Artificial Intelligence in the Customer Journey:
A Systematic Overview of the Most Popular Use Cases Through the Creation of AI Archetypes

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1 Introduction

The attention Artificial Intelligence (AI) has received in academia and public news often feels unprecedented. A disruptive technology with humble beginnings transformed into an omnipresent buzzword. Considering the research of Davenport and Bean (2019), the hype regarding the technology seems justified when measured by companies' adoption of it. The authors have interviewed 65 Fortune 1000 companies and made the following findings: 80% call AI the most disruptive emerging technology and 96.4% have already invested in AI (p. 10). McKinsey (2019, para. 3) made similar findings in their 2019 Global AI survey, where 58% of all respondents answered to have at least one AI capability implemented in their business already. Considering that AI is expected to add almost $16 trillion to the global economy until 2030 (PWC, 2017), these numbers are not surprising. In fact, the potential that comes with AI is unprecedented. In a survey conducted by Chui et al. (2018, p. 13), the authors discovered that in almost 70% of the investigated use cases, AI can enhance performance beyond the capabilities of any other analytic technique. In 16% of these use cases value could be created through AI only.

However, Davenport and Bean (2019, p. 11) also identified that 77.1% of all the companies they have interviewed consider the business adoption of AI a challenge. Ransbotham et al. (2017, p. 6) collected insights from more than 3'000 executives, managers, and analysts, identifying that 47% of all companies have no or very little understanding of AI and only 19% actually understand the technology and truly capture its value. In short, a disruptive technology is establishing throughout the business world but only a minority of companies are able to leverage its potential.

The interesting finding is that a significant part of the faced challenges is not of a technical nature. According to Davenport and Bean (2019, p. 7) 95% of these challenges originate from people and processes. Other researchers came to similar conclusions. Many executives struggle to understand the applications and benefits of AI (Bean, 2019). Often business problems that need to be solved aren't defined (Thomas, 2019, p. 11), business cases aren't available or unclear (Pettey, 2018; Ransbotham et al., 2017, p. 6), the company is lacking a clear AI strategy (McKinsey, 2018), executives don't understand the topic sufficiently (Ransbotham et al., 2017, p. 11) or there is a lack of existing, practical knowledge like integrating AI into Customer Journeys (CJ) (Peters & Zaki, 2018, p. 1).Tim O'Reilly, founder and head of O'Reilly publications, sums up the current situation as follows: "Everyone is talking about AI these days, but most companies have no real idea of how to put it to use in their own business" (Thomas, 2019, p. v).

To resolve this situation Ransbotham et al. (2017, p. 11) articulate the need for management to develop an intuitive understanding of AI. Such an understanding is founded on a fundamental knowledge of AI, which is not too technical but allows for comprehension of its capabilities and potential use cases. To build the described knowledge, the authors suggest simple courses and introductions that are in line with the needs of managers and decision makers (Ransbotham et al., 2017, p. 11).

1.1 Purpose of Research

Following the suggestions of Ransbotham et al., the goal of this paper is to contribute to solving the knowledge gap for managers and decision makers. The vastness of the application potential of AI dictates the need to focus the research on one field specifically. Accordingly, the authors chose AI in the customer journey (CJ) as a focal point. Not only are CJs in line with the authors' backgrounds but also show one of the biggest potentials in general. Chui et al. (2018, p. 19) were able to identify marketing as one of the greatest value opportunities for AI, highlighting tasks such as pricing, promotion, and customer service management; all components of the customer journey. Additionally, an initial desk research revealed that there are several tools and tutorials for managers regarding AI in general, but no such support exists when it comes to a focus on CJs.

Therefore, to fill this gap, this paper develops an information model of the most significant state-of-the-art AI use cases in the CJ providing all necessary information for decision makers and managers to leverage the technology. To do so, firstly the most significant state-of-the-art[1] AI use cases in the CJ need to be identified. Secondly, the information need of the target group needs to be derived. And thirdly, a synopsis of the two prior dimensions creates the final information model. These tasks are summed up as the three central research questions of this paper in the figure below.

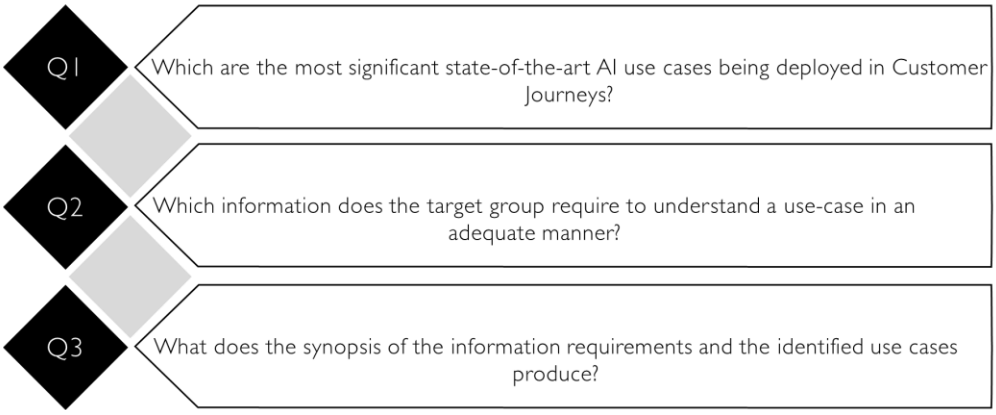

Figure 1 The three research questions underlying the paper (Source: Own figure)

All things considered the expected value of this work is to facilitate an individual's understanding regarding AI use cases in the CJ. It does so by giving an easy entry to the related topics and being an approachable orientation and overview tool. Through this approach, the scientific objective of gaining knowledge is closely connected with practical usefulness.

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[1] State-of-the-art in this context is understood as the level of development of currently and widely deployed use cases.

1.2 Methodology

Neither the use cases nor the information need of managers and decision makers have been investigated in the outlined context before. Accordingly, both dimensions need to be identified to be then overlapped, creating the intended information model.

- Identification of Use Cases

The use case identification follows a quantitative approach by conducting a descriptive, cross-sectional survey based on extensive desk research. The idea is to identify sources which show a company deploying an AI use case in their CJ. Through collecting these sources an extensive registry of use cases currently deployed in the CJ is created. From this registry the distribution of use case types and thus their popularity is derived allowing to focus the information model on the most significant ones. This method was chosen, as it offers the most objective and systematic way to gather a meaningful amount of use cases while regarding the scope of this paper. The information captured includes the deploying company, the type of use case, a description of deployment and respective sources. To the authors' knowledge such a registry has not been created in this context before and is therefore a novelty. To assign a use case to a CJ phase, the interpretation of Kotler and Keller (2016, pp. 195-201) named the 'Buying Decision Process' is applied. It is one of the most commonly used variations and represents a five-phase interpretation of a CJ which allows for an optimal allocation of each use case.

Additionally, both academic and online sources were considered to depict the current state of AI use cases as accurately as possible. This approach follows Smith's (2006, p. 179) criticism of peer reviewed publications who stresses that the time intensive reviewing process can lead to significant gaps between presented information and current developments and thus an inaccurate representation of the status quo.

The non-academic research was conducted via Google. The search-engine was chosen as it is not only the most popular and accustomed one with a worldwide market share of ca. 87% (StatCounter, 2020), Google also has a significant higher precision and relative recall than other search engines as e.g. Yahoo (Sabha & Sumeer, 2016 pp. 524-525). However, Google results, while still related to the topic, will gradually become vaguer (Sahu et al., 2016, p. 215). Therefore, during the research, each result on each Google page was examined. If three consecutive pages of Google results (~30 separate web pages) did not yield one use case, it was assumed that the results lost relevance and the Google search was therefore abandoned. Additionally, non-academic sources were investigated for content correctness, publication by recognized institutions and appropriate audience to guarantee the quality of adapted information.

All academic research was conducted via the meta-search provided by the library of the University of St. Gallen (HSG). The HSG Metasearch was chosen as it conducts the search in several renowned databases at once, including but not limited to: Business Source Ultimate, Scopus, Science Direct or the university's own catalogue. Furthermore, all research was conducted between 24.04.2020 and 22.05.2020 and through the HSG VPN, thus setting the location to Switzerland.

