Research Center
Finance & Information Management

Fraunhofer
FIT

Project Group
Business & Information
Systems Engineering

Discussion Paper

Conversational User Interfaces for Online Shops?
A Categorization of Use Cases

by

Daniel Baier, Alexandra Rese, Maximilian Röglinger

To be presented at: 39th International Conference on Information Systems (ICIS),
San Francisco, USA, December 2018

WI-822

University of Augsburg, D-86135 Augsburg
Visitors: Universitätsstr. 12, 86159 Augsburg
Phone: +49 821 598-4801 (Fax: -4899)

University of Bayreuth, D-95440 Bayreuth
Visitors: Wittelsbacherring 10, 95444 Bayreuth
Phone: +49 921 55-4710 (Fax: -844710)

www.fim-rc.de

Conversational User Interfaces for Online Shops? A Categorization of Use Cases

Completed Research Paper

Daniel Baier
Chair of Marketing & Innovation
University of Bayreuth
Universitätsstraße 30
95447 Bayreuth, Germany
daniel.baier@uni-bayreuth.de

Alexandra Rese
Chair of Marketing & Innovation
University of Bayreuth
Universitätsstraße 30
95447 Bayreuth, Germany
alexandra.rese@uni-bayreuth.de

Maximilian Röglinger
FIM Research Center
University of Bayreuth
Wittelsbacher Ring 10
95444 Bayreuth, Germany
maximilian.roeglinger@fim-rc.de

Abstract

How do conversational user interfaces for online shops via messaging services and voice assistants influence customers' satisfaction? Which use cases are attractive from a customer's view point? Which use cases are must-be and for which customer segments? The answer to these questions is looked for in this paper. A Segmented Kano perspective is used to derive use case groups and related customer segments simultaneously. The paper starts with an overview on conversational commerce and on chatbots for this purpose. Then, the research method and the use case development is described. Two representative surveys with 2,165 customers of a major German online fashion retailer evaluating 13 messaging service and 2,025 customers evaluating 13 voice assistant use cases were conducted and analyzed. The focus was on the intention to use conversational user interfaces for online shops and the influence on customer satisfaction.

Keywords: Chatbots, conversational commerce, conversational user interface, messaging service, Segmented Kano perspective, two-factor theory, voice assistant

Introduction

Communication has always been referred to be essential for any kind of commerce (Donna and Novak 1997). Many customers appreciate conversations with salespersons due to functional (e.g. advice, time savings, better purchase decisions) and social benefits (Reynolds and Beatty 1999). They want to be informed about the price-quality-relationship and availability of products, or need further support. The advent of the digital age has led to a growth of conversational formats for this purpose pushing the conventional, often menu-based dialog between producers, retailers, and their customers into the background (van Bruggen et al. 2010). So, nowadays, websites and mobile apps support natural language inquiries via mail, chat, or voice over IP (van Bruggen et al. 2010).

However, the often asynchronous character of this communication is criticized (Walsh et al. 2010). Demanding customers are no longer willing to accept waiting times for a response to an inquiry, or to get stuck in a telephone loop (Elmorshidy 2013). Technological solutions enabling real-time conversations at reasonable costs have to be looked for.

Consequently, online retailers currently discuss whether conversational user interfaces – basing, e.g., on messaging services or voice assistants as well as artificial intelligence (AI) enabled, cloud-hosted chatbots – could solve this problem. Such applications are usually referred to as conversational commerce and rely on a text- or voice-based interface which “accepts natural language as input and generates natural language as output” (Griol et al. 2013, p. 760). Other – criticized – communication forms such as “typing/speaking syntax-specific commands” or “clicking icons” can be replaced in this new paradigm. A natural language conversation with a salesperson or a helping friend is simulated. In the latest Gartner Hype Cycle for Emerging Technologies, conversational user interfaces are positioned as “innovation trigger” with 5 to 10 years to mainstream adoption (Gartner Inc. 2017a). This evolution in human computer interaction goes along with an increasing distribution of messaging services for smartphones such as WhatsApp (1.3 billion users), Facebook Messenger (1.3 billion users), WeChat (980 million users), or Line (203 million users) (Global Digital Report 2018) and a rising availability of chatbot toolkits that support the implementation.

Chatbots which had been introduced in the 1960s (Shawar and Atwell 2007) can now – with constrained efforts – be integrated into messaging services for personalized, (automated) real-time communications, and additional service offers (van Eeuwen 2017). In addition, voice assistants such as, e.g., Amazon Echo, Google Home – also referred to as smart speakers or dedicated voice command devices – are expected to be employed by 3.3% users worldwide in 2020 (Gartner Inc. 2016) and sales volume to rise from $0.72 billion in 2016 to $3.52 billion by 2021 (Gartner Inc. 2017b). While often used for information retrieval or entertainment, these new devices also gain relevance for commerce (Capgemini Inc. 2018). Since this usage of conversational user interfaces for online shops is still rather new and research on suitable use cases scarce, this paper aims to shed light onto the following questions:

How do conversational user interfaces for online shops via messaging services and voice assistants influence customers' satisfaction? Which use cases are attractive from a customer's view point? Which use cases are must-be and for which customer segments?

This paper seeks to give answers to these questions. Using a Segmented Kano perspective, groups of use cases and suitable customer segments are simultaneously derived. The paper starts with a short overview on the development of conversational commerce and chatbots. Then, the research method and developed use cases relying either on messaging services or voice assistants are discussed. We collected data from the customers of a major German online fashion retailer (2017/18: 700 million € sales, 12% growth from 2016 to 2017). Two large customer surveys evaluating 13 developed messaging service and 13 voice assistant use cases were analyzed. The focus was on the customers' intention to use conversational user interfaces to online shops and their impact on satisfaction. Finally, practical and research challenges regarding conversational commerce as a new paradigm for online retailing are discussed.

Background

Conversational Commerce

Since 2016 conversational commerce and (chat)bots are being widely talked about, e.g. as “chatbot craze” that “quickly took over Silicon Valley” (Yao, 2016). Renowned tech companies such as Facebook, Google, IBM, Microsoft, or Slack are heavily investing in bots and related AI technologies, such as natural language processing, machine learning, speech and voice recognition (Nguyen, 2017). Conversational commerce was first mentioned as a 2014 marketing trend by Dan Miller (2013). The term was largely clarified and defined by Chris Messina (2015), a former developer advocate at Google and former head of the developer experience team at Uber. Messina also introduced the Hashtag #ConvComm. Since 2015 conversational commerce is intensively discussed, mainly in dedicated blogs (see Table 1). The aspect of convenience of conversational commerce is a central part of several definitions. Messina (2015) started with emphasizing the simplicity and economy of time when shopping and described the nature of conversational commerce as follows: “No more tapping and swiping—it's easier to just hand-off to someone with a computer that's set up for complex information tasks like online shopping or research. And just because everyone has a screen in their pocket doesn't imply that they should be forced to look at it to interact with your service.”

Messina (2015)	Conversational commerce is about delivering convenience, personalization, and decision support while people are on the go, with only partial attention to spare.
Van Manen (2015)	Conversational commerce is primarily an interface that enables users to arrange (complex) tasks through a dialogue with another person or an algorithm. The strength of these interfaces is that they respond to skills that users already possess, so no new behavior needs to be learned. Conversational commerce is essentially about offering convenience, personalization, and supporting decision processes.
Messina (2016)	Conversational commerce largely pertains to utilizing chat, messaging, or other natural language interfaces (i.e. voice) to interact with people, brands, or services and bots that heretofore have had no real place in the bidirectional, asynchronous messaging context.
Shopify (2016)	Conversational commerce refers to the intersection of messaging apps and shopping. [...] Consumers can chat with company representatives, get customer support, ask questions, get personalized recommendations, read reviews, and click to purchase all from within messaging apps. With conversational commerce, the consumer engages in this interaction with a human representative, chatbot, or a mix of both.
Lawson (2016)	Conversational commerce it's a catchall term for a future of technology driven by messaging (and voice) interactions that transcend current communications modalities.
Van Eeuwen (2017 , p.3)	The application of artificially intelligent messenger chatbots or conversational agents for commercial purposes is part of a development called conversational commerce. [...] Conversational commerce refers to the integration of messaging apps and e-commerce.

