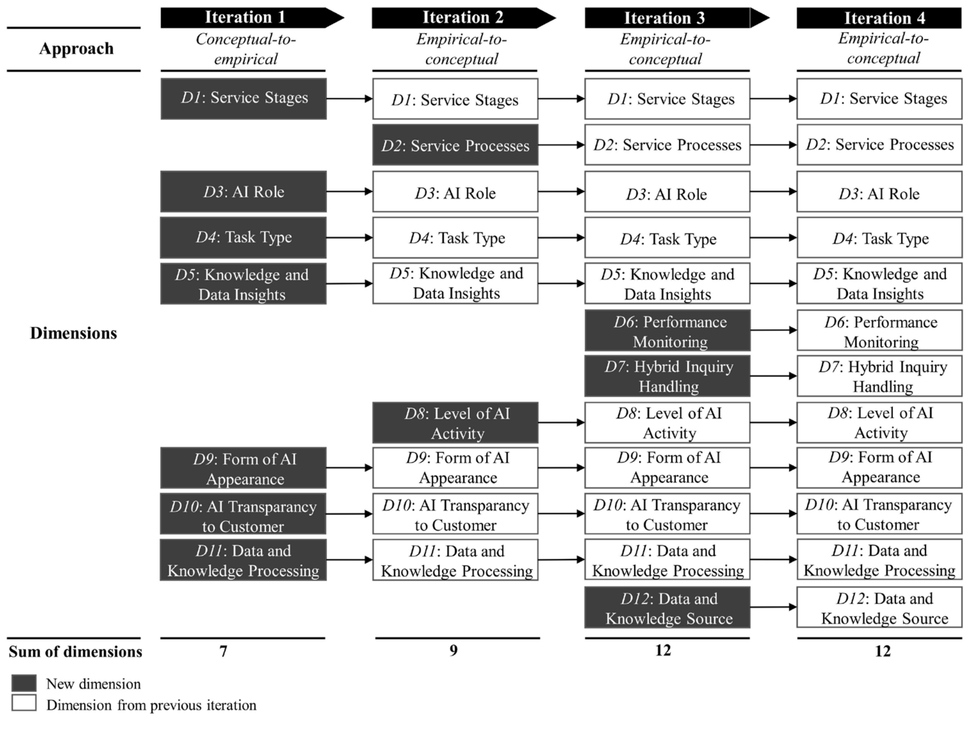

Figure 2. Taxonomy development process and evolution of dimensions.

Iteration 2: Following the conceptual iteration, we chose the empirical-to-conceptual approach to complement the taxonomy with insights induced from real-world objects. The focus in the second iteration was on obtaining real-world data to sustain knowledge about the integration of AI into companies’ service delivery processes. Following Short et al. (2002), we applied the stratified random sample method to acquire a representative sample of companies. In this way, a sample of companies can be subdivided into meaningful nonoverlapping groups to account for the diversity of industrial sectors. For the selection of international companies, we utilized the most recent Fortune 500 Global list (Fortune Media, 2019). With the objective of obtaining an appropriate sample size of 80 companies (Short et al., 2002), we selected four companies for each of the 20 industrial sectors, which are specified by Fortune Media. We conducted a systematic data collection process to examine companies' text-based and AI-enabled contact channels. To this end, companies' websites were visited and examined from a customer perspective to capture the types of text-based channels, characteristics of service interactions, and sequence of service processes via descriptions, process models, and screenshots. The subsequent qualitative analysis involved independent coding of documented case data by two researchers. With the help of the dimensions from the first iteration, we discovered that merely nine of 80 companies operating in seven sectors utilize AI for service encounters (see Appendix Table A1). Based on these insights, several characteristics were identified and merged into two additional dimensions for the taxonomy: *service processes* and *level of AI activity*.

Iteration 3: In the light of service stages with (frontstage) and without (backstage) direct customer contact, we examined 16 market solutions for AI-based customer service with AI-based customer service software. With reference to Gartner's Magic Quadrant (Gartner, 2020), in which vendors are evaluated based on their market positioning, leading, challenging, and visionary, solutions were selected and compared with entries from two suitable databases (capterra.com/customer-service-software, quicksprout.com/best-customer-service-software). For a structured data collection, we analyzed the websites of all vendors to document information in the form of reports, videos, and images. Qualitative analysis of these data, again conducted independently by two researchers, led to three additional dimensions: *performance monitoring*, *hybrid inquiry handling*, and *data and knowledge source*.