The applied search terms, restrictions, total results, results including inclusion and exclusion criteria, the derived sources, and the total amount of use cases obtained from each search can be seen in the following table:

Table 1: Summary of the desk research regarding AI use cases in the customer journey

Search Engine	Search Terms	Restrictions	Results	Inclusion/ Exclusion Criteria	Derived Sources	Amount of Use Cases
Google	artificial intelligence + use cases	English	408M	X[1]	102	**214**
	artificial intelligence + customer journey	English	48.8M	X[1]	19	**55**
	artificial intelligence + user journey	English	35.6M	X[1]	4	**9**
	artificial intelligence + customer experience	English	203M	X[1]	2	**5**
	artificial intelligence + best practices + marketing	English	193M	X[1]	8	**21**
HSG Metasearch	artificial intelligence AND customer journey	2017-2020; full text available; academic journals, journals, books, e-books; English	43	18	5	**25**
	artificial intelligence AND marketing AND use cases	2017-2020; full text available; academic journals, journals, books, e-books; English	54	12	6	**22**
	artificial intelligence AND marketing AND overview	2017-2020; full text available; academic journals, journals, books, e-books; English	33	6	0	**0**
					Sub-Total	**351**
			After Consolidation		Total	**327**

M=million [1] Instead of inclusion/exclusion criteria, at this step the quality standards set in chapter 1.2 for online ressources were applied

The research resulted in a sub-total of 351 use cases from 146 sources. All identified use cases were then reviewed and duplicates either removed or merged, reducing the number of use cases to a total of 327 after consolidation. The complete list of all consolidated use cases is available from the authors upon request.

For illustration purposes, two examples of such use cases are shown below.

Table 2: Exemplary presentation of two captured use cases

Google	Chatbots	Google's Duplex is a virtual assistant that can book appointments or respond to calls in a human like way	(Johari, 2020)
Shoepassion	Recommender	Through their existing data and segmentation, Shoepassion can differentiate between customers and recommend them the most relevant products	(Ganatra, 2018)

- Identification of Target Group Needs

The second part of the methodology had the goal to identify, what kind of information the target group of this paper requires, to purposefully grasp the use cases identified earlier. The applied mixed methods approach was based on two different steps.

The first one being the desk-research for the use cases. Throughout the research for the use cases, information that could provide valuable input for the need identification, was additionally captured. On this basis, initial hypotheses were derived from existing literature regarding the kind of information the target group needs, to sufficiently grasp a use case. These hypotheses were then aggregated and visualized in a prototype information model. The idea of this model is to act as a stencil to capture use cases in a uniform way and present necessary information concisely and uniformly.

The second step was to validate and adapt this information model from a prototype to a final version through an explanative online survey. Two consecutive iterations of the survey were held with representatives of the target group. The prototype was presented in a first survey round, meant to gather insights regarding the informative value for and the assessment from the target group. Based on the gathered feedback the prototype was adapted and improved. In a second survey the refined prototype was presented to a new crowd, to enhance the model once more and to derive a final and validated information model. The described approach was chosen, as insights could be gathered from a significant cross-section of the target group, thus enabling a purposeful development of the information model. Furthermore, the direct input from the target group enhanced the validity of the model, rendering unnecessary the need for a separate ex-post validation.

The approach is summed up in the following graphic, visualizing each step of the method:

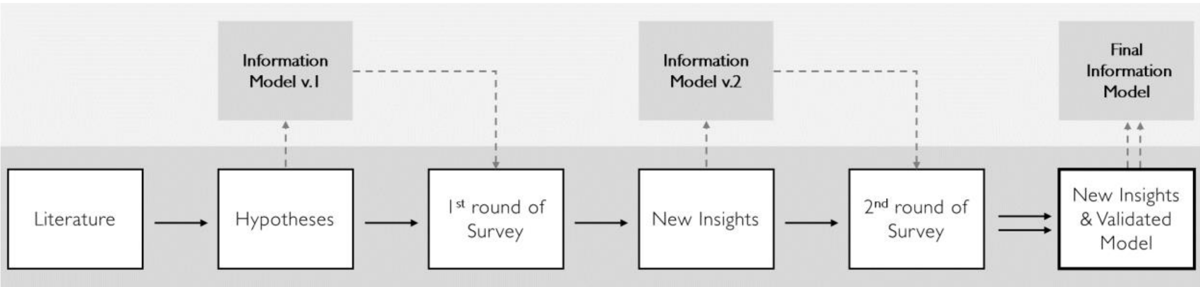


Figure 2 Visualization of the need identification approach (Source: Own figure)

Both survey iterations were conducted through a renowned online tool. The questions were standardized and could either be answered through multiple-choice or through ratings. In addition, the questions had the optional possibility to provide feedback to allow for individual input.

The surveys were based on the quality criteria set out by Berger-Grabner (2016). Emphasize was put on universal comprehensibility (Berger-Grabner, 2016, p. 191), so that the ability to understand the given information and to answer the questions is mostly independent from an individual's background. The questions were also aligned in form of a funnel (Berger-Grabner, 2016, p. 192), progressing from general to more specific ones. Furthermore, the survey iterations were designed to be answered within 15 minutes, to prevent fatigue among the participants (Berger-Grabner, 2016, p. 193).

As this paper's target group is defined as managers or decision makers with a topical focus on customer journeys, the representatives are commonly found in the marketing or innovation team. However, depending on the company size, also founders, CEOs, CTOs or CXOs can be relevant. Therefore, company size was not a differentiation factor. Interview candidates were selected primarily based on their affiliation with the topic and not their position.

Contact to these individuals was made through LinkedIn and the authors' personal network. A search based on keywords like 'Customer Experience', 'Customer Journey', 'Marketing' or 'Innovation' and combinations thereof returned profiles of fitting representatives. Through LinkedIn's in-mail feature these persons were contacted and asked to participate in the survey. Additionally, the authors' personal networks were scanned for appropriate candidates, which were then invited to share their insights. The chosen approach is therefore based on randomized cluster samples as the two sources of participants each represent a cluster (Berger-Grabner, 2016 p. 205). During the process it became apparent, that the personal networks were yielding a superior response rate and thus have been concentrated on. The invitations to the survey were sent directly to individuals only and not made available publicly. In total 84 individuals were contact throughout both rounds, 53 for the first and 31 for the second. 43 surveys were completed, 22 in the first and 21 in the second iteration.

Seven hypotheses regarding the information need were derived from literature. The topics covered thereby include a description of the use case, the fields of application, the tackled challenges, the data required, the type of AI applied, an example of an application as well as companies providing the solution.

Based on the mentioned hypotheses, the illustrations shown below were created.

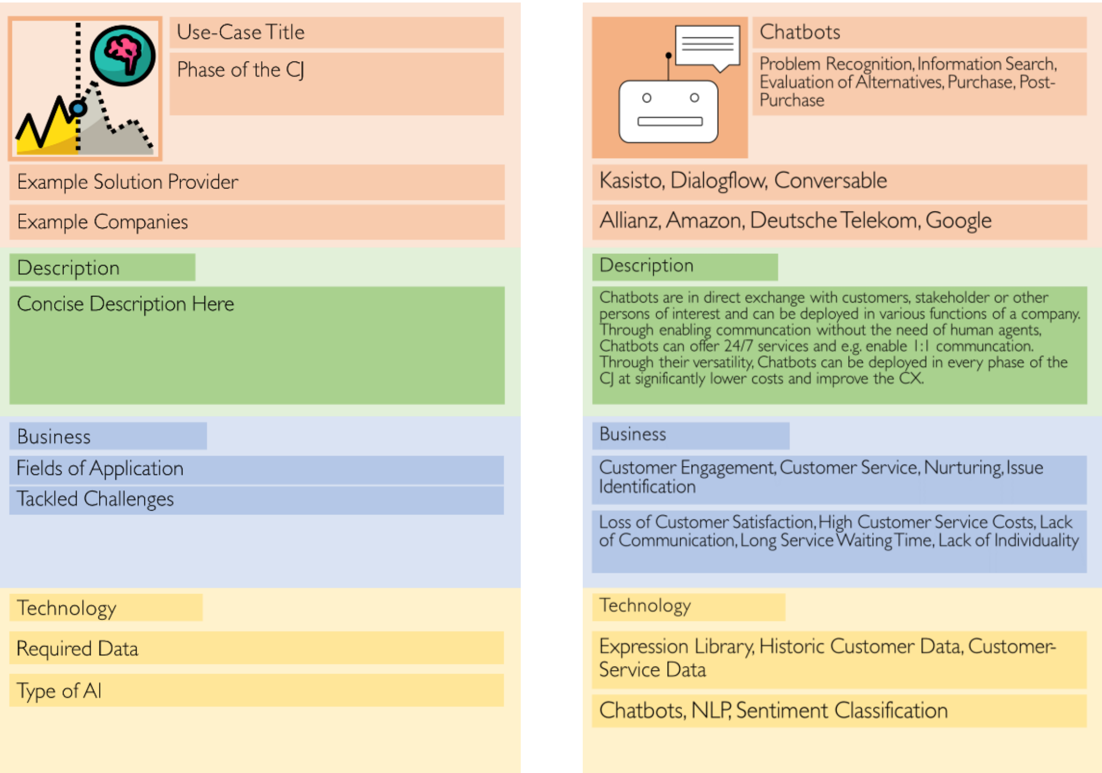


Figure 3 First prototype, raw and applied to the Chatbot use case (Source: Own figure)