Table 1. Conversational Commerce Definitions

Another common characteristic is the presence of a natural language interface either text- or voice-based. In addition, most definitions do not differentiate whether the services are provided by a human representative or a robot. According to Messina (2016) "over an increasing period of time, computer-driven bots will become more human-feeling, to the point where the user can't detect the difference". Moreover, the other way round, in May 2018 Google presented Duplex, a new AI system that consumers can ask to telephonically arrange appointments with service providers (e.g., hairdressers, physicians) in natural language (Leviathan 2018). For the paper the definition of van Eeuwen (2017) is most relevant. Taking up two definitions of news channels / magazines (Desaulniers 2016; Schlicht 2016) van Eeuwen (2017) narrows conversational commerce down to the extent AI is used in driving the conversation. Overall, conversational commerce driven by AI allows the company to offer an individual, bidirectional real-time communication with the customer without having to heavily invest in its own personnel. Waiting time has been identified as important aspect of service quality being strongly related to customer satisfaction, since "it is often the first touchpoint in the sequence of experiences that customers have with an organization" (McLean and Osei-Frimpong 2017, p. 496).

However, due to the difference to the use of customer service representatives, existing theories and frameworks in customer service relying on "real" persons, e.g. explaining the interface between customer and salesperson (Jones et al., 2003), are difficult to apply. Instead research on self-service (IT) technologies and customer satisfaction (Meuter et al. 2000) and the balance with human service (Ba et al. 2010) is more suitable. The core, and primary objective is to directly induce the customer to not only chat and use services, but ultimately to make a purchase of a product or service.

Thus, the entire customer journey beginning with product consultation and evaluation, sales process, purchase and customer services can be improved in terms of efficiency and convenience (Gentsch 2018, p. 84, p. 86). As business-related activities when companies employ messaging services van Eeuwen (2017) mentions providing buying recommendations (fashion brands), processing claims (insurances) or enabling check-in and updating flight information (airlines). While conversational commerce can also be integrated on company's websites or mobile apps (internal channels) the focus of this paper is on use cases based on external channels: messaging services like, e.g., WhatsApp or Facebook Messenger and voice assistants like, e.g., Amazon Alexa or Google Assistant.

Chatbots as Important Enablers for Conversational User Interfaces

The automation of natural language dialogs has been around for some time. McTear et al. (2016, p.16) point to that already in "the mid-1950s, researchers in artificial intelligence (AI) have wrestled with the challenge of creating computers that are capable of intelligent behavior." Turing's (1950) imitation game was introduced to test whether a computer or a program was able to give the impression of being a human player when communicating with other human players. In line with this, Brownlee (2016) defines a conversational user interface (CUI) as "any UI that mimics chatting with a real human". More specifically Pan (2017) highlights the combination of "chat, voice or any other natural language interface with graphical UI elements". Two main types can be distinguished: voice-driven interfaces (in the following: voice assistants) and text-based interfaces on messaging platforms (in the following: messaging services) (Brownelee 2016).

Chatbots have been defined as "machine conversation system[s] [that] interact with human users via natural conversational language" (Shawar and Atwell 2005, p. 489). The term is made up of (parts of) the two nouns "chat" and "robot" (Zumstein and Hundertmark 2017). Today, chatbots are built as a "cloud-hosted service" (Chung 2017, p. 101) that is connected to different platforms running on different devices. Zumstein and Hundertmark (2017, p.98) emphasize the originally text-based nature of chatbots: "Chatbots contain a text input and output mask, which allows mobile users to communicate with the software behind them, giving them the feeling of chatting with a real person." In 1966 the first chatbot ELIZA was introduced (Chung et al. 2017). However, besides text-only interfaces early on voice was considered "to be a natural fit for conversational interfaces" (Klopfenstein et al. 2017, p. 59). In the 1980s development began of research-oriented spoken dialog systems and commercial-related voice user interfaces in laboratories of universities and industry. Relying on interactive voice response systems an early automation of tasks was already enabled "such as call routing, directory assistance, information enquiries, and simple transactions" (McTear et al. 2016, p.56). However, accuracy is a problem with real human speech recognition, i.e. "unusual accents, interference on the channel, or background noise" (McTear et al. 2016, p. 54). Today, a wide range of tools in natural language processing has been made available that support textual and auditory understanding and is used by providers such as Amazon (Alexa) or Google (Assistant) (Dale 2016).

Technology advances over time in the fields of AI and human-computer interaction have resulted in systems becoming more intelligent with sophisticated algorithms (e.g. deep learning) enabling them to converse in an increasingly natural, but also more complex way (Chung et al. 2017). However only recently businesses became interested in text-based (but also voice-based) chatbots since messaging services have started to play a major role in everyday life (van Doorn and Duivenstein 2016, van Eeuwen 2017). The focus of these chatbots is not on entertainment or AI competition, but on task-orientation, e.g. "chatbots that use conversation to automate a task, such as scheduling a meeting or ordering a pizza" (McTear 2017, p.40). They are cloud-based, connected to user information and can therefore offer a more personalized service (Klopfenstein et.al., 2017; McTear, 2017). An example of a chatbot in fashion shopping is the one made available by the retailer H&M or the Canadian messaging platform Kik offering style tips (Suvorov 2016).

Research Method

Framework for Generation, Categorization, Selection and Test of Use Cases

To develop answers to the research questions, a framework (see Figure 1) was utilized that is closely related to the first four stages of the usual (cyclic) seven-stage process applied by many online retailers (e.g. members of the BAUR and the OTTO Groups in Germany, developed in analogy to Amazon's approach) in order to generate and decide on options to improve their site. Following these so-called site engineering processes (see, e.g., Lauber 2013 or Baier et al. 2018), "best" options to improve are selected in a cost-effective way out of large numbers of candidates in a funnel-like iterative stage-by-stage filtering approach:

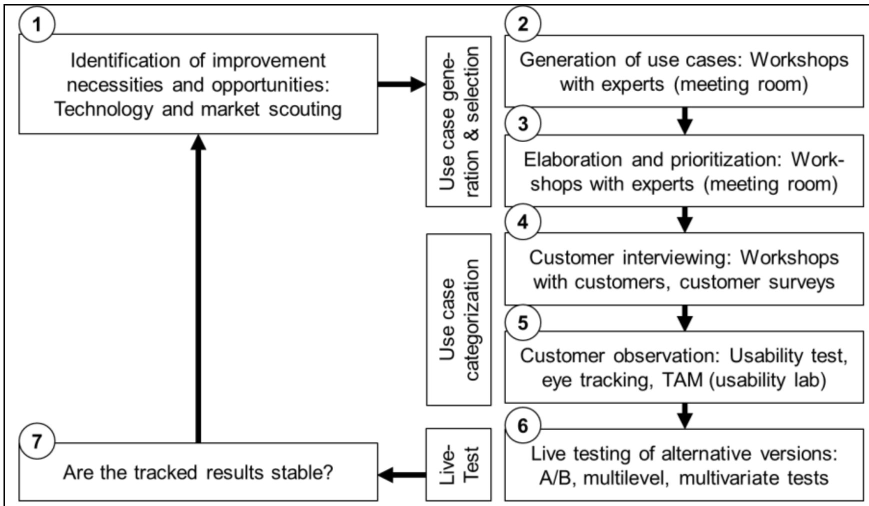

Figure 1. Research method for generation, selection, categorization, and test of use cases

In a first stage, improvement necessities and opportunities are identified (and defined). The use of technology and market scouting is one way of achieving this objective. For this purpose, online retailers apply secondary research (e.g. analysis of published surveys from market research institutes or other companies, overviews of competitor offerings, technological forecasts, complaint overviews concerning own offerings) and rely on knowledge transfer from other retailers, universities, research institutes, and start-ups. In addition, if possible, primary research is used (e.g. customer satisfaction surveys). Also, process mining, data mining, or web mining activities are applied. A second and a third stage is used to generate and preselect improvement ideas based on this input. Experts inside and outside the company are integrated in these activities which aim at develop ideas and prioritize them. In the fourth and fifth stage, samples of customers are engaged in interviewing and observation activities to integrate the customer's point of view. A main advantage of performing customer interviewing is that the options under study do not have to be implemented so far and it is possible to test several of them within one interview. However, in order to receive reliable and valid results, the options have to be presented in the "voice of the customer (VoC)". That means that they must be explained to the customer precisely in her/his words, using (if possible) visualizations and animations. After finishing the customer interviewing stage, the "best" options so far are implemented for customer observation in the usability lab. Small samples of customers are tracked when interacting with the site in a laboratory setting (using e.g. eye tracking, mouse tracking, and interviewing, see also Schreiber and Baier 2015; Rese et al. 2017). The process of implementing and observing should be repeated until the respondents say they are highly satisfied. Again, the customer's reactions help to reduce the number of candidates in the funnel since many online retailers are not able to implement and test larger numbers of options in a realistic setting. Finally, in the (costly) sixth and seventh stage, the options go "live", i.e. larger parts of the audience are confronted with the modified websites. In the sixth stage, A/B-tests are used to choose "best" candidates which then have to demonstrate their performance across all customers in the seventh stage. The discussed site engineering process formed the basis for our research method (see Figure 1): In a seven-stage process (the first four stages are discussed in this paper), use cases for conversational online shop user interfaces were similarly developed and tested as options to improve the interface. In the following we discuss the fourth stage of the research method – where the use cases are categorized – in more detail.

