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More than FAQ! Chatbot Taxonomy for Business-to-Business Customer Services

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Abstract. Chatbots are becoming increasingly important in the customer service sector due to their service automation, cost saving opportunities and broad customer satisfaction. Similarly, in the business-to-business (B2B) sector, more and more companies use chatbots on their websites and social media channels, to establish sales team contact, to provide information about their products and services or to help customers with their requests and claims. Customer relations in the B2B environment are especially characterized by a high level of personal contact service and support through expert explanations due to the complexity of the products and service offerings. In order to support these efforts, chatbots can be used to assist buying centers along the purchase decision process. However, B2B chatbots have so far only been marginally addressed in the scientific human-computer interaction and information systems literature. To provide both researchers and practitioners with knowledge about the characteristics and archetypal patterns of chatbots currently existing in B2B customer services, we develop and discuss a 17-dimensional chatbot taxonomy for B2B customer services based on Nickerson et al. [1]. By classifying 40 chatbots in a cluster analysis, this study has identified three archetypal structures prevailing in B2B customer service chatbot usage.

Keywords: Chatbot Taxonomy, Business-to-Business, Customer Services.

1 Introduction

Especially in B2B segments, customer care is seen as an essential part of any business service or product commercialization, while often being one of the most resource-intensive units within a business [2–4]. Customer service priorities are driven by the expectation of a simple and fast service, which must be as personalized and individualized as possible [2]. To remain competitive, organizations are currently investing heavily in digital and innovative self-service customer care solutions [3, 5]. In this context, chatbots offer enormous savings potential in customer care effort and costs through service automation [3]. In recent years, due to the further development of natural language processing and machine learning, chatbots are being increasingly used in application areas within the customer service sector, such as claim diagnosis or replacement provision

[2]. Even in the B2B sector, which is often characterized by long decision-making processes and complex products and services, chatbots are becoming extensively popular. Although single articles focusing on specific aspects and use cases of B2B customer service chatbots have been published [6–8], this does not reflect the theoretical and practical level in which a growing number of companies are discovering chatbots as a communication channel for themselves. What is much more lacking is an overview of how chatbots are used in B2B customer service in practice and what functions and characteristics they have. A taxonomy can help both practice and research to identify utilization possibilities as well as serve as a foundation for B2B chatbot research. Hence, we address the following research questions (RQ):

RQ1: Which conceptually grounded and empirically validated design elements for B2B customer service chatbots exist?

RQ2: Which archetypes can be empirically deduced for B2B customer services chatbots?

To answer the RQ1, we develop a chatbot taxonomy for B2B customer services by following the research approach of Nickerson et al. [1]. The taxonomy is developed in four iterations based on scientific literature about customer service chatbots and on empirical data obtained through the classification of 40 real-world B2B chatbots. To answer RQ2 and to show the status quo, we additionally perform a cluster analysis to identify B2B customer service chatbot archetypes. This is followed by a discussion of the results, including recommendations, implications, and limitations before the conclusions.

2 Chatbot Literature for Customer Services

Customer service is defined as the supply of information, help and support to the customers of an enterprise [9, 10]. Due to their efficiency, cost reduction and automation potential, chatbots as a self-service channel in customer service have received widespread attention, in both research and practice [3, 5]. Sangroya et al. [2] consider chatbots in the role of an intermediary between a customer and a customer care ecosystem with several services in that the chatbot interacts with the customer, identifies the needs, requirements, and emotions of the user. The chatbot as a controlling agent conducts a dialogue with the customer in order to detail certain subtasks by asking questions and performs the tasks for the customer by deciding which channel in the customer care environment is suitable for examining the request [2]. Essential drivers of dialogues with customer service chatbots are the users' questions, efficient and concise answers of the chatbots and the opportunity to be connected to a human employee if the dialogue is not satisfactory [5]. In principle, chatbots are not intended to replace the human customer service employee, rather chatbots are seen as the assistance of a human employee contributing to efficiency and effectiveness by prioritizing requests, answering automatically and processing subtasks before transferring or escalating to a human employee [3]. This handling is also called tiered approach [9]. Since the customer usually enters into a dialogue with the chatbot with a problem or a task, the dialogue with customer service chatbots is usually user-driven and designed for short-term [10]. Due to an increasing demand and usage of technology-based self-service channels for customer service purposes in practice [5], several scientific articles have been published dealing with quality aspects (e.g., [5]) communication styles (e.g., [11, 12]), user requirements (e.g., [3, 9]) and design aspects (e.g., [4, 13]) of chatbots in the customer service sector.