The concept was inspired by quartet cards and aimed at visualizing and summarising each hypotheses' core messages. It was the first iteration of the information model and therefore the prototype. The stencil nature is made visible through only describing the separate fields of the model through a generic description. When applied, the generic descriptions are replaced through the information of the respective use case. These illustrations were also the central part of the survey, illustrating the concept to the participants.

In addition to the hypotheses introduced above, the phases of the CJ and a visualization were added. The visualization was added for aesthetic reasons, improving the design and recognisability of a use case. The hypotheses were separated into four different thematic groups, visualized through the different colour schemes. To illustrate how the information-model can look like when filled with data, an exemplary mock-up is added as well. It is based on the Chatbot use case and rudimentary information, meant only for illustration. Both illustrations were presented in the survey, to give the recipients an accurate understanding of the concept. The final results of the survey and the refined information model are expounded in chapter 2.2.

2 Findings

The following chapter presents the results of the research. Therefore, the identified use cases are elaborated on at first. And secondly, the final information model is presented.

2.1 The State-Of-the-Art AI Use Cases in the Customer Journey

This chapter shows the distribution of the different use case types and allocates each use case type to the phases of the CJ they are being deployed in. Based on the registry, the following distribution of use case types becomes apparent:

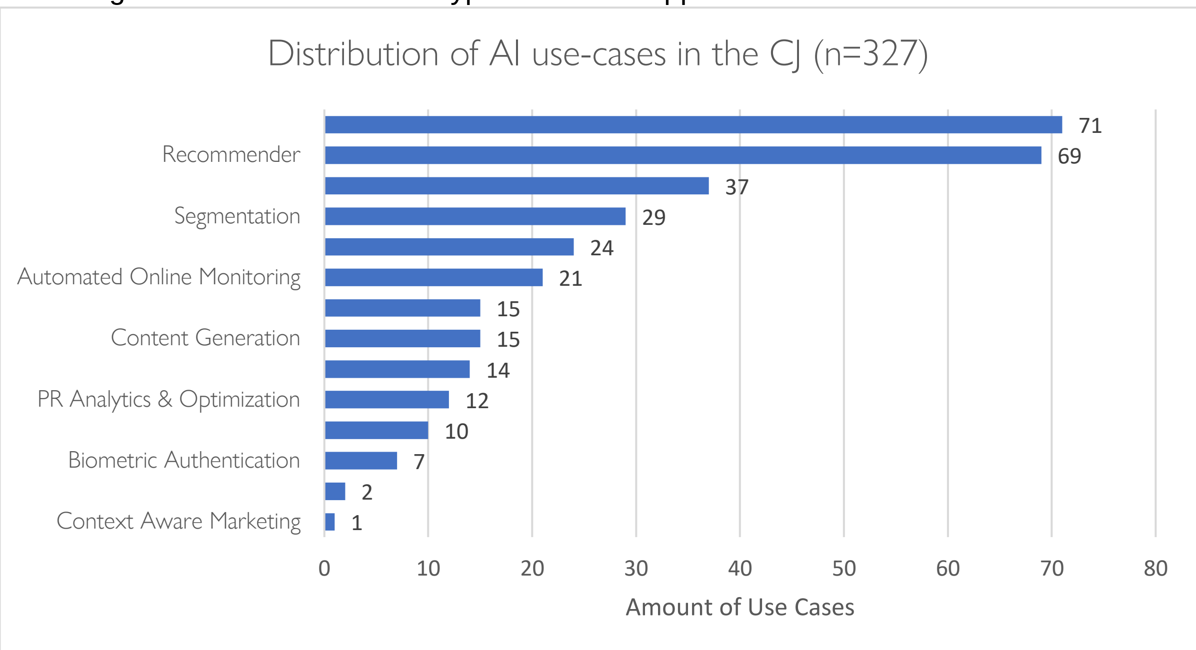


Figure 4: Distribution of AI use cases in the customer journey (Source: Own figure)

Chatbots (~21.6%) and Recommender (~21%) are the two most dominant applications, together representing more than 40% of all identified use cases. Following are Hyper Targeting (~11.3%), Segmentation (~8.8%), Sentiment Classification and Suggestions (~7.3%), and Automated Online Monitoring (~6.4%). All other use cases scored below 5%. Accordingly, the focus of this paper is put on these six use case types due to their relative popularity.

Furthermore, the graphic below visualizes in which CJ phase each use case occurs:

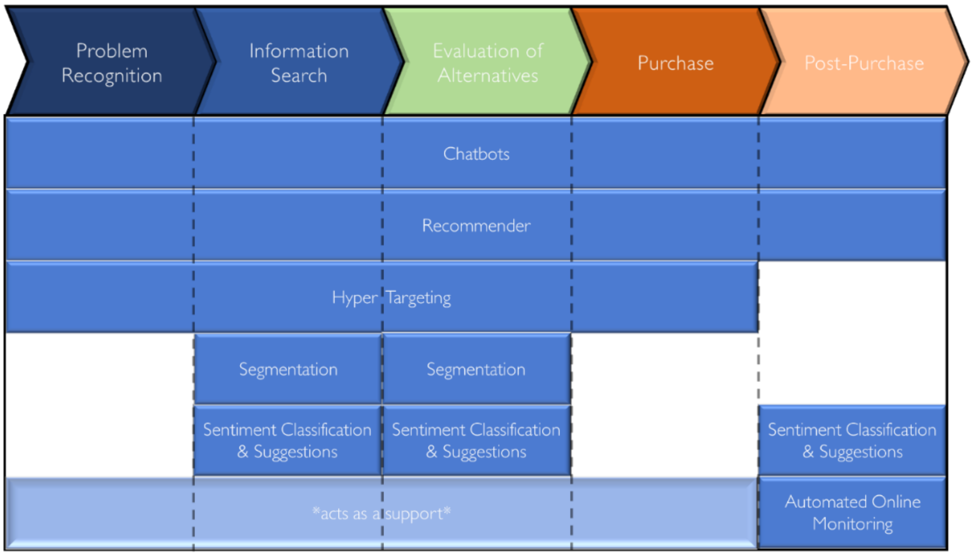


Figure 5 The use cases mapped to their deployment in the customer journey (Source: Own figure)

While all shown use cases were found to be applied in various phases of the CJ just with varying extent, Automated Online Monitoring is applied only in the Post-Purchase phase. However, the use case's impact can be found in every phase of the CJ when accounting for its support functionalities. When applied in general, the data gathered by the use case is able to enable several other applications. Therefore, its supportive role is highlighted in the graphic above.

2.2 The Use Case Information Model

Through the two survey iterations several insights were deduced, and the final information model iteratively developed. The information model is applied in full-length in chapter 2.3-2.4. This chapter presents the outcome of the research. The central findings that were made are the following:

All seven initial hypotheses regarding the information need were verified

The survey participants were asked to rate the importance of each hypothesis on a scale from 0 equalling useless to 4 equalling essential. The results are particularly clear regarding the first four hypotheses, with each one having the following score: Description of a use case ~3.59, fields of application ~3.41, tackled challenges 3.5 and type of needed data ~3.09. These results highlight the importance of the mentioned information. A little less distinctive, but still positive on average, are the results of hypotheses five to seven. Type of AI needed scored ~2.73, real-life examples ~2.95, and potential solution providers ~2.55. While scoring lower than the first four, the average sentiment is still positive, showing that all of the seven fields of information, represented by the hypotheses, have proven as relevant and thus will be covered by the information model. (see appendix 1).