Use Case Categorization

A standard method in product/service engineering to integrate the customers' view point is Kano's approach (Kano et al. 1984) where the "relationship between the objective performance of, and customer satisfaction with" (Nilsson-Witell and Fundin 2005, p. 157) features of a product/service (or: attributes, elements, components, here: use cases) is used for categorizing. The basic assumption in this so-called theory of attractive quality is that the satisfaction generated by a feature (low to high) depends on the performance or functionality of this feature (low to high or not to fully implemented), but that this dependency varies: (1) Must-be features (abbreviated to "M") are expected by customers: If they are not implemented, the customer's satisfaction is highly negative. However, if fully implemented the satisfaction is neutral at maximum, the customer takes them for granted. (2) Attractive features ("A") are appealing but not expected. If not implemented, satisfaction is neutral. However, if fully implemented, satisfaction is highly positive. (3) One-dimensional features ("O") are features where the relation between performance/functionality and satisfaction is proportional. The customer doesn't take them granted but honors "the more the better". (4) Indifferent features ("I") are features the customer is not interested in at all, whether implemented or not. (5) Reverse features ("R") are features the customer doesn't like if implemented. She/he prefers them not implemented. The theory of attractive quality is grounded in Herzberg et al.'s (1959) two-factor theory in the analysis of job satisfaction and dissatisfaction (Berger et al. 1993), a theory that can be used to categorize website elements from a customers' view point (Zhang et al 2000). Key similarities are the separation of motivators (attractive features in the Kano approach) and hygiene factors (must-be features). However, there is no analogy to the one-dimensional features with a proportional dependency between satisfaction and performance/functionality (Berger et al. 1993). The Kano approach recently has been applied, e.g., for categorizing information system components from a manager's view point (Mayer 2012). Measurement mainly consists of posing two questions for all features (here: use cases) and of collecting corresponding answers on 5-point semi-quantitative scales that reflect the extent to which satisfaction would be generated if the feature is implemented (functional question) or the extent to which dissatisfaction would be generated if not implemented (dysfunctional question):

- Functional question: "If the feature is implemented, how would you feel?", Possible answers: "I dislike it." (coded as -2 following Berger et al. 1993), "I can live with it." (-1), "I am indifferent." (0), "It should be that way." (2), "I like it that way very much." (4)
- Dysfunctional question: "If the feature is NOT implemented, how would you feel?", Possible answers: "I dislike it." (coded as 4 following Berger et al. 1993), "I can live with it." (2), "I am indifferent." (0), "It should be that way." (-1), "I like it that way very much." (-2)

Functional		Dysfunctional: Like -2	Must-be -1	Neutral 0	Live with 2	Dislike 4
Like	4	Q	A	A	A	O
Must-be	2	R	I	I	I	M
Neutral	0	R	I	I	I	M
Live with	-1	R	I	I	I	M
Dislike	-2	R	R	R	R	Q

Table 2. Kano Evaluation Table according to Berger et al. (1993)

The respondent's answers to the two questions allow to categorize the improvement using the so-called Kano evaluation table (see Table 2 from Berger et al. 1993). If the respondent answers "I like it that way very much." (shortly: like) to the functional question and "I can live with it." (shortly: live with) to the dysfunctional question the improvement would be categorized as attractive ("A") for this respondent since her/his satisfaction would increase if the feature is realized, but would not decrease if not realized. Similar argumentations hold for the other categories, "Q" represents questionable answers. The asymmetric scaling of the answers around the "indifferent" or "neutral" answers (coded as 0) to both questions (allowing values -2, -1, 0, 2, 4 as coded answers) was favored by Berger et al. (1993). They argue that answers that lead to "A", "O", "M" categories should be weighted stronger than answers that lead to "I", "R", and "Q" categories and therefore should have a stronger influence. This applies in particular if responses have to be aggregated across (sub-)samples by averaging their coded answers. Also, a clustering approach with respect to the respondents and the features – as discussed hereafter – can be directly applied. We refer to this clustering approach as the “Segmented Kano Perspective”. This approach is based on the well-known two-mode cluster analysis of a data matrix originally proposed by Hartigan (1972) were homogeneous row and column clusters respectively row by column blocks are looked for with small variation of data values within blocks (see van Mechelen et al. 2004, Schepers et al. 2017 for recent overviews):

Let $\mathbf{S}=((s_{ijm}))_{I\times J\times M}$ be the collected Kano data with i=1,…,I as an index for respondents (first mode) and j=1,…,J as an index for features (second mode). m=1,…,M is an index for the questions with s_{ijm} as the response from respondent i to feature j to the functional (m=1) and the dysfunctional question (m=2). The responses are asymmetrically scaled with values -2,…,4 as discussed to make averaging across (sub-)samples meaningful. The two-mode clustering algorithm now has to look for K first-mode clusters (with k=1,…,K as an index for clusters of respondents) and L second-mode clusters (with l=1,…,L as an index for clusters of features) where the observed responses show small variations within blocks. With model parameters

- $\mathbf{P}=((p_{ik}))_{I\times K}$ as first-mode cluster membership indicators ($p_{ik}=1$ if respondent i belongs to first-mode cluster k, =0 if not),
- $\mathbf{Q}=((q_{jl}))_{J\times L}$ as second-mode cluster membership indicators ($q_{jl}=1$ if feature j belongs to second-mode cluster l, =0 if not), and
- $\mathbf{W}=((w_{klm}))_{K\times L\times M}$ as “weights” (averaged values with respect to question m within the “block”),

two-mode clustering solves

$$Z=\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{m=1}^{M}(s_{ijm}-\hat{s}_{ijm})^2 \rightarrow \min! \quad \text{with} \quad \hat{s}_{ijm}=\sum_{k=1}^{K}\sum_{l=1}^{L}p_{ik}w_{klm}q_{jl}$$

according to some pre-specified clustering scheme, e.g., non-overlapping clustering where each object belongs to exactly one cluster (i.e. $\sum_{k=1}^{K}p_{ik}=1\ \forall i$ and $\sum_{l=1}^{L}q_{jl}=1\ \forall j$). The standard algorithm for solving this problem is the alternating least squares method, which starts from a random solution for **P**, **Q**, and **W**, and then iteratively improves the solution by alternatingly modifying **P**, **Q**, and **W** (see, e.g., Baier et al. 1997, Brusco and Doreian 2015 for a discussion of various schemes and algorithms for this purpose). The approach is closely related to the so-called double-k-Means or bi-clustering method (see Mirkin 1996, van Mechelen et al. 2004, Schepers et al. 2017 for overviews on these methods), but here, in contrast to most two-mode clustering algorithms, the underlying three-dimensional structure of the Kano data is taken into account. Model selection (e.g. the decision with respect to the optimal number of first-mode and second-mode clusters K and L) can be done by checking the Variance Accounted For (VAF) criterion

$$VAF=\frac{\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{m=1}^{M}(s_{ijm}-\hat{s}_{ijm})^2}{\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{m=1}^{M}(s_{ijm}-\bar{s}_{m})^2} \quad \text{with} \quad \hat{s}_{ijm}=\sum_{k=1}^{K}\sum_{l=1}^{L}p_{ik}w_{klm}q_{jl},\ \bar{s}_m=\sum_{i=1}^{I}\sum_{J=1}^{J}s_{ijm},$$

for different (K, L) settings with an elbow criterion or – when assuming an error model for the answers – by looking for minimum Akaike Information Criterion (AIC) values or Consistent AIC (CAIC) values.

Application of the Framework and Results

Use Case Generation and Selection

In the first three stages of our research framework, secondary research as well as expert workshops were employed: Together with internal experts the authors analyzed the online retailer’s website, the website of competitors, already implemented use cases with conversational user interfaces by competitors and companies in other branches, published customer satisfaction surveys dealing with online fashion retailing, technological forecasts, customer studies, as well as FAQs and complaint overviews from the online retailer’s website and customer database. For each conversational format – written natural language (e.g.

based on messaging services like Facebook Messenger or WhatsApp) and spoken natural language (e.g. based on voice assistants like Amazon Echo or Google Home) 13 use cases were developed: In nine use cases the customer starts a conversation (referred to as customer-active, e.g. by requesting the delivery status of an order) and in four use cases the online shop begins (referred to as customer-passive, e.g. by "automatically" receiving context-related recommendations). Table 3 shortly summarizes the generated and selected 13 use cases for each of the two conversational formats. Use cases 1 to 9 are customer-active, use cases 10 to 13 are customer-passive. The use cases vary with respect to assumed innovativeness for the customers as judged by the company's experts in the team. So e.g. the customer-active use case 5 – where payment of selected products is still handled on the company's website as usual – was assumed to be of lower innovativeness for the customers than the similar use case 9 – where payment is possible within and via the MS or VA. The use cases are sorted within the four groups (customer-active vs. -passive as well as messaging service vs. voice assistant) according to the (assumed) increasing innovativeness. The use cases across the two conversational formats were selected – besides the conversational format and consequences out of this format – to resemble each other as far as possible.