Iteration 4: The inclusion of additional dimensions in the preceding iteration required an additional empirical investigation. Therefore, similar to iteration three, a sample specifically focusing on conversational AI market solutions for the frontstage was produced. By using a practice-oriented evaluation from Forrester Research (Jacobs et al., 2019) and entries from two databases (g2.com/categories/conversational-intelligence, capterra.com/conversational-ai-platform-software), suitable solutions were identified. The resulting sample comprises 14 vendors, excluding duplicates from iteration three. The analysis of collected information via vendors' websites did not result in additional dimensions. Accordingly, in this iteration, the development phase was concluded as all objective ending conditions by Nickerson et al. (2013) were met. To prepare the evaluation of subjective ending conditions, we consolidated the taxonomy by inductively determining and ordering five meta-dimensions (*service context*, *capabilities*, *deliverables*, *integration*, and *intelligence*), which aggregately describe the content of the derived dimensions.

4.2 Ex-ante evaluation of subjective ending conditions

To ensure usefulness and applicability for research and practice, we assessed the content of the taxonomy with an ex-ante evaluation (Szopinski et al., 2019; Kundisch et al., 2021). Therefore, a mixed-method survey was utilized to collect quantitative and qualitative data from experts. To this end, our questionnaire included the taxonomy from iteration four with definitions for meta-dimensions, dimensions, characteristics, and questions covering the five subjective ending conditions (concise, robust, comprehensive, extendible, and explanatory) proposed by Nickerson et al. (2013). These ending conditions were each evaluated with a five-point Likert scale (from 1 (strongly disagree) to 5 (strongly agree)) and open-ended questions to receive extensive evaluation output and qualitative feedback for improvement. As the taxonomy is intended to guide researchers and practitioners alike in making design decisions to integrate AI into customer service, a heterogeneous group of experts from science (professor IS (ES1), research associates IS (ES2, ES4, ES5), associate professor IS (ES3)) and practice (machine learning engineer (EP1), senior architect (EP2), IS agent (EP3), software developer (EP4), software architect (EP5)) was recruited. For the selection, a purposive sampling strategy was chosen to obtain individuals who have (1) profound experience in taxonomy development and/or (2) knowledge about the role and deployment of AI in customer service.

By defining these selection criteria, relevant insights concerning content and formal aspects of the taxonomy could be derived. The analysis of the quantitative data delivered means and medians above 4.0 for the five subjective ending conditions: **concise** (*M* = 4.00; *SD* = 0.74; *Mdn* = 4), **robust** (*M* = 5.00; *SD* = 0.52; *Mdn* = 5), **comprehensive** (*M* = 4.00; *SD* = 0.52; *Mdn* = 4), **extendible** (*M* = 5.00; *SD* = 0.97; *Mdn* = 5) and **explanatory** (*M* = 4.00; *SD* = 0.52; *Mdn* = 4). These ratings at good to excellent level and the low dispersion of data illustrate the usefulness and applicability of the content and structure of the taxonomy. With respect to experts' qualitative comments, the analysis of data revealed recommendations for improvement that were implemented as follows. The label for the second dimension was changed from "Service Processes" to "Service Process Continuity" and the definition adapted (ES1). The definitions for the three characteristics of the third dimension were adjusted to clarify their focus (ES1, ES4). The description of the sixth dimension was extended to specify the meaning of the two characteristics. (ES4). The definitions for the tenth dimension and its two characteristics (ES1) and the characteristics of the eleventh dimension were refined (ES4, EP2, EP1). For the meta-dimension "Capabilities" the definition was refined (ES2), whereas the definition of the meta-dimension "Deliverables" was extended (ES2). These adjustments refer to refinements of content through adapting and extending definitions of meta-dimensions, dimensions, and characteristics. Thus, the objective ending conditions were still fulfilled.