A single quartet card only is not able to cover the information need

The surveys made apparent that even though the initial concept of a quartet card is appealing and appreciated by the target group, it is in conflict with the information need of the recipients in regard to the amount of information it can cover. The participants either asked for more types of information, like risk exposure or implementation costs, to be covered. Or provided comments asking for a more holistic view or labelling the provided information as too generic. One participant specifically asked for "[…] additional documents, which include some supplementary comments". Therefore, an additional free text was added to the model. The idea being that the quartet card serves as an informative wrap up for each use case and the additional text provides in-depth explanations. This description encompasses each field of information of the card and explains it more comprehensively. Through this approach, it is possible to identify the key points of a use case based on the quartet card and get more in-depth information through the free text when needed. (see appendix 1)

The information model is capable of increasing the reader's knowledge

The second survey iteration showed the model applied to the Chatbot use case and asked the recipients to rate their own knowledge regarding Chatbots in the CJ on a scale from 0 equalling useless, 3 equalling satisfactory, and 5 equalling excellent. On average the participants gave a score of 2.24. After being presented with the model, the participants were asked to answer the same question again, which resulted in an average score of 3.85 and thus an increase of 1.61. Before being presented with the model's insights, only 14.29% of all participants rated their knowledge as good or excellent which increased to 80% of all participants after being introduced to the model. (see appendix 2)

The information model sparks positive reception throughout the target group

Both survey iterations asked the participants to rate the model's capability of satisfying their information need on a scale of 0 equalling useless, 3 equalling satisfactory and 5 equalling excellent. In the second iteration the corresponding question resulted in an average rating of 3.95, up from 3.59 in the first iteration. 80% of all participants rated the model as good (55%) or excellent (25%). Not only does this increase demonstrate the value of the added free text. But this very positive outcome clearly demonstrates the approval of the target group and thus validates the model, showing that the promised value can be delivered. (see appendix 1 & 2)

The surveys yield leads for further research

Through the surveys the topics of risk and risk exposure, costs and time of implementation and performance indicators were also raised. While their potential gain in insights is acknowledged, the limited extent of this paper does not allow for the validation of the topics and the gathering of the needed information. The authors assume that to gather the needed data further interviews with solution provider and use case applicants would be needed as none of the existing sources yielded relevant insights. (see appendix 1 & 2)

2.3 Exemplary Application based on the Use Case ‘Chatbots’

While the full research output includes the information model applied to the six use cases mentioned before, the model will be shown in full for the Chatbots and Hyper Targeting use case only. All other use cases can be requested from the authors.

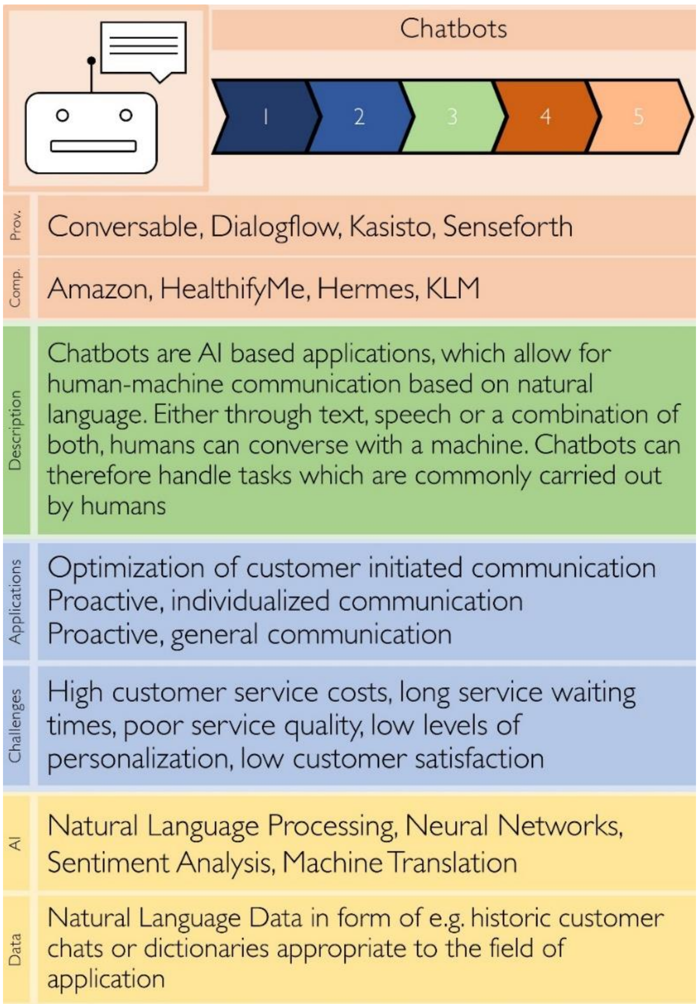


Figure 6: The Chatbots quartet card (Source: Own figure)

Chatbots are AI applications which enable human-machine communication through natural language input (Social presence and e-commerce B2B chat functions, 2020 p. 1220). These machines can autonomously communicate with humans and hence handle tasks, commonly taken care of by human agents. Generally, Chatbots are either text-based dialog systems or language-based dialog systems (Kreutzer & Sirrenberg, 2020, p. 30). Kreutzer and Sirrenberg (2020, p. 28) explain, that historically Chatbots evolved from pure text in- and output. In such a case, users can input text in a dedicated interface area and receive textual output in another area, thus enabling communication based on natural, written language. More advanced are language-based systems that can process speech as an input source and generate a speech output. Famous examples are personal assistants like Siri or Alexa, which the user can converse with. But generally, all variants of text or speech in- and outputs (text-to-text, text-to-speech, speech-to-text or speech-to-speech) are possible and can even vary in one system (Kreutzer et al., 2020, p. 28). Chatbots that are merely rule-based and e.g. deployed to answer frequently asked questions through predefined answers, are not based on AI and therefore not regarded in this context.

Chatbots are one of the most versatile applications of AI in the CJ. As the conducted research shows, the use case can be found in every stage of the CJ and a single application can span more than one phase of the journey at a time. On the contrary, the use case's touchpoints are straight forward. According to Woodford (2020 p. 3), 48% of chatbot interactions are through messenger applications and 43% through websites.
Kreutzer and Sirrenberg (2020, pp. 111-113) show that Chatbots can be applied for essentially three different tasks: to optimize customer-initiated communication, for proactive, individualized communication, and proactive, general communication. The first task focuses on helping users solve ordinary inquiries like searching for the right product or resolving questions (Kreutzer, et al., 2020 p. 111). These Chatbots are very popular in the Post-Purchase phase to take care of customer service needs, such as Hermes' Holly Chatbot (Thong, 2020) or Deutsche Telekom's Tinka (O'Boyle, 2018 p. 13). Proactive, individualized communication tasks are often automated marketing use cases (Kreutzer, et al., 2020 p. 112). The authors explain that in defined boundaries, Chatbots take over a predefined task. Such tasks can be follow-up messages after a processed complaint or come-back messages for idle customers. Generally, they are based on certain triggers, which are monitored for each customer and acted upon on occurrence. In such cases, Chatbots often overlap with the use case of Hyper Targeting. An illustrative example is KLM's Blue Bot, through which customers can book tickets but also receive booking or check-in confirmations or updates regarding their flight's status. The Chatbot proactively delivers important information to the customer and thus enhances the experience and decreases the amount of cost-intensive, customer-initiated inquiries (Kreutzer et al., 2020, p. 112). Proactive, general communication applications target the complete customer base or individual customer segments and provide a more general kind of information. These Chatbots are most often used to deliver information to a high number of customers at once (Kreutzer et al., 2020, pp. 112-113).
Chatbots offer a wide variety of benefits. On the business side, cost savings and efficiency are most significant. Through the 24/7 availability and lack of fatigue, Chatbots can handle many tasks cheaper and more consistent than a human agent can (Kreutzer et al., 2020, p. 115). Additionally, through abandoning the restrictions of limited available manpower, the use case allows for simple scalability, proactive communication, and personalization at the same time (Kreutzer, et al., 2020 pp. 115, 120). This has benefits for employees and customers alike. Existing human agents can be relieved of monotone and mundane tasks and their capabilities leveraged for more complicated and delicate encounters. Customers on the other hand can receive a faster and more personalized experience, encounters become more convenient and thus increase the overall customer experience (Kreutzer et al., 2020, p. 117). The described upsides can also result in better consumer engagement, customer retention or brand loyalty (Woodford, 2020 p. 4). Through combining Chatbots with other use cases such

as Recommender or Sentiment Classification & Suggestions, the benefits of several applications can be combined in one feature for the customer.