Customer-active	Less innovative →	1	Be able to **receive** the **newsletter** via MS	Be able to **play music** or audiobooks via VA
		2	Be able to **complain** about products or customer service to the merchant via MS	Be able to use your VA to **send messages** and receive general information
		3	Be able to **request** the **delivery status** of your orders via MS	Be able to **request** the **delivery status** of your orders via VA
		4	Be able to quickly **get answers** to product, payment, or **service** related questions via MS	Be able to quickly **get answers** to product, payment, or **service** related questions via VA
		5	Be able to **pay** your selected products **via** MS by being forwarded to our **website**	Be able to **pay** your selected products **via** VA by being forwarded to our **website**
		6	Be able to quickly **find products** by chatting with us via MS, see selected product offerings on your smartphone	Be able to quickly **find products** by chatting with us via VA, see selected product offerings on your smartphone
		7	Be able to **find products by sending photos** with similar ones via MS	Be able to **receive** other customers' **comments and evaluations** via VA
		8	Be able to **receive** personalized and individualized **style advice** via MS	Be able to **receive** personalized and individualized **style advice** via VA
		9	Be able to directly select, order, and **pay** products **via MS**	Be able to directly select, order, and **pay** products **via VA**
Customer-passive	Less innovative →	10	Automatically **receive notifications about availability** changes of products via MS	Automatically **receive notifications about availability** changes of products via VA
		11	Automatically **receive personalized offers** via MS such as discount promotions, coupons	Automatically **receive personalized offers** via VA such as discount promotions, coupons
		12	Automatically **receive product recommendations based on** your last **purchases** via MS	Automatically **receive product recommendations based on** your last **purchases** via VA
		13	Automatically **receive context-related recommendations** via MS	Automatically **receive notifications of** return and payment **deadlines** of orders

Table 3. Messaging Services (MS) Use Cases (left) and Voice Assistants (VA) Use Cases (right)

Use Case Categorization

For prioritizing the selected 13 messaging service (MS) and the selected 13 voice assistant (VA) use cases, Kano questionnaires were developed to be easily understood by the customers of the cooperating online retailer. Each use case was explained using pretested precise and understandable descriptions, and (if possible) explaining videos and visualizations. Then, respondents were asked to answer the functional ("If you could …, how would you feel?") and the dysfunctional question ("If you could NOT …, how would you feel?"). The questionnaires were implemented electronically (using Qualtrics) and distributed among the online retailer's customers through an (optional) newsletter link in December 2017 with a reminder in January 2018. Respondents were linked alternatively to a questionnaire either with the MS use cases or with the VA use cases. The response rate was surprisingly high: The questionnaire with the MS use cases was opened by 3,964 customers and completed by 2,165 respondents (54.6%). The questionnaire with the VA use cases was opened by 3,722 customers and completed by 2,025 respondents (54.4%).

The resulting so-called MS sample (respondents who answered the questionnaires with the MS use cases) consisted of 77.9% female respondents, the VA sample (with the VA use cases) of 78.4% female respondents. The age distribution was in the MS sample as follows: 18-29 years old: 5.7%, 30-39: 12.7%, 40-49: 23.5%, 50-59: 36.7%, 60+: 20.9%. In the VA sample the distribution was as follows: 18-29 years old: 4.8%, 30-39: 11.7%, 40-49: 22.6%, 50-59: 37.3%, 60+: 22.5%. Also, 32.7% of the respondents of the MS sample buy fashion at least once a month, another 36.5% at least once in three months with similar frequencies in the VA sample. According to the online retailer's management, the two samples reflect the company's customer base quite well with respect to gender, age, and buying frequency distribution. In the MS sample, 72.3% of the respondents use messaging services on a daily basis, another 22.3% at least once a week. 73.3% are used to communicate with the company via email, 57.6% via phone, 18.5% via chat with sales persons on the company's website (multiple answers allowed). 18.0% already use messaging services to communicate with companies, 28.6% could imagine doing this in the future. WhatsApp was the most used messaging service with usage by 78.4% of the respondents, Facebook Messenger was used by 37.6%, Google Assistant was used by 18.8% (multiple answers allowed).

In the VA sample, 80.9% are used to communicate with the company via email, 32.2% via phone, 7.7% via chat with sales persons on the company's website. Only 1.3% already use voice assistants to communicate with companies, 23.2% could imagine doing this in the future. 4.2% of the respondents own an Amazon Echo device, 1.3% a Google Home device. 14.9% think it is a good idea that companies use chatbots to communicate with customers in the future, 58.7% think this is not a good idea. Concerning the above sample descriptions and the collected answers to the functional and dysfunctional questions (discussed in the following), various split-half techniques were performed to check reliability: The answers of the respondents from the first week were compared to all others and other random splits were used. Across most comparisons no significant differences appeared. Overall, the collected data were positively checked for being representative, reliable, and valid.

Then, the answers to the Kano questions in the two samples were analyzed using the standard – unsegmented – approach and also the Segmented Kano perspective with different numbers of first-mode clusters (respondents) K and numbers of second-mode clusters (use cases) L. In both samples, the MS and the VA sample, the elbow criterion with respect to VAF values was used to decide on suitable K and L values. So, the elbow criterion voted for a five customer segment solution (K=5) when use cases were not allowed to cluster (L=13, **Q** equals the unity matrix): In the MS sample the VAF values for K=1,…,15 customer segments (all with L=13 use case "clusters") were VAF=0.096, 0.363, 0.4290, 0.4686, 0.4936, 0.5142, 0.5322, 0.5451, 0.5551, 0.5626, 0.5715, 0.5773, 0.5835, 0.5877, 0.5924. In the DA sample the VAF values for K=1,…,15 customer segments (all with L=13 use case "clusters") were VAF=0.0233, 0.3552, 0.4429, 0.4865, 0.5254, 0.5524, 0.5666, 0.5782, 0.5886, 0.5963, 0.6039, 0.6071, 0.6130, 0.6189, 0.6223.

Starting with K=1 major VAF-improvements occurred when dividing the sample from one to two segments and from four to five segments with respect to K showing that the heterogeneity of the respondents in the two samples should not be neglected (as usually done in the unsegmented Kano perspective).

Also, as in the case with second-mode clusters consisting of one improvement (L=13), for varying numbers of second mode cluster L, K=5 was selected as the optimum number of first-mode clusters and – additionally – L=3 (in the MS sample) respectively L=2 (in the VA sample). For space restrictions this selection of the number of second-mode clusters is only discussed for the K=5 solutions with varying L from 1 to 13. In the MS sample the VAF values for K=5 customer segments and L=1,…,13 use case clusters were VAF=0.3736, 0.4709, 04769, 0.4782, 0.4851, 0.4862, 0.4856, 0.4874, 0.4874, 0.4895, 0.4875, 0.4877, 0.4936. In the DA sample the VAF values were 0.4941, 0.5168, 0.5209, 0.5211, 0.5212, 0.5214, 0.5224, 0.5227, 0.5215, 0.5222, 0.5224, 0.5234, 0.5254 for K=5 customer segments and L=1,…,13 use case clusters.

In the following, we discuss and compare the results with K=1 (unsegmented Kano model), K=5 with L=13 (segmented Kano perspective without clustering the use cases) and K=5 with L=3 in the MS case and K=5 with L=2 in the DA sample (segmented Kano perspective). The results from the Kano analysis without segmentation (see Figure 2) show that – on average – the respondents rate the various MS and VA use cases differently: The customer-active use case "Request delivery status" (3) generates most satisfaction if offered and this applies when implemented with both communication forms (written and spoken natural language) respectively the MS and VA sample. Other customer-active use cases – e.g. "Get service answers" (2), "Complain" or "Send messages" (4), "Pay via website" (5), and "Find products" (6) are also highly valued by both samples.