5 Taxonomy of AI Integration into Customer Service

After four development iterations and content-related revisions initiated by the ex-ante evaluation, the final version of the taxonomy encompasses 12 dimensions, and 32 characteristics organized into five meta-dimensions (see Figure 3). Following Püschel et al. (2016), we classified the characteristics of each dimension as either mutually exclusive or non-exclusive to create a clearly structured and concise taxonomy. By establishing clear and delimited definitions, redundancy was counteracted to allow for the selection of a confined set of characteristics. To structure the taxonomy, we arranged the meta-dimensions in sequential order of their application for analysis and design to facilitate design decisions for the integration of AI for service delivery into customer service contexts. With *service context*, the application area of AI in customer service is determined. Subsequently, AI's *capabilities* are defined to determine the *deliverables* in the form of distinct outputs. By specifying the *integration* of AI, the interaction with customers and SEs, the appearance and behavior are defined. Concluding, the *intelligence* of AI is determined in accordance with the previous design decisions. In the following sub-sections, we present and describe the dimensions and characteristics for each of these meta-dimensions with justificatory references from research and practice (see Appendix Table A1 for practice references).

Service context: Based on the service context, the deployment of AI in customer service is determined in relation to *service stages* (D_1) and the nature of *service process continuity* (D_2). With respect to ***service stages***, AI can be utilized in the *frontstage* (D_1,C_1) to handle inquiries in direct contact with customers (Robinson et al., 2020; Fingerle et al., 2002). The application of AI in the *backstage* (D_1,C_2) involves processing of inquiries without direct customer contact (Zhang et al., 2020; Campbell et al., 2020). Associated with the deployment of AI in service stages is the determination of the type of ***service process continuity***, which refers to the temporal alignment of AI-integrated service delivery processes. *Disconnected* (D_2,C_1) processes imply unconnected inquiry processing steps between service stages involving SEs and AI with time lags and/or contact channel switches (I2U, I2W, I2WD). A *connected* (D_2,C_2) process continuity represents a direct connection between the service stages for request processing steps involving SEs and AI (I2N, I2AD, I2C, I2AM, I2AT, I2H).

MD	Dimensions		Characteristics			
Service Context	*D_1:* Service Stages	NE	Frontstage	Backstage		
	D_2: Service Process Continuity	NE	Disconnected	Connected		
Capabilities	*D_3:* AI Role	NE	Support	Augmentation	Performance	
	D_4: Task Type	NE	Mechanical	Analytical	Intuitive	Empathetic
Deliverables	*D_5:* Knowledge and Data Insights	NE	Inquiry-related	Process-focused	Customer-related	Socio-emotional
	D_6: Performance Monitoring	NE	Human Agent Monitoring	AI Monitoring		
Integration	*D_7:* Hybrid Inquiry Handling	ME	Simultaneous	Consecutive - toward human	Consecutive - toward AI	Consecutive - alternating
	D_8: Level of AI Activity	NE	Reactive	Proactive		
	D_9: Form of AI Appearance	ME	AI-enabled agent	Embedded AI		
	D_{10}: AI Transparency to Customers	ME	Unknown	Known		
Intelligence	*D_{11}:* Data and Knowledge Processing	NE	Machine Learning	Rule-based Reasoning		
	D_{12}: Data and Knowledge Source	NE	Input before Interaction	Input during Interaction	Input after Interaction	

Note: MD = meta-dimension; ME = mutually exclusive; NE = non-exclusive

Figure 3. Taxonomy of AI integration into customer service.

Capabilities: The scope of application for AI in customer service is guided by its capabilities, which are subdivided into the dimensions *AI role* (D_3) and *task type* (D_4). Regarding the ***role AI*** plays in service delivery, a distinction can be made between support, augmentation, and performance. AI can provide *support* (D_3,C_1) to deliver service by executing and handing over results of (sub-)tasks (Canhoto and Clear, 2020; Ostrom et al., 2019; Keyser et al., 2019). By actively collaborating on a task with SEs, AI can *augment* (D_3,C_2) service delivery tasks (Xu et al., 2020; Amorim et al., 2019; Campbell et al., 2020; Ameen et al., 2021). Furthermore, AI can *perform* (D_3,C_3) (sub-)tasks autonomously (Canhoto and Clear, 2020; Macnish and Fernandez Inguanzo, 2019; Zhang et al., 2020; Göker and Roth-Berghofer, 1999). The utilization of AI capabilities also refers to different ***task types*** in customer service. When applied to *mechanical tasks* (D_4,C_1), AI can be used for standardizable, repetitive, routine, and transactional tasks that require consistency in execution (Canhoto and Clear, 2020; Huang and Rust, 2018). For tasks with an *analytical* (D_4,C_2) nature that require logical thinking and are executed based on data, information, and knowledge, AI can provide analytical functions (Huang and Rust, 2018; Canhoto and Clear, 2020). Furthermore, AI can be applied for *intuitive tasks* (D_4,C_3) that require experiential and context-based interaction and thinking. In addition, AI can be utilized for *empathetic tasks* (D_4,C_4) with a salient emotional and interactive character that requires empathy and emotional analytics (Canhoto and Clear, 2020; Huang and Rust, 2018).