Companies struggling with a high amount of simple customer-service requests can deploy chatbots to take over such tasks and significantly decrease waiting time for customers and the time needed to respond to enquiries (Kreutzer, et al., 2020 p. 115). Swift customer service is essential as a study by Forrester shows (Leggett, 2016): 53% of individuals interviewed are likely to abandon their purchase when answers to their questions are not provided fast enough. And 73% even claim that the most essential factor to a good customer service is valuing a customer's time. Thus, Chatbots can be an important asset for companies struggling with high cart-abandonment rates or low customer service satisfaction. Technologically, Chatbots are based on various forms of AI, though the very basis is natural language processing (NLP) and in the case of voice conversations also neural networks (Kumar et al., 2019, p. 138). NLP is an AI subfield, dedicated to enabling human-machine conversation through making machines comprehend natural language (Akerkar, 2019 p. 54). This field incorporates subtypes like natural language understanding, natural language generation (NLG), sentiment analysis, or machine translation (Kreutzer et al., 2020, p. 27-28). Depending on the Chatbot application, varying forms of NLP will find use. Accordingly, natural language data is needed to train the bots. Such data could be historic customer chats or dictionaries. Regarding AI, the right training data is essential in general but in the case of Chatbots it is especially important. As Chatbots communicate directly with customers, poor quality data can lead to a bad experience, which can significantly harm a brand and a customer's experience. Additionally, the data needs to be appropriate for the field of application, as a Chatbot for suggesting sport gear needs to understand different phrases than a customer-service bot for a chemical supplies company.

There are several solution providers for Chatbot applications such as Conversable, Dialogflow or Senseforth. In the field of Chatbots, the identified solution providers often focus on a specific niche. For example, John Paul offers solutions for concierge services and Kasisto's KAI bot is tailored to the context of banking.

2.4 Exemplary application based on the use case 'Hyper Targeting'

Hyper Targeting in the context of this paper, describes the application of AI for (hyper-) personalized communication.

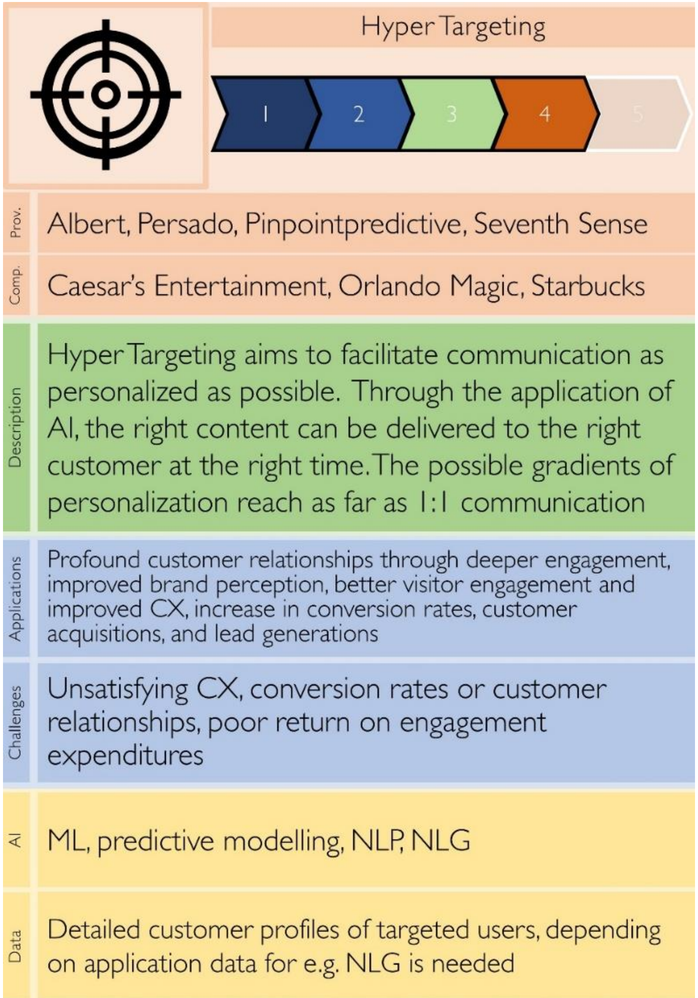


Figure 7: The Hyper Targeting quartet card (Source: Own figure)

Kumar et al. (2020) describe it as delivering "[…] the right content to the right customer at the right time" (p. 7). Simply said, the use case aims at enabling communication as personalized and tailored to an individual as possible. Though the described approach is a prevalent goal, as companies continuously strive to personalize their communication, AI allows for unprecedented levels in doing so. As shown before through the mentioned Accenture survey, customer expectations regarding personalized experiences have been rising significantly. 91% of consumers are more likely to shop with a brand that offers a personalized experience (Accenture, 2018, p. 7). Similar findings were made by Evergage (2018 p. 2) through interviewing 300 marketing experts, which agreed by 88% that their customers expect a personalized experience. Hyper Targeting fittingly tackles these expectations as it can satisfy a customer's need for meaningful engagements throughout the entire CJ. When taken far enough, AI in the form of Hyper Targeting even makes one on one communication feasible at scale (Brutman & Isaacson, 2019, para. 1).

A notable example for Hyper Targeting in practice is Starbucks. Through leveraging the data Starbucks receives through its rewards program in combination with a real-time AI personalization engine, the company can automatically create 400'000 personalized e-mail variants each week. Additionally, it provides real-time offers, based on customer's current and anticipated behaviour, which are completely unique and tailored to the individual customer. Through these advances, Starbucks was able to improve their response rate by 200%. (Richman, 2016, para. 2)

Another successful application of the use case is by the basketball team Orlando Magic. The sports club uses Wordsmith, which allows them to tailor in-app messages and e-mails to each of their members. One of the challenges they face is that season ticket holders regularly have to resell their tickets as they cannot visit every game. Reselling can be difficult and lead to frustration or membership cancellations. Therefore, the Orlando Magics analyse each customer's data and specifically contact those whose tickets are likely not to be resold. These e-mails are automatically generated, tailored to the customer, and explain their situation in natural language. Additionally, they also contain advice on how to handle the reselling process, by e.g. displaying information if the asked price is too high, how many more tickets are on sale or the opportunity to trade in their tickets for membership rewards. The approach was received very well by Orlando Magic's customers, with over 80% responding positively. (Automated Insights, n.d.a)

While these examples show some possible levers of personalization, there are in fact much more. Sterne (2017, p. 192) presents a very elaborate list of factors that can be used for personalization, with the following topics representing only an excerpt: time of day, day of week, from line, subject line & length, header, headline, content text, content images, layout, colour scheme, language tone, offer, embedded links or a call to action. As one can see the possibilities are vast and vividly illustrate why AI plays a crucial role for personalization.

When it comes to the underlying AI, Hyper Targeting is quite versatile. Many AI fields can be used and combined. At the basis of the use case though lies machine learning, predictive modelling, and natural language generation (Kumar et al., 2019, p. 138). To enable highly individualized communication, detailed information is needed about the conversation partner. That is why the use case Segmentation complements Hyper Targeting very well. Based on attributes like age, gender, interests, spending habits, devices being used or various real-time information, communication can be tailored to the individual (Akerkar, 2019, p. 27; Kumar et al., 2020, p. 7). When it comes to executing the communication, the needed data varies based on the chosen approach. For e.g. tailored e-mails, NLP and the according data outlined in the chapter of Chatbots is needed whereas individualized website banners rely on a set of graphics and themes to choose from.

Based on the identified use cases, it became apparent that Hyper Targeting is applied in the CJ phases of Need Recognition, Information Search, Evaluation of Alternatives and Purchase. According to a survey by Evergage (2018, p. 7), the most popular touchpoints are e-mails (77%), websites (52%), mobile apps (31%) and web applications (24%). Some of the most chosen formats for these touchpoints are banners (45%), call-out messages (40%) or pop-ups (29%) (Evergage, 2018, p. 14).