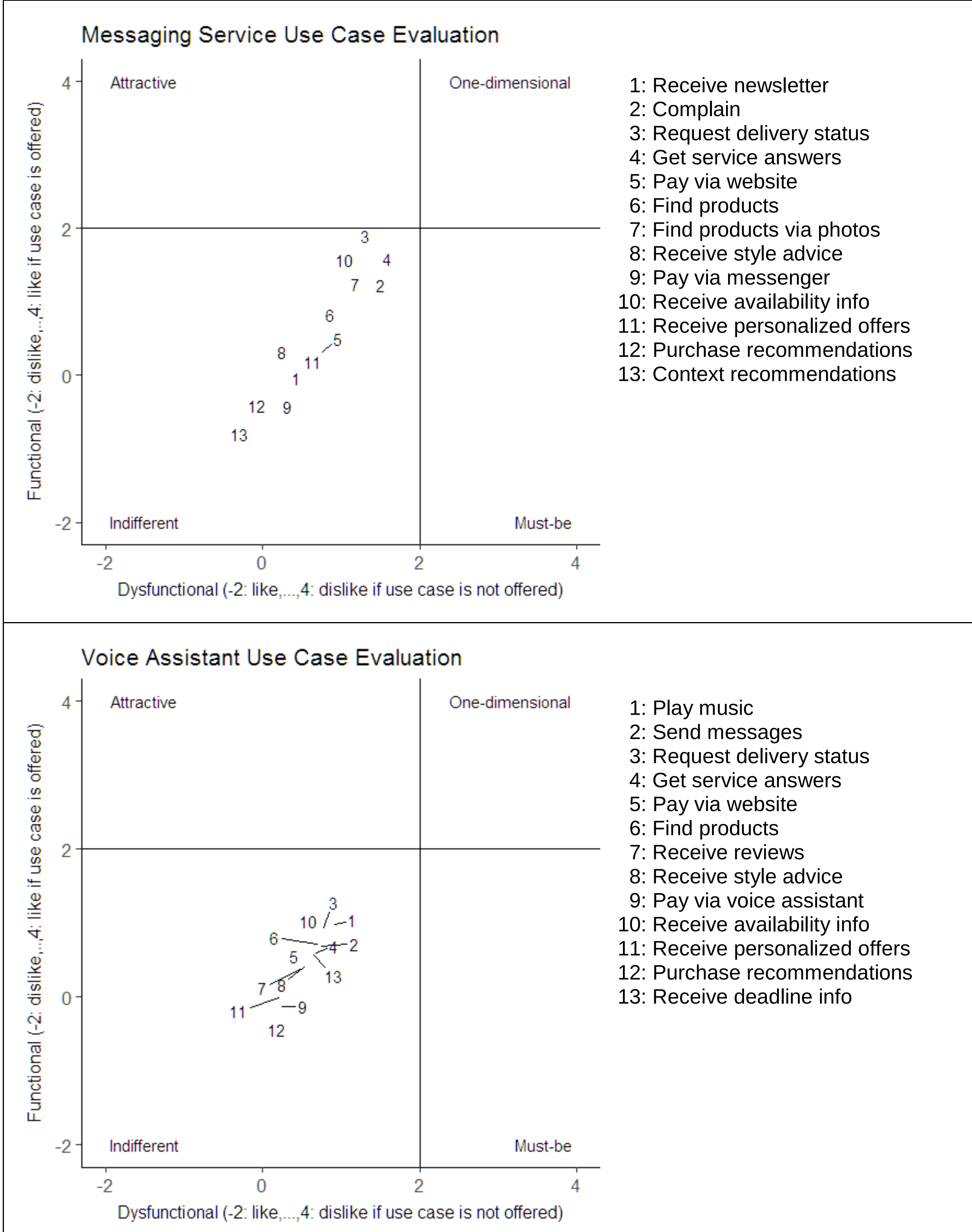

Figure 2. Use Case Evaluations (all)

The same is true for the customer-passive use case “Receive availability info” (10), which is also highly valued in both samples, and the customer-passive use case “Receive deadline info” (13) in the VA sample. In contrast to this positive evaluation, the customer-passive use cases “Context recommendations” (13 in the MS sample), “Purchase recommendations” (12), and “Receive personalized offers” (11) receive low ratings. However, it should be mentioned that – on average – most of the potential improvements based on conversational user interfaces fall into the “indifferent” Kano category. This supports – at a first glance – the opinion that the majority of the interviewed customers – at least currently – do not mind whether the company improves the user interface by the described MS and VA use cases. The developed use cases would neither increase satisfaction if offered nor dissatisfaction if not offered.

Here, the new Segmented Kano perspective can help to find out, whether the average ratings represent all respondents or whether the customers have to be treated as separate market segments that rate the use cases homogenously. Figure 3 and 4 as well as Table 4 and 5 show the results of this analysis. Each solution shows that two of the five segments rate most MS and VA use cases as attractive or one-dimensional. Again, in most customer segments, the use cases “Request delivery status” (3), “Receive availability info” (10), “Get service answers” (4), “Find products” (6) receive high ratings. However, the average ratings across all use cases differ significantly between the segments. So, in each solution there is a segment with very low ratings for all use cases which means that they dislike the feature when offered and like it if not offered (all use cases categorized as indifferent or even reverse). Also, each solution has a segment where all use cases are similarly categorized (all use cases categorized as indifferent or even reverse) but rated with higher average values according to the dysfunctional function which means that they “can live with it” if offered. The Segmented Kano perspective with grouping use cases strengthens the findings found with the unsegmented and the segmented Kano perspective without grouping of use cases: The use cases are clustered in preferred and less-preferred uses cases across all customer segments: In the MS sample the cluster with the preferred use cases (l=1) consists of “Complain”, “Request delivery status”, “Get service answers”, “Find products”, “Find products via photos”, and “Receive availability info”. In the VA sample it consists of “Play music”, “Send messages”, “Request delivery status”, “Get service answers”, “Pay via website”, “Find products”, “Receive reviews”, “Receive style advice”, “Receive availability info”, “Receive deadline info”. The less preferred clusters consist in the MS sample of “Pay via messenger”, “Purchase recommendations”, “Context recommendations”, in the VA sample of “Pay via voice assistant”, “Receive personalized offers”, “Purchase recommendations”. A closer look into the customer segment descriptions (Table 4 and Table 5) reveals that these segments in particular differ with respect to their messaging service and voice assistant usage today and in the future as well as their chatbot affinity and concerns.

Conclusion

In the age of digitalization and significant competition between online shops, it is important for retailers to always be in line with the current state of the art to act. This includes recognizing trends early on, offering an innovative range of services, at the same time satisfying customer requirements in the best possible way and thus ensuring a high level of satisfaction. It is the only way to differentiate oneself from the competition, to be successful in the long term. This also applies to the trend of conversational commerce via messaging services and voice assistants with whom the present work was concerned. In the course of an empirical investigation, 26 use cases were evaluated by two samples each of more than 2,000 customers of an online fashion retailer. With the help of the Kano approach and the Segmented Kano perspective, the requirements were categorized to determine the resulting effect on the satisfaction of the customers. The results of the study show that, due to the novel object of the study and correspondingly low experience among the participants, the classification of the services as indifferent or reverse was predominant. This means that large parts of the customer side are currently still relatively neutral in addressing the topic, so that accordingly there is hardly any influence on their satisfaction. However, it was interesting to note that people who are already more familiar with the technology, i.e. intensive users of messaging services or owner of voice assistants seem to have different requirements than those of the majority and evaluated the scenarios differently. Thus, they showed a much greater enthusiasm and less rejection, so that some use cases have already been classified as attractive. Due to the recognizable future potential of conversational user interfaces (see, among others, Gartner 2017b), it may still be worthwhile for online retailers to implement particularly attractive use cases like, e.g., “Complain”, “Request delivery status”, “Get service answers”, “Find products”, “Receive availability info”, “Receive reviews”, “Receive style info” or even “Receive deadline info”.