Deliverables: In customer service, AI can produce two types of output as deliverables: *knowledge and data insights* (D_5) and *performance monitoring* (D_6). The ***knowledge and data*** AI can supply to customers and/or SEs relate to four different forms of insights. AI can provide knowledge and/or information that relate to the *content of an inquiry* (D_5,C_1) (Xu et al., 2020; Amorim et al., 2019). *Process-focused* (D_5,C_2) clues can be presented for service interactions (Canhoto and Clear, 2020; Amorim et al., 2019). Insights related to the customer can comprise *customer-related* (D_5,C_3) information (e.g., history of contact) (Libai et al., 2020; Campbell et al., 2020) or *socio-emotional* (D_5,C_4) insights related to customers' sentiments (Amorim et al., 2019; Canhoto and Clear, 2020). The ***performance monitoring*** for and with AI relates to *human agent monitoring* (D_6,C_1) or *AI monitoring* (D_6,C_2). The former provides insights on SEs' workload, inquiry volume, and trends (I3S, I3SN, I3M, I4AI, I3V, I3Z, I3S, I3CR). The latter refers to insights into AI's performance in terms of interaction behavior and the status of the knowledge base to identify potential for improvement (I4L, I4AV, I4IN, I3S, I4KO, I3V).

Integration: The representation and integration of AI into customer service encompass four dimensions: *hybrid inquiry handling* (D_7), *level of activity* (D_8), *form of appearance* (D_9), and *AI* *transparency to customers* (D_{10}). The ***hybrid inquiry handling*** determines the sequence, in which inquiries are handled by the SE and AI. On the one hand, the sequence can be *simultaneous* (D_7,C_1), i.e., the SE and AI are working together on an inquiry at the same time (I3SN, I3M, I3AP, I3F, I4EG, I3K, I4VS, I4O, I3P, I3SAP, I3Z, I4L, I4N, I4I, I4SF). On the other hand, the sequence can be *consecutive*, either *toward human* (D_7,C_2) or *toward AI* (D_7,C_3). Toward human, the AI handles the inquiry autonomously and forwards it to the SE once a determined condition is fulfilled, and vice versa toward AI (I3SN, I3Z, I3F, I4N, I4OA, I4IS, I4CO, I3E, I3C, I4IN, I4KO, I4L, I4VS, I4SF). A third alternative is a *consecutive-alternating* (D_7,C_4) sequence. In this case, the AI and SE handle the inquiry autonomously and hand it over to each other every time a determined condition is fulfilled (I4AI). The ***level of activity*** represents the activity behavior of the AI in interactions with SEs or customers. Either the AI is *reactive* (D_8,C_1) or *proactive* (D_8,C_2) in its behavior. When the AI is reactive, it is passive and interacts once it is triggered (I2U, I2C, I2N, I2AD, I2WD, I2W). When it is proactive, the AI is active and interacts of its own accord (I2AM). The ***form of AI appearance*** defines the form, in which AI appears in customer service. If the AI has an identity as agent with a virtual representation and interacts through natural language with SEs or customers, it is an *AI-enabled agent* (D_9,C_1) (Prentice and Nguyen, 2020; Xu et al., 2020; Campbell et al., 2020; Canhoto and Clear, 2020; Macnish and Fernandez Inguanzo, 2019; Svenningsson and Faraon, 2019; Gelbrich et al., 2020; Zhang et al., 2020). If it is integrated into platforms or applications in use and neither has an identity nor a visual representation, it represents an *embedded AI* (D_9,C_2) (Zhang et al., 2020; Chromik et al., 2020; Göker and Roth-Berghofer, 1999). The ***transparency of AI to customers*** refers to the degree, to which the presence of AI is apparent to customers. The customers are either not aware of AI's presence during service delivery, which makes it *unknown* (D_{10},C_1) (Canhoto and Clear, 2020; Aoki, 2021; Robinson et al., 2020), or they are aware of AI's presence, which makes it *known* (D_{10},C_2) (Canhoto and Clear, 2020; Robinson et al., 2020; Macnish and Fernandez Inguanzo, 2019; Svenningsson and Faraon, 2019; Aoki, 2021).