According to Evergage (2018, p. 21) the five most common benefits that are being realized through Hyper Targeting are increased visitor engagement, improved CX, increased conversion rates, improved customer acquisition and lead generation as well as improved brand perception. Similar findings were made by Brutman and Isaacson (2019, para. 1), who highlight the potential of deeper engagement, stronger customer relationships and better ROI. Accordingly, Hyper Targeting is a great use case for companies, which struggle with their customer experience in general, their conversion rates and customer relationships, and unsatisfying returns on engagement expenditures.

Worth mentioning is that when the use cases of Hyper Targeting, Segmentation and Recommender are combined in a seamless way, a company can offer their customers personalized engagement marketing. The customer experience can then be personalized to a point, where products, prices, website content, and communication messages are tailored to the individual user’s preferences and needs (Kumar et al., 2019, p. 138).

There is a variety of solution providers for Hyper Targeting applications. One of the most renowned companies is Albert, which can run highly individualized ad campaigns based on the combination of Segmentation and Hyper Targeting. Other providers include Persado, which can tailor messages to customers, Seventh Sense, which tracks users and engages with them when the contact is most likely to be successful or Pinpointpredective, which tailors communication to customers based on psychological profiles.

3 Critical Reflection & Closing Remarks

The goal of this paper was to create a support tool for managers and decision makers that are facing the challenges of integrating AI into their companies and business processes. As it was shown, a lack of understanding and capabilities regarding AI is apparent throughout this target group. Therefore, to support the adoption of AI, an information model was created which summarises the most popular AI use cases in the CJ in regard to the information need of managers and decision makers. To do so, at first the most popular applications were identified by systematically scanning available information on the web and in academic literature for examples of AI use cases in the CJ. This process resulted in an extensive registry of application examples, from which a distribution of different use case types was derived, and the most popular ones identified. In a second step, an information model was created by deducing hypotheses from relevant business literature regarding the information need of the target group. Through two consecutive rounds of survey iterations, the hypotheses and the developed information model could be validated and iteratively improved.

The six most popular use cases are Chatbots, Recommender, Hyper Targeting, Segmentation, Sentiment Classifications and Suggestions, and Automated Online Monitoring. On the basis of the surveys, it was possible to show through individual comments and the given ratings, that the target group strongly endorses the introduced concept of an information model regarding AI use cases in the CJ and appreciates its informational value. Due to the limited scope of this paper, several promising insights that were made during the surveys could not be adopted. These include the consideration of time and costs of implementation, risk factors and exposure as well as ways to evaluate the success of each use case. The reason being for the dismissal of the mentioned factors was the lack of information that could be deduced during the research. It was assumed that in order to generate the needed insights, additional interviews with companies deploying and solution providers developing the respective use cases would be needed. Doing so exceeded the scope of this paper. Furthermore, the undertaken survey rounds were conducted with a modest set of representatives of the target group. Even though extensive insights were gained, a higher number of survey participants could have resulted in additional views or opinions. Furthermore, the approach of randomized cluster samples incorporates the risk of an outcome bias due to the interviewed clusters. Similar restrictions apply to the capturing of the use cases. The chosen approach aimed at identifying a distribution pattern within the use cases. Therefore, it cannot be guaranteed that through more extensive research, incorporating further and more diversified sources, a different distribution or additional use case types would not have emerged.

Nevertheless, the results of this paper are very promising, and the received feedback of the target group vividly demonstrates the relevance of the topic. Therefore, further research should be conducted in order to refine the created information model and the list of deployed use cases. Through interviewing a higher number of representatives of the target group, additional insights regarding potential fields of information can be made and the model tested more profoundly. Additionally, companies deploying and developing use cases need to be involved in further research to access knowledge regarding the topics mentioned earlier and potentially identify hitherto unknown needs, fields of information or deployed use cases.

Finally, the authors want to stress the significant value that can be created when academic research is strongly aligned to the needs of a target group. Particularly the field of AI shows great potential when it comes to bridging the gap between the existing knowledge and the need of businesses to understand and apply the technology.

4 List of Figures

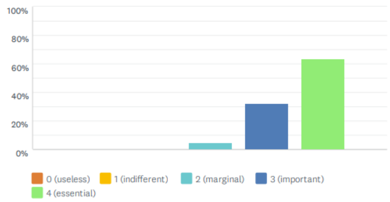
5 List of Tables

6 Appendix

Appendix 1 Relevant results of the first survey iteration

Q2 How important do You consider a Description of the use-case, introducing and outlining it?

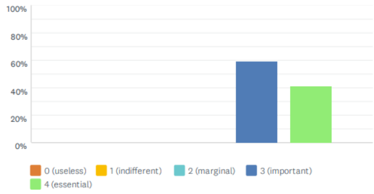
Answered: 22 Skipped: 0



0 (USELESS)	1 (INDIFFERENT)	2 (MARGINAL)	3 (IMPORTANT)	4 (ESSENTIAL)	TOTAL	WEIGHTED AVERAGE
0.00% 0	0.00% 0	4.55% 1	31.82% 7	63.64% 14	22	3.59

Q3 How important do You consider learning about the Fields of Application of the use-case, meaning their purpose and in which way they generate value?

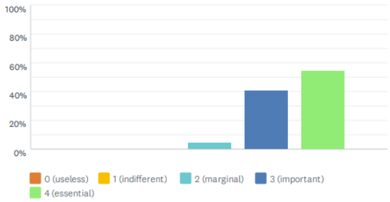
Answered: 22 Skipped: 0



0 (USELESS)	1 (INDIFFERENT)	2 (MARGINAL)	3 (IMPORTANT)	4 (ESSENTIAL)	TOTAL	WEIGHTED AVERAGE
0.00% 0	0.00% 0	0.00% 0	59.09% 13	40.91% 9	22	3.41

Q4 How important do You consider to know about the Challenges a use-case can tackle, e.g. reducing churn or falling customer satisfaction?

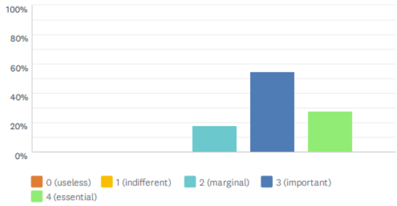
Answered: 22 Skipped: 0



0 (USELESS)	1 (INDIFFERENT)	2 (MARGINAL)	3 (IMPORTANT)	4 (ESSENTIAL)	TOTAL	WEIGHTED AVERAGE
0.00% 0	0.00% 0	4.55% 1	40.91% 9	54.55% 12	22	3.50

Q5 How important do You consider to know about the Type of Data, e.g. historic purchase data, that is needed for a use-case?

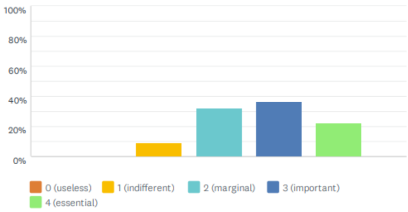
Answered: 22 Skipped: 0



0 (USELESS)	1 (INDIFFERENT)	2 (MARGINAL)	3 (IMPORTANT)	4 (ESSENTIAL)	TOTAL	WEIGHTED AVERAGE
0.00% 0	0.00% 0	18.18% 4	54.55% 12	27.27% 6	22	3.09

Q6 How important do You consider to know about the Type of AI, e.g. natural language understanding, that is needed for a use-case?

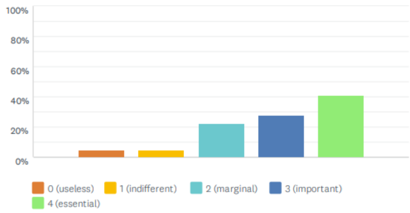
Answered: 22 Skipped: 0



0 (USELESS)	1 (INDIFFERENT)	2 (MARGINAL)	3 (IMPORTANT)	4 (ESSENTIAL)	TOTAL	WEIGHTED AVERAGE
0.00% 0	9.09% 2	31.82% 7	36.36% 8	22.73% 5	22	2.73

Q7 How important do You consider real-life Examples to understand a use-case?