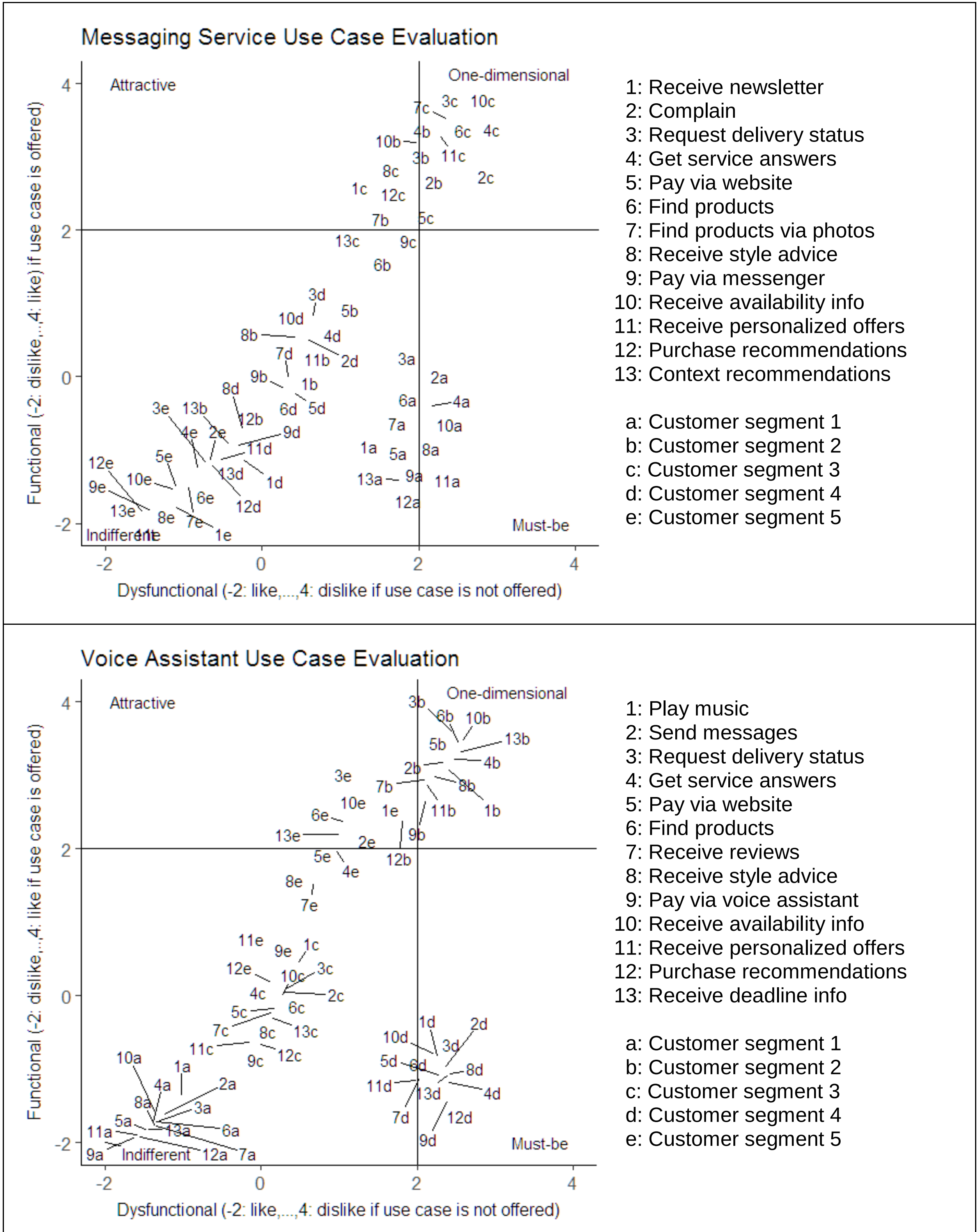

Figure 3. Use Case Evaluations (five customer segments each, no use case clustering)

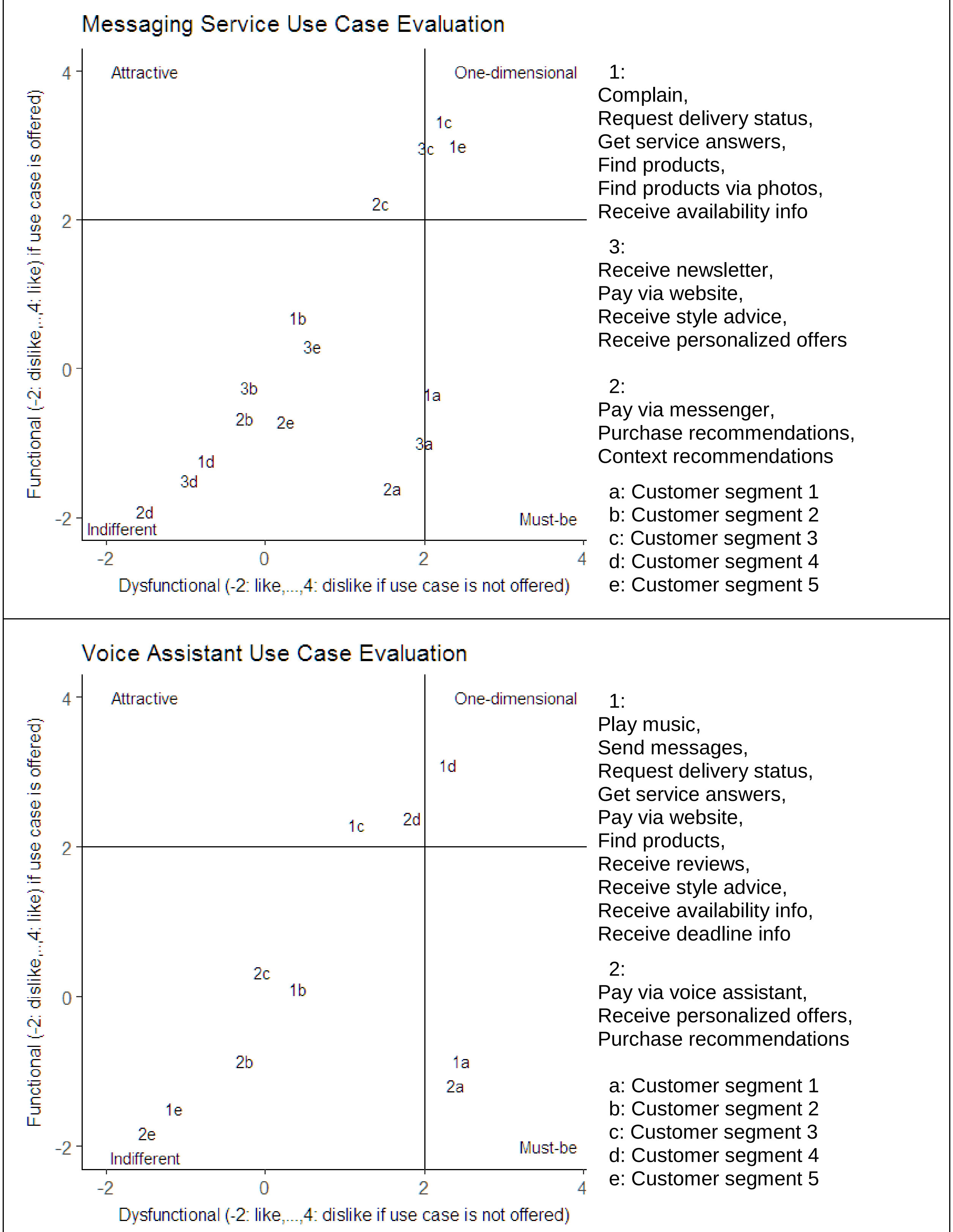

Figure 4. Use Case Category Evaluations (5 customer segments each, 3 resp. 2 use case clusters)

Segment: Size	a: 9.1%	b: 25.8%	c: 18.1%	d: 20.9%	e: 26.2%	All
Female	80.7%	75.8%	72.1%	80.5%	81.0%	77.9%
Age:18-29	3.6%	6.6%	5.6%	1.3%	9.0%	5.7%
Age:30-39	8.1%	13.6%	14.1%	10.2%	14.3%	12.7%
Age:40-49	15.7%	28.1%	23.8%	22.1%	22.4%	23.5%
Age:50-59	39.1%	33.2%	35.8%	41.8%	35.8%	36.7%
Age:60+	32.5%	17.4%	20.5%	24.1%	18.0%	20.9%
MS usage						
- daily	70.5%	71.1%	73.4%	68.0%	76.2%	72.3%
- weekly	23.0%	24.2%	20.2%	24.5%	19.7%	22.1%
MS with comp.						
- today	9.6%	16.7%	29.9%	7.5%	22.4%	18.0%
- in future	16.8%	23.8%	48.3%	8.8%	39.5%	28.6%
Chatbot affinity						
- like	2.5%	4.5%	29.7%	0.4%	7.8%	8.9%
- maybe	5.7%	20.7%	29.9%	4.5%	40.7%	26.6%
Chatbot concns.						
- impersonal	8.5%	29.0%	5.9%	34.2%	22.3%	25.6%
- inaccurate	8.0%	27.5%	6.0%	31.0%	27.5%	9.2%
- inconvenient	12.5%	29.7%	8.6%	32.0%	17.2%	5.9%
- useless	11.4%	27.5%	3.4%	44.7%	13.0%	19.1%
- feel observed	11.0%	29.1%	3.4%	40.2%	16.3%	15.1%
Categories						
- use case cl.1	“M”/”I”	“I”	“O”	“I”	“O”	“I”
- use case cl.3	“M”/”I”	“I”	“O”	“I”/”R”	“I”	“I”
- use case cl.2	“I”/”R”	“I”	“A”	“I”/”R”	“I”	“I”