Traditional marketing distinguishes between business-to-customer (B2C) markets, where companies market their products and services to individual private consumers, and B2B markets, where companies sell their products and services to other businesses, often involving several people, also called buying centers, into the process, which in turn influences the use of communication channels and the communication itself [14]. Referring to the chatbot environment, however so far, only sporadically articles exist about the use of customer service chatbots in the B2B sector. Damnjanovic [8] has sketched application areas of chatbots along the B2B customer acquisition processes focusing on the interaction and co-existing of automated services and salespeople. According to the researcher, the role is to provide information to the potential customers and collect data about the potential customers for salespeople [8]. In the awareness and interest phase of a B2B sales funnel, chatbots can give the potential customers more detailed information about the desired offers, as well as create awareness and interest for the products and offerings of the organization, while first information about potential customers, their speech patterns and preferences can be collected for the company [8]. Whereas in the conversion and qualification phase as well as in the closing phase, the focus lays on proving the potential customer with detailed and personalized information and offers, which is delivered merely by sales representatives on basis of the information collected through the interaction with the chatbot [8]. Gnewuch et al. [6] focused on presenting insights from developing a B2B chatbot for a service provider in the energy industry. Rossmann et al. [7] focused on developing a performance measurement model by comparing results of a hotline and a chatbot in a B2B manufacturing context. These are however only very specific use cases and the use of customer service chatbots in the B2B area has not yet been sufficiently considered [6]. An article, offering a holistic view of B2B customer service chatbots in form of a taxonomy is missing.

Several chatbot taxonomies have been published in the scientific literature in recent years, but most of them have carried out a general analysis of chatbots (e.g., [15]) or classified specific areas such as collaborative work (e.g., [16]) or platforms for conversational agent development (e.g., [17]). Følstad et al. [10] developed a chatbot classification by concentrating on two typology dimensions ‘‘duration of relation’’ and ‘‘locus of control’’ while classifying 57 chatbots within the customer support and three further domains. Feine et al. [18] concentrated on building a taxonomy of social cues of conversational agents focused on verbal, visual, auditory and invisible aspects. Janssen et al. [15] developed a chatbot taxonomy classifying 102 domain-specific chatbots within 17 dimensions while focusing on the perspectives intelligence, interaction and context. During development, the authors aimed to examine chatbots from the most wide-spread application areas, which they in turn classified into six application domains. 21% of the sample was classified into the characteristic e-customer service and 48% of these e-customer service chatbots were assigned to the archetype "utility expert chatbot" [15].

In summary, it can be concluded that there are already some chatbot taxonomies, which provide insights into customer service chatbots. However, all chatbot taxonomies lack the focus B2B customer service specifications. Since we believe that there are further specific characteristics as well as application scenarios where chatbots are used in B2B sector, the goal is to develop a taxonomy that represents the characteristics of chatbots for B2B customer services.