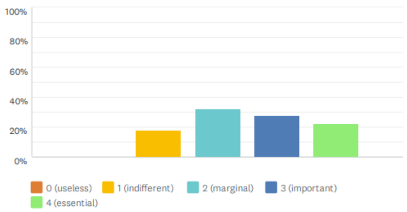
Answered: 22 Skipped: 0



0 (USELESS)	1 (INDIFFERENT)	2 (MARGINAL)	3 (IMPORTANT)	4 (ESSENTIAL)	TOTAL	WEIGHTED AVERAGE
4.55% 1	4.55% 1	22.73% 5	27.27% 6	40.91% 9	22	2.95

Q8 How important do You consider to know about potential Solution Providers, which offer the use-case?

Answered: 22 Skipped: 0



0 (USELESS)	1 (INDIFFERENT)	2 (MARGINAL)	3 (IMPORTANT)	4 (ESSENTIAL)	TOTAL	WEIGHTED AVERAGE
0.00% 0	18.18% 4	31.82% 7	27.27% 6	22.73% 5	22	2.55

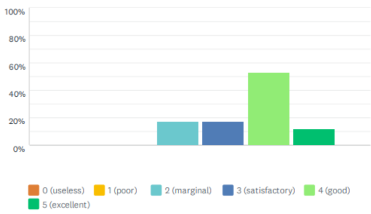
Q9 Is there any other field of information You would like to know about?

Answered: 2 Skipped: 20

#	RESPONSES	DATE
1	Scalability & repeatability - how do you evaluate a solution, and pivot or persevere based on how it's working	7/26/2020 7:12 PM
2	Data privacy and other legal constraints to consider, as well as risk exposure as a result of the new solution	7/21/2020 11:45 AM

Q10 How do You rate the current prototype's ability to satisfy Your information need?

Answered: 17 Skipped: 5



0 (USELESS)	1 (POOR)	2 (MARGINAL)	3 (SATISFACTORY)	4 (GOOD)	5 (EXCELLENT)	TOTAL	WEIGHTED AVERAGE
0.00% 0	0.00% 0	17.65% 3	17.65% 3	52.94% 9	11.76% 2	17	3.59

#	FEEL FREE TO COMMENT HERE...	DATE
1	Quite generic/could be found through Googling. What could be more helpful could be a kind of AI readiness assessment to point out the benefits but also challenges of getting to a chatbot solution, and whether or not your company is yet ready for that	7/26/2020 7:14 PM
2	Who will need to face change in their day-to-day work?	7/23/2020 10:12 AM
3	I would add something like pros / cons in comparison to other solutions (other AI and non-AI) to get a more holistic view of the limitations and expectations of the solution	7/21/2020 11:53 AM
4	I miss the sublines: Headline is Business Subline: Fields of application, text Subline tackled Challenges text	7/20/2020 9:26 AM

Q17 Would You like to comment anything else?

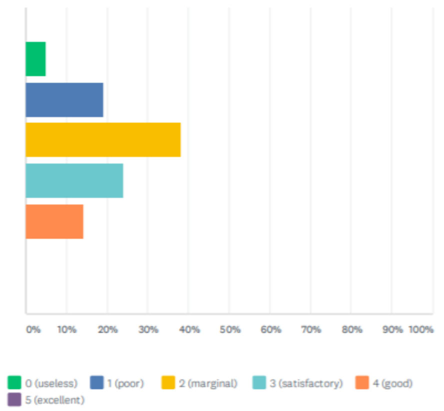
Answered: 4 Skipped: 18

#	RESPONSES	DATE
1	This is a great topic. As an IT manager, I can tell you that tackling the problem of making AI effective and not just a buzzword is a big gap in today's companies, so if you tackle this youll be solving a great problem! Good luck in your studies!!	7/26/2020 7:20 PM
2	The Concept with your Cards is very helpful! Love the Idea behind it and the execution is top notch! But what would help me personally, beside these Cards, are some additional Documents which include some supplementary comments. Anyways, nice work you did there!	7/24/2020 11:00 AM
3	Very useful idea - even more if you have to compare different solutions	7/20/2020 9:39 AM
4	Those use case cards are more for roles in the buying circle which have no clue. It does not really show any benefits of the solutions really - it just tells that it solved a problem. But I can tell a lot of things...	7/10/2020 2:06 PM

Appendix 2 Relevant results of the second survey iteration

Q1 How do You rate Your personal knowledge regarding Chatbots applied in Customer Journeys?

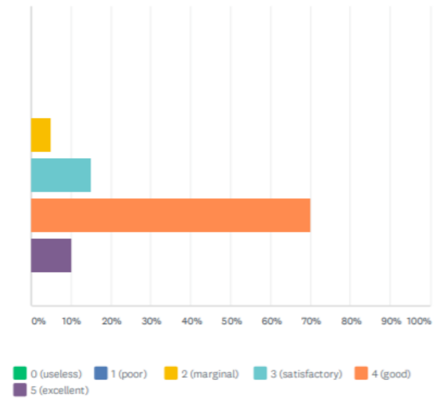
Answered: 21 Skipped: 0



0 (USELESS)	1 (POOR)	2 (MARGINAL)	3 (SATISFACTORY)	4 (GOOD)	5 (EXCELLENT)	TOTAL	WEIGHTED AVERAGE
4.76% 1	19.05% 4	38.10% 8	23.81% 5	14.29% 3	0.00% 0	21	2.24

Q2 How do You rate Your personal knowledge regarding Chatbots applied in Customer Journeys after having read the provided information?

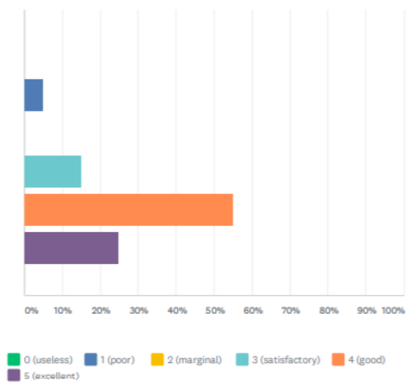
Answered: 20 Skipped: 1



0 (USELESS)	1 (POOR)	2 (MARGINAL)	3 (SATISFACTORY)	4 (GOOD)	5 (EXCELLENT)	TOTAL	WEIGHTED AVERAGE
0.00% 0	0.00% 0	5.00% 1	15.00% 3	70.00% 14	10.00% 2	20	3.85

Q3 How do You rate the introduced model's capability of satisfying your information need?

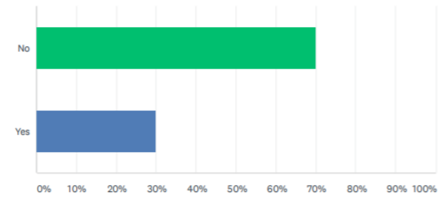
Answered: 20 Skipped: 1



0 (USELESS)	1 (POOR)	2 (MARGINAL)	3 (SATISFACTORY)	4 (GOOD)	5 (EXCELLENT)	TOTAL	WEIGHTED AVERAGE
0.00% 0	5.00% 1	0.00% 0	15.00% 3	55.00% 11	25.00% 5	20	3.95

Q4 Is there any other information You would wish to learn through the model?

Answered: 20 Skipped: 1



ANSWER CHOICES	RESPONSES	
No	70.00%	14
Yes	30.00%	6
TOTAL		20

#	YES	DATE
1	New, potential fields (use cases) in the future in which chatbots can be disruptive to particular industries.	8/12/2020 2:19 PM
2	The model was presented and explained very clearly. Due to the short description in combination with the graphics, the model was basically well understood even without previous knowledge. Nevertheless, from the management's point of view, it would be desirable for the model to be based more on figures and data. For example, it would be interesting to know how long the integration of this model can take on average or how much the implementation can cost. Of course, it is difficult to collect accurate data for such questions.	8/10/2020 9:10 PM
3	Coverage of customers and satisfaction of the interaction	8/2/2020 8:24 PM
4	Might be interesting to have an indicator of the complexity of the underlying AI or the scope of realizing such a project	8/2/2020 5:06 PM
5	It might be nice to have further literature on that topic	8/2/2020 12:04 PM
6	This model is basically close to perfect from my point of view! Great Job! But as a manager and therefore a management perspective i would like to know more about facts and figures.. How much does it cost to implement? How long will the implementation process take? Etc. I know this is really tricky maybe even impossible to say (at least in such a general manner) but it would really appreciate it! Hope i could help you or at least give you some new insides.. Don't hesitate to send me your final results, would love to see where all your work leads to!	8/1/2020 12:56 PM

7 List of Sources

Accenture. 2018. Accenture. *Making It Personal.* [Online] 2018. [Cited: 10 July 2020.] https://www.accenture.com/t20171031T052156Z__w__/us-en/_acnmedia/PDF-34/Accenture-Pulse-Check-Dive-Key-Findings-Personalized-Experiences.pdf.