Table 4. Messaging service customer segment descriptions

Segment: Size	a: 7.6%	b: 37.2%	c: 21.9%	d: 17.1%	e: 16.1%	All
Female	81.0%	77.5%	75.2%	80.7%	81.3%	78.4%
Age:18-29	0.7%	4.1%	9.9%	5.8%	0.3%	4.8%
Age:30-39	9.8%	10.5%	16.0%	14.7%	6.1%	11.7%
Age:40-49	24.8%	22.0%	23.0%	21.9%	23.2%	22.6%
Age:50-59	34.5%	37.0%	36.3%	35.2%	43.1%	37.3%
Age:60+	28.8%	24.9%	14.2%	22.2%	25.4%	22.5%
VA usage						
- in future	3.9%	8.1%	44.5%	74.4%	1.2%	24.7%
Chatbot concns.						
- good idea	3.3%	2.7%	24.3%	47.8%	0.9%	14.9%
- no good idea	65.4%	63.8%	45.7%	30.8%	90.8%	58.7%
Categories						
- use case cl.1	“M”/”I”	“I”	“A”	“O”	“I”/”R”	“I”
- use case cl.2	“M”/”I”	“I”	“I”	“A”	“I”/”R”	“I”

Table 5. Voice assistant customer segment descriptions

Although an implementation of these use cases will not lead to an immediate increase in satisfaction of all customers, they do have the potential to be perceived by the public broadly as an attractive offer via the classification dynamic. In the run-up to an actual implementation, a test phase with customers may be an option, to check the functionality and user-friendliness of the applications and to consider possible improvements before market launch. The early involvement of the digital voice as a communication channel may offer companies the opportunity to benefit from the early adopters of these devices. Moreover, it is currently still possible for retailers to differentiate themselves from competitors due to the rather sparse distribution of voice assistant based applications in online fashion to date, thus possibly winning new customers and building up a knowledge advantage over latecomers. In the event of an establishment of conversational commerce in the market or even as a standard, a general increase in satisfaction might be achieved and customer loyalty enhanced.

In the context of future research on the topic, studies with regard to the further steps in the site engineering process are of interest, e.g. usability tests (step 5) or live testing (step 6) are highly recommended (and currently on the way at the online fashion retailer). Nevertheless, more devices and platforms must be tested. With regard to step 7, repeating the study in the near future would allow to reflect changes in the assessments of the various application scenarios. On the one hand, this could empirically prove the postulated dynamics, on the other hand, it would also take the limitation of the temporal instability of the results into account. In addition, it would be particularly desirable to carry out a similarly designed investigation again with a heterogeneous structured and in particular younger group of customers and to contrast the findings obtained with each other. With the help of this research it could be shown that the attitude towards conversational commerce by means of messaging services and voice assistants is still largely characterized by indifference and enthusiasm, depending on the belonging to the identified segments. Nonetheless, the findings suggest that the issue, driven by increasing adoption of the technology, will become significantly more relevant to businesses in the foreseeable future. It is therefore already worthwhile to provide services in selected areas via messaging services and voice assistants to raise customer awareness and ensure that they benefit from the economic potential of conversational commerce in the future. In addition, differences with regard to gender should be investigated in more detail. While the sample reflected the company's customer base well in terms of gender, there are differences in men's and women's online shopping behavior also affecting website design (Buyvoets 2016). With regard to adoption, effects on the behavior of the user (word choice, speech pace, body language) as well as on emotion, cognition and personality should be investigated in more detail. The same holds for retailer's credibility and trust in the service.

Acknowledgement

The authors thank the two reviewers and the editor for their careful reading and suggestions for improvement. We also want to thank our research group at the University of Bayreuth – especially Ms. Jana Liebisch and Mr. Florian Robisch – for their support in preparing questionnaires and collecting data.

References

Ba, S., Stallaert, J., and Zhang, Z., 2010. "Balancing It with the Human Touch: Optimal Investment in IT-Based Customer Service," Information Systems Research (21: 3), pp. 423-442.

Baier, D., Gaul, W., and Schader, M., 1997. "Two-Mode Overlapping Clustering with Applications to Simultaneous Benefit Segmentation and Market Structuring," in R. Klar, O. Opitz (eds.), Classification and Knowledge Organization, Berlin Heidelberg: Springer Gabler, pp. 557-566.

Baier, D., Rese, A., Nonenmacher, N., Treybig, S, and Bressem, B., 2018. "Digital Technologies for Ordering and Delivering Fashion: How BAUR Integrates the Customer's Point of View," in *Digitalization Cases,* N. Urbach, M. Röglinger (Eds.), Wiesbaden: Springer Gabler.

Berger, C., Blauth, R., Boger, D. et al., 1993. "Kano's Methods for Understanding Customer-Defined Quality," *Center for Quality Management Journal* (2:4), pp. 3-36.

Brownlee, J., 2016. "Conversational Interfaces, Explained," available at https://www.fastcompany.com/3058546/conversational-interfaces-explained (accessed 28th August 2018).

Brusco, M. J., and Doreian, P., 2015. "An Exact Algorithm for the Two-Mode KL-Means Partitioning Problem," *Journal of Classification* (32:3), pp.481-515.

Buyvoets, R. D., 2016. "Differences Between How Men and Women Do Online Shopping," available at https://medium.com/@rodgerdwightbuyvoets/differences-between-how-men-and-women-do-online-shopping-6e590e54d06f (accessed 25th August 2018).

Capgemini Inc., 2018. "Conversational Commerce. Why Consumers Are Embracing Voice Assistants in Their Lives," Capgemini Digital Transformation Institute, available at https://www.capgemini.com/wp-content/uploads/2018/01/dti-conversational-commerce.pdf (accessed 25th April 2018).