3 Research Design, Methodology, and Results

3.1 Taxonomy Development Procedure

In order to develop a taxonomy of design elements for B2B customer service chatbots, we followed the framework of Nickerson et al. [1, p. 340]. According to Nickerson et al. [1], a taxonomy (T) consists of a set of dimensions with each dimension (D_i) having its own subset (k_i) of characteristics ($C_{i,j}$). One dimension must consist of at least two characteristics. Each object classified according to the taxonomy must have exactly one characteristic of each dimension, not more or less. Nickerson et al. [1] illustrate the former conditions with the following formula:

$$T = \{D_{i,} i = 1, \dots, n | D_i = \{C_{ij}, j = 1, \dots, k_i; k_i \geq 2\}$$

The applied taxonomy development framework comprises seven iterative steps. First, a meta-characteristic must be set for the taxonomy, meaning the focus of the taxonomy must be defined. In this case the meta-characteristic are the design elements for B2B customer service chatbots, i.e., the socio-technical features defining the structural and functional composition of B2B customer service chatbots. Second, a set of ending conditions must be determined, since the process is iterative, without predefined ending conditions the development of a taxonomy can be an infinite process. In this case the ending condition chosen correspond to all the objective and subjective ending conditions proposed by Nickerson et al. [1, p. 344]. Posteriorly, in line with Nickerson et al. [1] two viable approaches can be used for the creation of the taxonomy: empirical-to-conceptual or conceptual-to-empirical. These approaches can be applied on an alternating basis until the adopted ending conditions are met and therefore, the development process of the taxonomy can be regarded as finished.

To integrate the extant theoretical knowledge in the field of chatbots and empirical findings related to real-world B2B service chatbots, we adopted a conceptual-to-empirical approach to begin the taxonomy development process. Accordingly, we performed a literature review and the findings thereof were used for the deductive conceptualization of the dimensions and characteristics for an initial taxonomy of potential relevant dimensions and characteristics. Subsequently, we adapted this initial taxonomy through an iterative empirical analysis of a total set of 40 existing B2B chatbots in customer service. A list of the examined chatbots for the taxonomy development is available upon request. After four iterations, we complied with all ending conditions (see Table 1) and achieved a final taxonomic structure. Below we delineate the actions conducted in each iteration.

Table 1. Compliance with the adopted ending conditions

Iteration 1	Iteration 2	Iteration 3	Iteration 4	Ending conditions
				Subjective ending conditions (Nickerson et al. [1])
		●	●	Mutually exclusive: no object has two different characteristics in a dimension
		●	●	Collectively exhaustive: each chatbot has at least one characteristic in each dimension
			●	Concise: dimensions and characteristics are limited
	●	●	●	Robust: sufficient number of dimensions and characteristics
			●	Comprehensive: identification of all (relevant) dimensions of an object
●	●	●	●	Extendable: possibility to easily add dimensions and characteristics in the future
		●	●	Explanatory: dimensions and characteristics sufficiently explain the object
				Objective ending conditions (Nickerson et al. [1])
	● (5)	● (12)	● (23)	All chatbots (or a representative sample) were analyzed
			●	No object was merged or split
		●	●	At least one object assigned to each characteristic
			●	No new dimensions or characteristics were added
			●	No dimensions or characteristics were merged or split
●	●	●	●	Every dimension is unique
●	●	●	●	Every characteristic within the dimension is unique
		●	●	Every combination of characteristics is unique

3.2 Iteration 1

In this iteration, following a conceptual-to-empirical approach, a first taxonomic structure was conceptualized using the knowledge derived from a review of the scientific literature on chatbots in customer service. The scope of the literature review included the databases of AISeL, IEEE Xplore, SpringerLink, ACM, and JSTOR. We applied the search string (“chatbot” OR “conversational agent”) AND (“customer service” OR “customer support”) within the aforementioned databases that yielded a total of 565 articles within the five databases. Thereby, by reading title and abstract, and applying backward, forward and similarity search, we identified a total of 14 relevant articles providing features and functions of chatbots in customer service which were used as a basis for the creation of the first dimensions and characteristics. Most of ending conditions were not fulfilled in this iteration because of its conceptual nature (see Table 1). The first iteration resulted in 18 dimensions and 53 mutually exclusive characteristics drawn from the literature as detailed in Table 2.