Intelligence: The intelligence of AI-integrated customer service is defined by the way it receives and handles data and knowledge for customer service tasks. With this, it covers two dimensions: *data and knowledge processing* (D_{11}) and *data and knowledge source* (D_{12}). The ***data and knowledge processing*** describes the underlying technology, which defines how AI processes information and knowledge. For one thing, AI can be trained and based on *Machine Learning* (D_{11},C_1) using learning algorithms for processing existing data toward pattern and entity recognition. This also covers the ability of AI to process and analyze natural language data to understand and generate natural language (Canhoto and Clear, 2020; Campbell et al., 2020). For another thing, AI can also be based on "if-then" pattern-matching rules through *rule-based reasoning* (D_{11},C_2) (Fingerle et al., 2002; Cheung et al., 2003; Göker and Roth-Berghofer, 1999). The ***data and knowledge source*** identifies the source from where the AI gets the data and knowledge. This data *input* can happen *before* (D_{12},C_1), *during* (D_{12},C_2), or *after* (D_{12},C_3) the *interaction*. First, the AI's knowledge base can be built by data and knowledge provided before the interaction (I4AV, I4CO). Then, the AI's knowledge base can continuously evolve through optimization based on and during the interaction (I4IS, I4AI, I4L, I4N, I4AI, I3P). And at last, AI's knowledge base can continuously evolve through implementing feedback and learnings after each interaction (I3E, I4KO, I4AV, I4IN, I4AI, I3F, I4CO).

6 Ex-Post Evaluation: Taxonomy Application

To adopt a rigorous evaluation strategy, we applied the framework by Szopinski et al. (2019) and chose the method 'illustrative scenario' to assess the coherence of the final taxonomy with the meta-characteristic. To this end, two real-world AI use cases were classified as objects with the taxonomy. To verify the validity of the taxonomy's purpose, on the one hand, a case was selected, where an AI-enabled agent in the form of a CA has already been implemented for service delivery in the frontstage (organization X). On the other hand, a case was chosen, in which the deployment of an embedded AI solution is planned to assist SEs in frontstage interactions (organization Y). To analyze the reliability of the taxonomy, two researchers and three practitioners utilized the taxonomy along the sequential order of meta-dimensions for design decisions. For organization X, the researchers and one practitioner with affiliation to the organization classified the existing AI use case. Two members from organization Y and the same researchers performed the classification for the planned AI use case in organization Y. The two researchers were enabled to classify the two use cases by a presentation of the core features derived from a qualitative data analysis based on eleven semi-structured interviews (organization X = five, organization Y = six) with business unit members, product owners, and documents about the IT architecture and modules. The results of the classification are presented in Table 1 by providing the rations of selected characteristics per dimension for each use case.

<table>
<tr><th colspan="12">Hit ratios for characteristics (X ; Y)</th></tr>
<tr><td colspan="6">D_1,C_1: 100 % ; 0 %</td><td colspan="6">D_1,C_2: 0 % ; 100 %</td></tr>
<tr><td colspan="6">D_2,C_1: 100 % ; 0 %</td><td colspan="6">D_2,C_2: 0 % ; 100 %</td></tr>
<tr><td colspan="4">D_3,C_1: 100 % ; 75 %</td><td colspan="4">D_3,C_2: 0 % ; 100 %</td><td colspan="4">D_3,C_3: 67 % ; 0 %</td></tr>
<tr><td colspan="3">D_4,C_1: 100 % ; 25 %</td><td colspan="3">D_4,C_2: 0 % ; 75 %</td><td colspan="3">D_4,C_3: 0 % ; 0 %</td><td colspan="3">D_4, C_4: 0 % ; 0 %</td></tr>
<tr><td colspan="3">D_5,C_1: 100 % ; 75 %</td><td colspan="3">D_5,C_2: 100 % ; 100 %</td><td colspan="3">D_5,C_3: 33 % ; 25 %</td><td colspan="3">D_5,C_4: 0 % ; 0 %</td></tr>
<tr><td colspan="6">D_6,C_1: 100 % ; 0 %</td><td colspan="6">D_6,C_2: 100 % ; 100 %</td></tr>
<tr><td colspan="3">D_7,C_1: 0 % ; 75 %</td><td colspan="3">D_7,C_2: 100 % ; 0 %</td><td colspan="3">D_7,C_3: 0 % ; 0 %</td><td colspan="3">D_7,C_4: 0 % ; 25 %</td></tr>
<tr><td colspan="6">D_8,C_1: 67 % ; 75 %</td><td colspan="6">D_8,C_2: 33 % ; 25 %</td></tr>
<tr><td colspan="6">D_9,C_1: 100 % ; 75 %</td><td colspan="6">D_9,C_2: 0 % ; 25 %</td></tr>
<tr><td colspan="6">D_{10},C_1: 0 % ; 100 %</td><td colspan="6">D_{10},C_2: 100 % ; 0 %</td></tr>
<tr><td colspan="6">D_{11},C_1: 100 % ; 100 %</td><td colspan="6">D_{11},C_2: 100 % ; 0 %</td></tr>
<tr><td colspan="4">D_{12},C_1: 100 % ; 75 %</td><td colspan="4">D_{12},C_2: 0 % ; 75 %</td><td colspan="4">D_{12},C_3: 100 % ; 75 %</td></tr>
</table>