Akerkar, Rajendra. 2019. *Artificial Intelligence for Business.* Cham : Springer, 2019.

AppliedAI. 2020. 100+ AI Use Cases/Applications: A Comprehensive Guide. *appliedAI.* [Online] 2020. [Cited: 21 April 2020.] https://appliedai.com/use-cases/1.

Automated Insights. n.d.b. Bodybuilding.com. *Automated Insights.* [Online] n.d.b. [Cited: 06 May 2020.] https://automatedinsights.com/customer-stories/bodybuilding.

—. n.d.a. Orlando Magic. *Automated Insights.* [Online] n.d.a. [Cited: 01 May 2020.] https://automatedinsights.com/customer-stories/orlando-magic/.

Berger-Grabner, Doris. 2016. *Wissenschaftliches Arbeiten in den Wirtschafts- und Sozialwissenschaften.* Wiesbaden : Springer Gabler, 2016.

Bernecker, Michael. 2019. Künstliche Intelligenz - Was ist das eigentlich? *Marketinginstitut.* [Online] 2019. [Cited: 23 July 2020.] https://www.marketinginstitut.biz/blog/kuenstliche-intelligenz/#43_hyper_targeting.

Best Practice AI. n.d.a. Explore Top AI Use Cases in Functions > Marketing. *BestPracticeAI.* [Online] n.d.a. [Cited: 28 April 2020.] https://www.bestpractice.ai/functions/marketing.

Brutman, David and Isaacson, Peter. 2019. How to Leverage AI and Hyper-Personalization to Transform Mass Marketing to Precision Marketing. *Martechseries.* [Online] 2019. [Cited: 10 July 2020.] https://martechseries.com/mts-insights/guest-authors/leverage-ai-hyper-personalization-transform-mass-marketing-precision-marketing/.

Chui, Michael, et al. 2018. *Notes from the AI Frontier - Insights from hundreds of use cases.* New York City : McKinsey&Company, 2018.

Comparative Study of Search Engines in Context of Features and Semantics.
Sahu, Sanjib Kumar, Mahapatra, D P and Balabantaray, R C. 2016. 2, 2016, Journal of Theoretical and Applied Information Technology, Vol. 88, pp. 210-218.

Davenport, Thomas H. and Bean, Randy. 2019. *Big Data and AI Executive Survey 2019.* Boston : New Vantage Partners, 2019.

Dochartaigh, Niall. 2012. *Internet Research Skills.* 3. London : Sage Publications, 2012.

Evergage. 2018. Evergage. *2018 Trends in Personalization.* [Online] 2018. [Cited: 10 July 2020.] http://www.evergage.com/wp-content/uploads/2016/06/2016-Trends-in-Personalization-Survey-Report-Evergage-final.pdf.

Ganatra, Rupa. 2018. Is Artificial Intelligence in Marketing Overhyped? *Forbes.* [Online] 2018. [Cited: 01 May 2020.] https://www.forbes.com/sites/rganatra/2018/03/04/is-artificial-intelligence-in-marketing-overhyped/#79af0de86681.

Gentsch, Peter. 2019. *AI in Marketing, Sales and Service - How Marketers without a Data Science Degree can use AI, Big Data and Bots.* Cham : Springer International Publishing, 2019. pp. 1-125.

Influence of new-age technologies on marketing: A research agenda.
Kumar, V, Ramachandran, Divya and Kumar, Binay. 2020. 2020, Journal of Business Research.

Johari, Aayushi. 2020. AI Applications: Top 10 Real World Artificial Intelligence Applications. *edureka!* [Online] 2020. [Cited: 27 April 2020.] https://www.edureka.co/blog/artificial-intelligence-applications/.

Kotler, P and Keller, K. L. 2016. *Marketing Management.* 15th ed. - Global. Harlow : Pearson, 2016.

Kreutzer, Ralf T and Sirrenberg, Marie. 2020. *Understanding Artificial Intelligence - Fundamentals, Use Cases and Methods for a Corporate AI Journey.* Cham : Springer, 2020.

Leggett, Kate. 2016. Online Self Service Dominates Yet Again. Why? Its An Effortless Way To Get To Your Answers. *Forrester.* [Online] 2016. [Cited: 06 July 2020.] https://go.forrester.com/blogs/16-01-28-online_self_service_dominates_yet_again_why_its_an_effortless_way_to_get_to_your_answers/.

McKinsey. 2019. Global AI Survey: AI proves it worth, but few scale impact. *McKinsey.* [Online] 2019. [Cited: 20 March 2020.] https://www.mckinsey.com/featured-insights/artificial-intelligence/global-ai-survey-ai-proves-its-worth-but-few-scale-impact.

O'Boyle, Sandra. 2018. AI & customer experience: Emerging best practices. *InForm.* [Online] 2018. [Cited: 09 May 2020.] https://inform.tmforum.org/research-reports/ai-customer-experience-emerging-best-practices/.

Peters, Christoph and Zaki, Mohamed. 2018. *Modular Service Structures for the Successful Design of Flexible Customer Journeys for AI Services and Business Models - Orchestration and Interplay of Services.* Cambridge : Cambridge Service Alliance, 2018.

Pettey, Christy. 2018. How to Build a Business Case for Artificial Intelligence. *Gartner.* [Online] 2018. [Cited: 10 March 2020.] https://www.gartner.com/smarterwithgartner/how-to-build-a-business-case-for-artificial-intelligence/.

PWC. 2017. AI to drive GDP gains of $15.7 trillion with productivity, personalisation improvements. *PWC.* [Online] 2017. [Cited: 08 March 2020.] https://www.pwc.com/gx/en/news-room/press-releases/2017/ai-to-drive-gdp-gains-of-15_7-trillion-with-productivity-personalisation-improvements.html.

Ransbotham, Sam, et al. 2017. *Reshaping Business With Artificial Intelligence.* Cambridge, Massachusetts : MITSloan Management Review, 2017.

Richman, Dan. 2016. GeekWire. *How Starbucks is using artificial intelligence to connect with customers and boost sales.* [Online] 2016. [Cited: 10 July 2020.] https://www.geekwire.com/2016/starbucks-using-artificial-intelligence-connect-customers-boost-sales/.

Search engine effectiveness using query classification: a study.

Sabha, Ali and Sumeer, Gul. 2016. 4, 2016, Online Information Review, Vol. 40, pp. 515-528.

Social presence and e-commerce B2B chat functions.

StatCounter. 2020. Worldwide desktop market share of leading search engines from January 2010 to January 2020. *Statista.* [Online] 2020. [Cited: 08 June 2020.] https://www.statista.com/statistics/216573/worldwide-market-share-of-search-engines/.

Sterne, Jim. 2017. *Artificial Intelligence for Marketing.* Hoboken, New Jersey : John Wiley & Sons, 2017.

Thomas, Rob. 2019. *The AI Ladder - Demystifying AI Challenges.* Sebastopol : O'Reily, 2019.

Thong, Monica. 2020. Connecting Customer Experiences with Artificial Intelligence. *Oracle.* [Online] 2020. [Cited: 10 May 2020.] https://blogs.oracle.com/cx/connecting-customer-experiences-with-artificial-intelligence.

Turabian, Kate L. 2007. *A Manual for Writers of Research Papers, Theses, and Dissertations.* 7. Chicago and London : The University of Chicago Press, 2007.

Understanding the Role of Artificial Intelligence in Personalized Engagement Marketing. **Kumar, V, et al. 2019.** 4, 2019, California Management Review, Vol. 61, pp. 135-155.

Woodford, Scarlett. 2020. Why Chatbots are essential to Retail. *Juniper Research.* [Online] 2020. [Cited: 07 June 2020.] https://www.juniperresearch.com/document-library/white-papers/why-chatbots-are-essential-to-retail.