Table 2. Taxonomy dimensions conceptualized from the literature

Dimension	[3]	[4]	[5]	[8]	[9]	[13]	[19]	[20]	[21]	[22]	[23]	[24]	[25]	[26]
D_1 Business integration			●											●
D_2 Access to business data							●							
D_3 Dialogue structure	●	●				●		●			●			
D_4 Conversation beyond Q&A interaction			●							●				●
D_5 Data policy	●													
D_6 Handoff to human agent	●				●				●		●	●		
D_7 Small talk		●								●			●	●
D_8 Features presentation							●							
D_9 Conversational memory							●	●	●					
D_{10} Human-like avatar					●									
D_{11} Content related service						●								
D_{12} Account related services						●								
D_{13} Account authentication						●								
D_{14} Requests													●	
D_{15} Question personalization				●				●					●	
D_{16} Customer service orientation												●		
D_{17} User assistance design										●				●
D_{18} Context management						●								

3.3 Iteration 2

In the second iteration, an empirical-to-conceptual approach was chosen and a first random sample of 5 chatbots for B2B customer service (see Table A.1 in online appendix, http://bit.ly/Supplementary_Material) presented in chatbots conferences (e.g., [27]) were examined to adapt the conceptual dimensions and characteristics abstracted in the first iteration. Based on the empirical analysis of chatbots, first we eliminated the dimensions that were found to be not relevant for describing the set of analyzed chatbots (i.e. $D_4, D_8, D_9, D_{12}, D_{17}, D_{18}$). The former dimensions have been described in the literature, however they could not be confirmed in the empirical review. For example, socio-technical features as the presence of conversational memory in chatbots has been described in the literature (see e.g., [19–21]), but was not present in any of the chatbots examined. Furthermore, we added to the initial taxonomy 4 empirically identified dimensions of chatbots in B2B customer service, composed in the following manner: *service/product information= {no, yes}; success stories= {no, yes}; book/show a demo= {no, yes}; and career information= {no, yes}.* Since all ending conditions were not achieved, an additional iteration was required.

3.4 Iteration 3

Subsequently, we conducted a further empirical-to-conceptual approach. For this purpose, we additionally examined 12 chatbots from the B2B customer service (see Table A.1 in online appendix). The chatbots were drawn from chatbot databases (e.g., [28]), websites of large and medium-sized B2B companies and customer lists from chatbot providers. In this iteration, we identified 6 new dimensions allocating 14 new characteristics as follows: *industry classification= {financial services industry, manufacturing industry, marketing industry, software industry}; pricing= {no, yes}; support question/ticket= {no, yes}; callback request= {no, yes}; billing details= {no, yes}; user* *management= {no, yes}*. Given the similar nature of the new identified function-related dimensions, we merged the dimension of *book/show a demo, callback request* into an overarching dimension named *action request*, and similarly, the dimensions of s*upport question/ticket, billing details, user management* were consolidated into a wide-ranging dimension designated as *service request.* Likewise, the dimensions of service/product information and success stories were found to be redundant and were therefore merged. Furthermore, 5 new characteristics were added to the dimensions of account authentication (i.e., $C_{i,j}$ *optional*); action request (i.e., $C_{i,j}$ *both, none*); service request (i.e., $C_{i,j}$ *multiple, none*) to increase their descriptive power. After that the final conditions were checked again. Since new dimensions were identified and new characteristics were added, all ending conditions have not yet been satisfied in this iteration.

3.5 Iteration 4

Since not all ending conditions were fulfilled in the previous iteration, we performed an additional empirical-to-conceptual iteration. For this purpose, a larger random sample consisting of 23 chatbots from the B2B customer service were examined (see Table A.1 in online appendix). The examined chatbots identified through and assessment focused on blogs providing B2B chatbot use cases or comparing and rating chatbots or chatbot platforms. In this iteration, no new dimensions and characteristics of B2B customer service chatbots could be identified, as well, no dimensions or characteristics were eliminated, merged or split. Hence, after this iteration all objective and subjective ending conditions proposed by Nickerson et al. [1] were fulfilled and the taxonomy development process was completed. The final chatbot taxonomy for B2B customer services consisting of 17 dimensions and 45 characteristics is presented in Table 3, along with the distribution of the characteristics identified within the sample of 40 classified B2B customer service chatbots.