Table 1. Classification Results of AI Use Cases.

For the use case of organization X, the practitioner and researchers agreed on all characteristics in nine dimensions; for eleven dimensions, they agreed on at least one characteristic. For the use case of organization Y, the practitioners and researchers agreed on all characteristics for five dimensions; in seven dimensions they agreed on at least one characteristic. Only for five characteristics in four dimensions in use case Y, classifications did not match. However, it is difficult to achieve perfect interrater agreement for the whole taxonomy regarding the option to choose more than one characteristic in most dimensions. With this, the classification of the two specific use cases along the characteristics of the taxonomy reveals a good reliability and well-suited applicability of the taxonomy for practice. Moreover, the achieved characterization of the two use cases with reference to their attributes indicates a substantial validity of the taxonomy. After classifying their use cases, we also asked the practitioners for further feedback on different aspects related to the application of the taxonomy. First, the taxonomy appears understandable and clear. Especially for the planning scenario, it provided ideas and perspectives to the development, which need to be considered. Second, practitioners found it easy to use, i.e., they knew where and how it can be applied in their real-world scenario. At last, they argued for good feasibility and applicability of the taxonomy indicating the usefulness of our taxonomy. Based on these insights, we can confirm the coherence of the final taxonomy with the meta-characteristic to facilitate researchers and practitioners in their analysis and design undertakings concerning design decisions for the integration of AI in service delivery processes for customer service.

7 Discussion and Conclusion

With the developed taxonomy, we provide a first structured and elaborated overview of relevant design choices to integrate AI into the front- and/or backstage of customer service contexts. The compilation of characteristics across five meta-dimensions and 12 dimensions systematizes scattered knowledge from research and commercial applications in the still evolving research field of AI-enabled service. Thereby, two current research streams focusing on conceptual or technological aspects are integrated. Based on and complementing these insights with data from practice, we present an in-depth analysis of pertinent aspects of how AI can be integrated into customer service (Benbya et al., 2021). In addition, we answer the call for an investigation of the mutual interrelation between AI and the social as well as technical systems in service organizations (Bock et al., 2020). By adopting a holistic, socio-technical perspective for the development, the taxonomy reveals changes in connection to AI integration referring to service processes spanning front- and backstage, division of labor, and interaction between humans and AI. In particular, the taxonomy emphasizes that different constellations of the entities customer, SE, and AI emerge depending on the design decisions to integrate AI. As AI is not yet capable of solving all types of inquiries independently in the frontstage, the service process comprises sections where all entities interact simultaneously or handovers are initiated, introducing a change in interaction partners. Accordingly, depending on the AI use case, specific task- and process-related dependencies arise between AI and SE, which in turn impact the interaction with customers. Similarly, the integration of AI in the backstage has an impact on SEs, as working practices change through interaction with AI. Building on the current state of research and practice of AI and its deployment in customer service, our taxonomy enables the classification of use cases that are planned to be scientifically investigated or developed and/or planned for deployment in practice. By providing a sequential order of design decisions that are organized along the meta-dimensions, the selection of a confined set of characteristics regarding service context, capabilities, deliverables, integration, and intelligence of a specific AI use case is facilitated. In this respect, the results of the ex-post evaluation demonstrate a good handling of the taxonomy. Furthermore, a valid and reliable classification of AI use cases for customer service can be achieved by utilizing the taxonomy. These results underline the completeness, applicability, and effectiveness of the created taxonomy. Accordingly, our rigorously developed and evaluated taxonomy provides prescriptive design knowledge on how AI can be integrated into customer service to sustain the design and implementation process as well as the analysis of AI-based customer service applications (Kundisch et al., 2021; Gregor and Hevner, 2013).