Chung, H., Iorga, M., Voas, J. and Lee, S. 2017. "Alexa, Can I Trust You?", *Computer* (50:9), 100-104.
Dale, R., 2016. "The Return of the Chatbots," *Natural Language Engineering* (22:5), pp. 811-817.
Desaulniers, S., 2016. "Chatbots Rise, and the Future May Be 'Re-written'", available at https://www.cnbc.com/2016/04/08/chatbots-rise-and-the-future-may-be-re-written.html (acc. 25th August 2018).)
Donna, L., and Novak, H. T. P. 1997. "A New Marketing Paradigm for Electronic Commerce," *The Information Society* (13:1), pp. 43-54.
Elmorshidy, A. 2013. "Applying the Technology Acceptance and Service Quality Models to Live Customer Support Chat for E-Commerce Websites," *Journal of Applied Business Research*, (29:2), pp. 589-595.
Gartner Inc., 2016. "Gartner Says Worldwide Spending on VPA-Enabled Wireless Speakers Will Top $2 Billion by 2020," av. at https://www.gartner.com/newsroom/id/3464317 (accessed 25th April 2018).
Gartner Inc., 2017a. "Gartner Identifies Three Megatrends That Will Drive Digital Business Into the Next Decade," av. at https://www.gartner.com/newsroom/id/3784363 (accessed 25th April 2018).
Gartner Inc., 2017b. "Gartner Says Worldwide Spending on VPA-Enabled Wireless Speakers Will Top $3.5 Billion by 2021," av. at https://www.gartner.com/newsroom/id/3790964 (accessed 25th April 2018).
Gentsch, P., 2018. "Conversational Commerce: Bots, Messaging, Algorithmen und AI," in *Künstliche Intelligenz für Sales, Marketing und Service,* P. Gentsch (ed.), Wiesbaden: Springer Gabler, pp. 83-116.
Global Digital Report, 2018. "Digital in 2018: Essential Insights into Internet, Social Media, Mobile, and Ecommerce Use Around the World," https://digitalreport.wearesocial.com/ (accessed 25th April 2018).
Griol, D., Carbó, J., and Molina, J. M., 2013. "An Automatic Dialog Simulation Technique to Develop and Evaluate Interactive Conversational Agents," *Applied Artificial Intelligence* (27:9), pp. 759-780.
Hartigan, J. A., 1972. "Direct Clustering of a Data Matrix," *Journal of the American Statistical Association* (62), pp. 123-129.
Herzberg, F., Mausner, B., and Snyderman, B. B., 1959. *The Motivation to Work*, New York: Wiley, 157 p.
Jones, E., Busch, P., and Dacin, P., 2003. "Firm Market Orientation and Salesperson Customer Orientation: Interpersonal and Intrapersonal Influences on Customer Service and Retention in Business-to-Business Buyer-Seller Relationships," *Journal of Business Research* (56:4), pp.323-340.
Kano, N., Seraku, N., Takahashi, F., and Tsuji, S., 1984. "Attractive Quality and Must-Be Quality," *Journal of the Japanese Society for Quality Control* (14:2), pp. 39-48.
Klopfenstein, L. C., Delpriori, S., Malatini, S. and Bogliolo, A. 2017. "The Rise of Bots: A Survey of Conversational Interfaces, Patterns, and Paradigms," in *Proceedings of the 2017 Conference on Designing Interactive Systems*, pp. 555-565.
Lauber, D. (2013): "E-Commerce an der Schwelle zur Sättigungsphase: Produktivität von E-Commerce-Aktivitäten wird erfolgskritisch," in *Digitalisierung des Handels mit ePace*, G. Heinemann, K. Haug, and M. Gehrckens (Eds.), Wiesbaden: Springer Gabler, pp. 105-122.
Lawson, J., 2016. "The 5 Branches of Conversational Commerce: A Guide to the Bot World," available at https://venturebeat.com/2016/05/21/the-5-branches-of-conversational-commerce-a-guide-for-the-bot-curious/ (accessed 25th April 2018).
Leviathan, Y., 2018. "Google Duplex: An AI System for Accomplishing Real-World Tasks Over the Phone," available at https://ai.googleblog.com/2018/05/duplex-ai-system-for-natural-conversation.html (accessed 25th August 2018).
Mayer, J. H., 2012. "Using the Kano Model to Identify Attractive User-Interface Software Components," in *Proceedings of the 33th International Conference on Information Systems*, M.H. Huang, G. Piccoli, V. Sambamurthy (eds.).
McLean, G., and Osei-Frimpong, K., 2017. "Examining Satisfaction with the Experience During a Live Chat Service Encounter; Implications for Website Providers," *Computers in Human Behavior*, 76, pp. 494-508.
McTear, M.; Callejas, Z., and Griol, D. 2016. "The Dawn of the Conversational Interface," in *The Conversational Interface. Talking to Smart Devices*, M. McTear, Z. Callejas, and D. Griol (eds.), Cham: Springer, pp. 11-24.
McTear, M. F., 2017. "The Rise of the Conversational Interface: A New Kid on the Block?" in *Future and Emerging Trends in Language Technology. Machine Learning and Big Data*. Second International Workshop, FETLT 2016, Seville, Spain, November 30 –December 2, 2016, Revised Selected Papers, J. F. Quesada, F.-J. Martín Mateos and T. López Soto (eds.), Cham: Springer International Publishing (Lecture Notes in Computer Science, 10341), pp. 38-49.
Messina, C. 2015. "Conversational Commerce. Messaging Apps Bring the Point of Sale to You", *Medium [Web log post]*. Retrieved from https://medium.com/chris-messina/conversational-commerce-92e0bccfc3ff (accessed 25th April 2018).

Messina, C. (2016). "2016 Will be the Year of Conversational Commerce," *Medium [Web log post].* Retrieved from https://medium.com/chris-messina/2016-will-be-the-year-of-conversational-commerce-1586e85e3991 (accessed 25th April 2018).

Meuter, M. L., Ostrom, A. L., Roundtree, R. I., and Bitner, M. J., 2000. Self-Service Technologies: Understanding Customer Satisfaction with Technology-Based Service Encounters," *Journal of Marketing*, (64:3), pp.50-64.

Miller, D. 2013. "10 Trends to Watch: Conversational Commerce," avail. at https://opus-research.net/wordpress/2013/12/13/10-trends-to-watch-conversational-commerce-2014/ (acc. 25th April 2018).

Mirkin, B. G., 1996. *Mathematical Classification and Clustering*, Dordrecht: Kluwer Academic Press.

Nilsson-Witell, L. and Fundin, A., 2005. "Dynamics of Service *Attributes: A Test of Kano's Theory of Attractive Quality," International* Journal of Service Industry Management, (16:2), pp.152-168.

Nguyen, M.-H. 2017. "Why the World's Largest Tech Companies are Building Machine Learning AI Bots Capable of Humanlike Communication," available at https://www.businessinsider.de/why-google-microsoft-ibm-tech-companies-investing-chatbots-2017-11?r=US&IR=T (accessed 25th April 2018).

Pan, J., 2017. "Conversational Interfaces: The Future of Chatbots," *Chatbots Magazine,* available at https://chatbotsmagazine.com/conversational-interfaces-the-future-of-chatbots-18975a91fe5a (accessed 28th August 2018).

Rese A., Baier D., Geyer-Schulz A., and Schreiber S., 2017. "How Augmented Reality Apps Are Accepted by Customers: A Comparative Analysis Using Scales and Opinions", *Technological Forecasting and Social Change* (127:November), pp. 306-319.

Reynolds, K. E., and Beatty, S. E., 1999. "Customer Benefits and Company Consequences of Customer-Salesperson Relationships in Retailing," *Journal of Retailing* 75(1), pp.11-32.

Schepers, J., Bock, H.-H., and van Mechelen, I., 2017. "Maximal Interaction Two-Mode Clustering," Journal of Classification (34:1), pp. 49-75.

Schlicht, M., 2016. "The Complete Beginner's Guide To Chatbots," *Chatbots Magazine*, available at https://chatbotsmagazine.com/the-complete-beginner-sguide-to-chatbots-8280b7b906ca#.5vs9cl5ut (accessed 25th August 2018).

Schreiber, S., and Baier, D., 2015. "Multivariate Landing Page Optimization Using Hierarchical Bayes CBC Analysis," *Studies in Classification, Data Analysis, and Knowledge Organization* (50), pp. 465-474.

Shopify. (2016). "Conversational Commerce Definition – What is Conversational Commerce". Retrieved from https://www.shopify.com/encyclopedia/conversationalcommerce (accessed 25th April 2018).

Shawar, B. A., and Atwell, E. 2007. "Chatbots: Are They Really Useful?", *LDV Forum* (22:1), pp. 29-49.

Suvorov, I. 2016. "Shopping in Messengers: May 2016," *Chatbots Magazine*, available at https://chatbotsmagazine.com/shopping-in-messengers-may-2016-c4d28841a817 (accessed 25th April 2018).

Turing, A. M. 1950. "Computing Machinery and Intelligence," *Mind* (59:236), pp. 433–460.

Van Bruggen, G. H., Antia, K. D., Jap, S. D., Reinartz, W. J., and Pallas, F. 2010. "Managing Marketing Channel Multiplicity," *Journal of Service Research*, (13:3), pp. 331-340.

Van Doorn, M., and Duivestein, S., 2016. "The Bot Effect: 'Friending Your Brand'," Machine Intelligence. Report 2 of 4. SogetiLabs, available at http://labs.sogeti.com/wp-content/uploads/2016/06/The-Bot-Effect-US.pdf, (accessed 25th April 2018).

Van Eeuwen, M. 2017. "Mobile Conversational Commerce: Messenger Chatbots as the next Interface Between Businesses and Consumers," Master's thesis, University of Twente, available at http://essay.utwente.nl/71706/1/van%20Eeuwen_MA_BMS.pdf (accessed 25th April 2018).

Van Manen, T. 2016. "Bot or not: dit is waarom Facebook inzet op chatbots," available at https://www.marketingfacts.nl/berichten/chatbots-facebook-inzet-chatbots-messenger (accessed 25th April 2018).

Van Mechelen, I., Bock, H. H., and De Boeck, P., 2004. "Two-Mode Clustering Methods: A Structured Overview," *Statistical Methods in Medical Research* 13(5), pp.363-394.

Walsh, G., Hennig-Thurau, T., Sassenberg, K., and Bornemann, D. 2010. "Does Relationship Quality Matter in E-Services? A Comparison of Online and Offline Retailing", *Journal of Retailing and Consumer Services, (*17:2), pp. 130-142.

Yao, M. 2016. "What VCs Look for in Bot Investments," available at https://www.topbots.com/vc-bot-investor-look-bot-investment/ (accessed 25th April 2018).

Zhang, P., Small, R. V., von Dran, G. M., and Barcellos, S. 2000. "A Two Factor Theory for Website Design," in Proceedings of the 33rd Annual Hawaii International Conference on System Sciences, pp. 1–10.

Zumstein, D. and Hundertmark, S. 2017. "Chatbots: An Interactive Technology for Personalized Communication, transaction and services," *IADIS International Journal on WWW/Internet*, (15:1), pp. 96-109.