Table 3. Final chatbot taxonomy for B2B customer services

Dimensions D_i	**Characteristics $C_{i,j}$ (% distribution)**		
***D_1* Industry classification**	$C_{1,1}$ Financial services industry (5%) $C_{1,3}$ Marketing industry (10%)		$C_{1,2}$ Manufacturing industry (22%) $C_{1,4}$ Software industry (63%)
***D_2* Business integration**	$C_{2,1}$ No (68%)		$C_{2,2}$ Yes (32%)
***D_3* Access to business data**	$C_{3,1}$ No (90%)		$C_{3,2}$ Yes (10%)
***D_4* Dialogue structure**	$C_{4,1}$ Predefined (48%)	$C_{4,2}$ Open (15%)	$C_{4,3}$ Both (37%)
***D_5* Data policy**	$C_{5,1}$ Not provided (65%)		$C_{5,2}$ Provided (35%)
***D_6* Handoff to human agent**	$C_{6,1}$ Not possible (12%)		$C_{6,2}$ Possible (88%)
***D_7* Small talk**	$C_{7,1}$ Not possible (80%)		$C_{7,2}$ Possible (20%)
***D_8* Human-like avatar**	$C_{8,1}$ No (90%)		$C_{8,2}$ Yes (10%)
***D_9* Content related service**	$C_{9,1}$ Content advertisement (70%)		$C_{9,2}$ Content consumption (30%)
***D_{10}* Account authentication**	$C_{10,1}$ Not required (63%)	$C_{10,2}$ Optional (12%)	$C_{10,3}$ Required (25%)
***D_{11}* Question personalization**	$C_{11,1}$ None (12%) $C_{11,3}$ Personalized account questions (30%)		$C_{11,2}$ FAQ (50%) $C_{11,4}$ Highly personalized questions (8%)
***D_{12}* Customer service orientation**	$C_{12,1}$ Knowledge-oriented (53%)		$C_{12,2}$ Task-oriented (47%)
***D_{13}* Company information**	$C_{13,1}$ No (70%)		$C_{13,2}$ Yes (30%)
***D_{14}* Service/product information**	$C_{14,1}$ No (15%)		$C_{14,2}$ Yes (85%)
***D_{15}* Pricing**	$C_{15,1}$ No (80%)		$C_{15,2}$ Yes (20%)
***D_{16}* Action request**	$C_{16,1}$ Book/show a demo (8%) $C_{16,3}$ Both (35%)		$C_{16,2}$ Callback request (32%) $C_{16,4}$ None (25%)
***D_{17}* Service request**	$C_{17,1}$ Support question /ticket (32%) $C_{17,17}$ Multiple (10%)	$C_{17,2}$ Billing details (3%)	$C_{17,3}$ User management (3%) $C_{17,5}$ None (52%)

To ease interpretation and increase the explanatory power of the taxonomy, we describe the characteristics that may not be self-explanatory in the Appendix Table 5.For example, the dimensions D_{16} action request and D_{17} service request describe respectively the functional actions or service inquires related to customer service elements present in the analyzed chatbots (e.g., pricing, user management).

To assess the inter-coder reliability of our results, a random sample of 8 chatbots was again classified by all authors involved in the coding process and, subsequently, the quality of the inter-coder agreement was evaluated using the kappa coefficient of Fleiss [29]. As a result, a kappa coefficient of 0.64 was obtained, which indicates a substantial strength of inter-coder agreement [30].

4 Findings and Chatbot Archetypes

To identify which clusters are represented within our dataset, we applied the Ward [31] algorithm that calculates the distances between all elements of our dataset [32]. The Ward algorithm has the advantage that it can be used without having to specify a certain number of clusters in advance, as opposed to, e.g., the K-means or K-medois algorithms, which are non-hierarchical [15]. However, in the scientific literature it is recommended to combine hierarchical algorithms and non-hierarchical partitioning algorithms to unite the advantages of both algorithm types [33]. Using the dendogram obtained by means of the Ward algorithm, we have graphically determined the number of archetypes based on the distances between the groupings (see Figure 1). Within the dendogram (see Figure 1), a first splitting is visible on the height of 2.1, followed by a split at approximately 1.75 and 1.5. Therefore, we investigated the possibility of three and four archetypes using the partitioning K-means algorithm before deciding on three archetypes based on the content-related plausibility.