The presented taxonomy provides many-faceted theoretical and practical contributions. Regarding research, we created, to the best of our knowledge, the first taxonomy that summarizes scientific insights and the status quo in practice on characteristics for the integration of AI in customer service. As a result, the structure for classification improves and fosters understanding in this research domain regarding characteristics for AI-infused customer service. Hence, these insights might encourage the extension and continuation of research for progressing AI-powered customer service solutions. Furthermore, it serves as a tool to systematically derive relevant and specific design decisions by incorporating various aspects that should be considered for the development of AI solutions. Moreover, we contribute insights on the integration of AI for, both, the external (frontstage) and internal (backstage) customer service environment (see Figure 4).

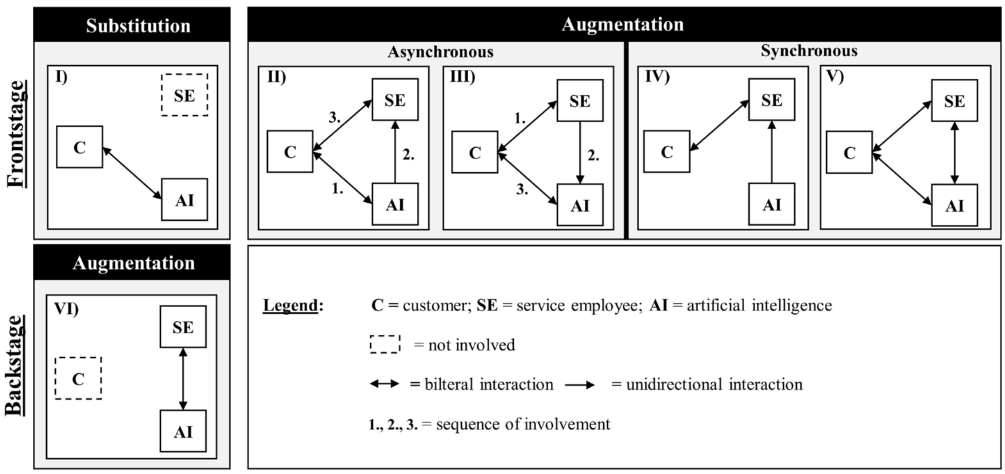

Figure 4. AI infusion archetypes covering front- and backstage.

We validate existing infusion archetypes from Keyser et al. (2019) and Ostrom et al. (2019). More specifically, substitution (see Figure 4, I) and augmentation (see Figure 4, IV & V) of SEs by AI in frontstage service encounters could be confirmed. Furthermore, we identified additional infusion archetypes. In the frontstage, we introduce asynchronous augmentation (see Figure 4, II & III) where inquiries are handled consecutively with handovers from AI toward SEs or vice versa in cases a predetermined condition is fulfilled (e.g., imminent failure of AI). In addition, for the customer service backstage, we establish an infusion archetype of the type "augmentation" for the first time (see Figure 4, VI). For this archetype, the focus lies on AI use cases that facilitate service processes and tasks without direct customer contact, which are also of eminent relevance for service delivery. In this context, AI is deployed to augment SEs in processing inquiries by, inter alia, displaying suitable information that might facilitate decision-making.

In terms of practice, IT management and development can use the categorization to analyze deployed solutions to uncover gaps or plan implementation by determining characteristics of a specific use case. Therefore, the taxonomy provides a suitable blueprint to structure AI integration initiatives by classifying projects along the dimensions. Especially for planning AI integration, it adds more ideas and perspectives to be considered for the development. In fact, practitioners benefit from insights, which shed light on relevant AI-related characteristics, e.g., its role and task, which have been extensively developed by researchers. In addition, for integrating AI in their customer service processes, they can refer to state-of-the-art solutions we provide from practice. Eventually, the sequential order of our taxonomy can guide practitioners either through planning, executing, or analyzing AI integration for their specific use case.