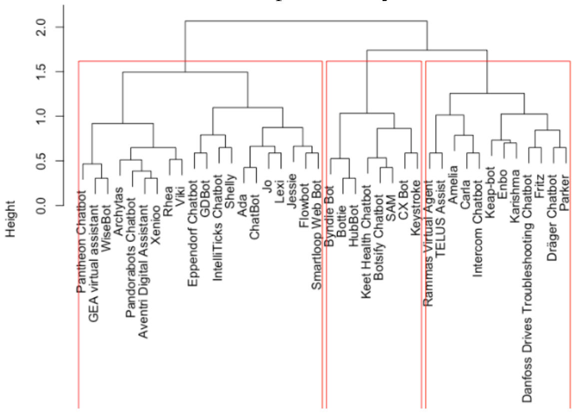

Figure 1. Dendogram visualization of the conducted Ward clustering

Table 4 shows the distributions of the characteristics in the three archetypes, which we named *lead generation chatbot* (archetype 1, n=8), *aftersales facilitator chatbot* (archetype 2, n=10) and *advertising FAQ chatbot* (archetype 3, n=22). These archetypes are intended to guide chatbot developers as an orientation to identify relevant attributes within the development based on their customer service purposes within B2B business.

Table 4. Results of the k-means cluster analysis

	Label	Lead generation chatbot	Aftersales facilitator chatbot	Advertising FAQ chatbot
	Archetype	1	2	3
	n	8	10	22
Industry classification	Financial services industry	0%	10%	5%
	Manufacturing industry	0%	50%	18%
	Marketing industry	0%	10%	14%
	Software industry	100%	30%	64%
Business integration	No	75%	40%	77%
	Yes	25%	60%	23%
Access to business data	No	88%	70%	100%
	Yes	13%	30%	0%
Dialogue structure	Predefined	88%	20%	45%
	Open	0%	40%	9%
	Both	13%	40%	45%
Data Policy	Not provided	38%	60%	77%
	Provided	63%	40%	23%
Handoff to human agent	Not possible	0%	20%	14%
	Possible	100%	80%	86%
Small talk	Not possible	100%	60%	82%
	Possible	0%	40%	18%
Human-like avatar	No	100%	70%	95%
	Yes	0%	30%	5%
Content related service	Content advertisement	75%	0%	100%
	Content consumption	25%	100%	0%
Account authentification	Not required	50%	60%	68%
	Optional	0%	20%	14%
	Required	50%	20%	18%
Question personalization	None	50%	0%	5%
	FAQ	0%	20%	82%
	Personalized account questions	38%	70%	9%
	Highly personalized questions	13%	10%	5%
Customer service orientation	Knowledge-oriented	0%	0%	95%
	Task-oriented	100%	100%	5%
Company information	No	100%	60%	64%
	Yes	0%	40%	36%
Service/product information	No	38%	10%	9%
	Yes	63%	90%	91%
Pricing	No	100%	60%	82%
	Yes	0%	40%	18%
Action request	Book/show a demo	25%	0%	5%
	Callback request	25%	40%	32%
	Both	50%	20%	36%
	None	0%	40%	27%
Service request	Support question/ticket	13%	40%	36%
	Billing details	0%	0%	5%
	User management	0%	10%	0%
	Multiple	0%	40%	0%
	None	88%	10%	59%

Due to rounding inaccuracies, the sum of a column in a dimension is not always exactly 100%