Besides the promising contributions of this research, there are a few limitations to consider. First, our empirical data is based on a representative sample of solutions from practice. However, selecting and adding different or more solutions to our sample of empirical solutions could reveal and lead to different or more insights. Furthermore, even though we considered three domain-relevant IS databases, the results might vary when selecting different or more databases. This also applies to changes of our search string. Eventually, the selected samples of empirical cases and research contributions define and limit the taxonomy with its dimensions and characteristics. At last, regarding the reliability of our taxonomy, we could only consider two illustrative use case scenarios. To achieve and establish reliability, more practitioners may use and apply the taxonomy to their specific use cases. These limitations and obtained insights give rise to future research. In general, future work can build on our taxonomy, validate, or extend dimensions and characteristics. Considering our ex-post evaluation, we call for descriptive research to specifically enhance the applicability of the taxonomy and better showcase what design decisions must be made for the integration of an AI solution in customer service. Furthermore, different aspects can be addressed in more detail with respect to the individual meta-dimensions of the taxonomy. First, in terms of service context, the current state of knowledge indicates that AI solutions for backstage customer service are, so far, under-researched. In this context, research should focus on the development and design of AI solutions that promote hybrid service delivery without direct customer contact. Related to this, solutions should be developed that enable an AI-integrated, seamless, and efficient processing of inquiries across front- and backstage involving AI and SEs. Additionally, research should focus on mechanisms to establish acceptance toward AI and incentive systems for SEs and customers to utilize AI for service delivery. Lastly, approaches for learning scenarios are needed that allow for a continuous development of the competencies and knowledge base of the AI.

Appendix

Iteration 2			
Company	**URL**	**Company**	**URL**
Amazon (I2AM)	www.amazon.com/gp/help/customer/display.html?nodeId=508510&ref_=nav_cs_customerservice_2bf4fe8c5ec54e6bae2d1c24043f012b	United Parcel Service (I2U)	www.ups.com/us/en/help-support-center.page
China Mobile Communication (I2C)	eshop.hk.chinamobile.com/en/corporate_information/Customer_Service/index.html	AT&T (I2AT)	www.att.com/support/topic

Home Depot (I2H)	www.homedepot.com/c/customer_service	Walmart (I2W)	www.walmart.com/help
Walt Disney (I2WD)	help.shopdisney.com/hc/en-us	Adidas (I2AD)	www.adidas.com/us/help
Nike (I2N)	www.nike.com/us/help		
Iteration 3 *AI-based Customer Service Software*			
Salesforce (I3S)	www.salesforce.com/products/service-cloud/features	Pegasystems (I3P)	www.pega.com/products/platform/email-bot
Service Now (I3SN)	www.servicenow.com/content/dam/servicenow-assets/public/en-us/doc-type/resource-center/data-sheet/ds-customer-service-management.pdf	Microsoft (I3M)	dynamics.microsoft.com/de-de/customer-service/overview
Zendesk (I3Z)	support.zendesk.com/hc/en-us/articles/360057455393?_ga=2.178859299.64267010.1608134017-830973252.1608134017	Oracle (I4OA)	www.oracle.com/cx/service/b2c
SAP (I3SAP)	www.sap.com/products/service-cloud.html?btp=0106c0a9-f57d-429f-ab94-bd740a7f68e8	Freshworks (I3F)	freshdesk.com/freddy-ai-for-cx
Verint Systems (I3V)	www.verint.com/customer-engagement-cloud	Appian (I3AP)	appian.com/platform/overview.html
Creatio (I3C)	www.creatio.com/service	eGain (I3E)	www.egain.com/solutions/contact-centers
SugarCRM (I3S)	www.sugarcrm.com/de/solutions/sugar-serve	Kustomer (I3K)	www.kustomer.com/product/customer-service
Zoho (I3Z)	www.zoho.com/desk/zia.html	CRMNEXT (I3CR)	www.crmnext.com/crm/service
Iteration 4 *Conversational AI*			
LogMeIn (I4L)	www.bold360.com	Salesforce (I4SF)	www.salesforce.com/products/service-cloud/automated-customer-service
Nuance (I4N)	www.nuance.com/index.html	Verint Systems (I4VS)	www.verint.com/engagement/our-offerings/solutions/intelligent-self-service/virtual-assistant
Interactions (I4I)	www.interactions.com	eGain (I4EG)	www.egain.com/products/chatbot-virtual-assistant-software
Inbenta (I4IN)	www.inbenta.com/products/chatbot	Kore (I4KO)	kore.ai
Aivo (I4AI)	www.aivo.co	Cognigy (I4CO)	www.cognigy.com
Avaamo (I4AV)	avaamo.ai	IPSoft (I4IS)	amelia.com
247ai (I4AI)	www.247.ai	Omilia (I4O)	omilia.com

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