0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%

The **lead generation chatbot archetype** contains chatbots from software industry that are aimed at actively generating leads by encouraging users to book demos and/or provide their contact details (e.g., business email address or company name) to be called back by human employees. These task-oriented chatbots are characterized by having a predefined dialog structure guiding the user without small talk to an action. While some chatbots in this archetype have the sole function of collecting the customer's contact data (e.g., Botsify chatbot), other chatbots ask specific questions to assess the appropriate sales executive depending on the customer's needs (e.g., Keet Health chatbot). On the other hand, the **aftersales facilitator chatbot archetype** includes task-oriented chatbots that offer more personalized dialogues by asking the user for requirements, such as the number of employees working on the CRM system (e.g., Carla Chatbot), before providing the appropriate product and service information or offering a request. These chatbots are characterized by content consumption trough asking personalized questions. Thereby, they are intended to execute a task by giving the user support for example when the account operator profile is locked (e.g., Intercom chatbot) or when "motor won't start" (e.g., Danfoss Drives Troubleshooting Chatbot). Lastly, the **advertising FAQ chatbot archetype** contains knowledge-oriented chatbots that have the goal of advertising products and services, for which the chatbots answer standard FAQs within the dialog, whereby some of them linking articles on the website (e.g., Eppendorf Chatbot) or embedding videos (e.g., ChatBot).

5 Discussion, Implications, Recommendations, Limitations, and a Further Research Agenda

To answer the research questions, we developed a chatbot taxonomy for B2B customer services, classified 40 chatbots and identified three archetypes. The taxonomy and the analysis of the examined chatbots reveal several implications and limitations, which are discussed and from which eleven research directions (RD) are derived below.

The empirical analysis of the 40 chatbots shows that 88% of the B2B chatbots for customer services offer the possibility to contact a human agent (D_6), in contrast to the results of other taxonomic studies such as Janssen et al. [15], where only 20% of the considered chatbots from various application areas offered this possibility. While handoff is seen as a highly important topic in research [3, 9, 21] the empirical result shows that customer contact is also extremely important in the B2B sector and products and services often require explanation. Much more, chatbots are used to generate leads by offering action requests (65%) through callback requests or demo booking (D_{16}). This is so far that in 25% of the chatbots it is necessary to enter contact data (D_{10}), like the business email address, before the chatbot dialogue is continued. It is noticeable that the scientific literature mainly prescribes the use of chatbots in the first stages of the sales funnel [6–8]. However, the chatbot taxonomy shows that 48% of the B2B chatbots also offer service requests (D_{17}) in the form of, e.g., support ticket creation and are therefore also used after the purchase is completed. But billing details (3%) or user management (3%) are rarely provided within the dialogue, which can be adapted by further companies. Further research can examine the use of chatbots in different levels along the sales funnel (RD1). Additionally, it is recommended to investigate what information the customers expect from a chatbot at the different phases of the customer journey and across diverse industries (RD2). The feature of information personalization also requires closer examination. Taking a look on the sample, access to business data (D_3) is not present in 90% of the chatbots considered. This topic holds great potential for B2B sector, as there are often extremely specific requirements that often necessitate a batch size of 1. A possible personalization may also require the provision and adherence to a data policy (D_5), to which 35% referred. In further research, it is of theoretical and practical value to examine the trade-off between the degree of personalization (e.g., custom responses) and data privacy concerns relating to, e.g., B2B customer data obtained during the interaction (RD3), which must be compared to results of the explorative interview-based study on trust in B2C customer service chatbots conducted by Følstad et al. [30]. While some chatbot researchers emphasize the importance of small talk in customer service [4, 22, 25], in the B2B sector little emphasis is placed on the presence of this capability, as only 20% of chatbots were capable of small talk (D_7). However, this also supports the generic marketing communication attribute described B2C markets are rather characterized by emotionality and B2B companies ascribe rationality to their customers [14], which in turn influences the content aspects of communication. Our results show that the distinction between B2B and B2C use of chatbots exists in practice and must also be reflected in research (RD4). On the other hand, it also shows that classic B2B marketing characteristics, such as rationality in decision-making, are also adopted by companies in the chatbot environment. However, quantitative studies can contribute to identify the critical factors, as well as the causal relationships between them, in order to provide further insights into the underlying differences (e.g., in view of the intention to use, functional expectations or shifting motivations) among B2B and B2C chatbots (RD5) from the user's point of view. It is also interesting to examine the way B2B customers communicate with a chatbot (RD6) and the expectations of B2B users regarding socio-emotional behavior and social cues (RD7) using cross-industry cases.

To answer RQ2, we identified three currently existing archetypes. The lead generation (archetype 1) and advertising FAQ (archetype 3) chatbot archetypes are mainly located in the pre-purchase step whereas with different emphases. While archetype 1 aims to collect customer information for further personal contact, archetype 3 focuses on providing information to stimulate buying interest. Chatbots in the aftersales facilitator chatbot archetype (archetype 2), on the other hand, have also the functionalities of giving information about products and services but completely content consumption and customer oriented. In addition, these chatbots have also the possibility to help the customers after the purchase with requests or claims and act therefore much more as facilitators. Since we believe that the functionalities of a chatbot should not stop with the purchase but should be completely focused on the users' demands we see great potential for archetype 2 which is why it should be explored more closely in the further research (RD8).

Due to the lack of availability of B2B literature, we almost exclusively used scientific literature from the general chatbot customer service to develop the taxonomy. Hence, building on the extant literature in the field of chatbots, we have contributed to present a foundation to further B2B chatbot research. Hence, it is useful to do a further conceptual-to-empirical iteration when this area has been further researched (RD9). Furthermore, only chatbots that can be accessed externally were tested. Whereas, chatbots that are publicly accessible but require authentication or naming of the business email address or other personal data within the dialogue were included (D_{10}). Under certain circumstances, the inclusion of internal chatbots from B2B customer service, which require a more company-bound login, can lead to different results as they can have more access to business data or more personalization (RD10). The B2B customer service chatbots were tested in July and August 2020. The deployment, adoption, and skills of chatbots are evolving rapidly, so it makes sense to repeat the empirical-to-conceptual step in further research to identify further dimensions and characteristics that can be used to spot emerging trends (RD11) as well as to conduct an evaluation with researchers and practitioners to verify the applicability of the taxonomy (RD12).

6 Conclusions

We developed a taxonomy of chatbots for B2B customer services and thus elaborated these B2B specific characteristics. In addition to the conducted literature research, 40 B2B customer service chatbots were empirically analyzed and classified. Within four iterations a final taxonomy was developed which contains 17 dimensions and 45 characteristics. We discovered that chatbots from the B2B customer service predominantly give detailed information about services and products, unfortunately, mostly without having access to business data, but offer the possibility to get in contact with a human employee. However, there are major differences between these chatbots in terms of customer service orientation and content related services which is why three archetypes were identified.

Appendix

Table 5. Definitions of taxonomy dimensions and underlying conceptual bases

Dim*ension* D_i	Definition
D_1 Industry classification	Describes the industry to which the company offering the B2B chatbot service belongs.
D_2 Business integration	Describes whether the chatbot is supported by integrated product or customer databases [5], [26].
D_3 Access to business data	Describes whether the chatbot has access to non-public business data and uses it to enhance its responses [19].
D_9 Content related service	Describes whether the chatbot provides only commercial content on products or services, or enable the user to acquire them [13].
D_{10} Account authentication	Describes whether the chatbot requires the authentication of the user by means of a business email address or username and password to begin the interaction [13].
D_{11} Question personalization	Describes the degree of response customization of the chatbot, e.g., the capacity of the chatbot to tailored highly personalized questions require information obtained through the interaction with the user [8], [20], [25].
D_{12} Customer service orientation	Describes whether a chatbot is primarily oriented to provide information or to perform a task [24].
D_{16} Action request	Describes the functional actions related to customer service that the chatbot is able to perform [25].
D_{17} Service request	Describes the functional service inquires related to customer service elements present in the chatbots [25].

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