

MASTER

Personalization in automated digital customer support an explorative and experimental study

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Personalization in Automated Digital Customer Support:

An Explorative and Experimental Study

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Abstract

The service industry is rapidly transforming from mass-standardization to mass-personalization. With the use of virtual assistants, automated digital customer support can be done more efficient and more personalized. Personalization methods have been studied for traditional customer support, but a deep understanding of specific method description and implementation lacks for the online environment. By studying the effects of personalization methods in automated digital customer support, this research aims to contribute to the research area of digital personalization and to support industry in implementing personalization in their digital customer support activities. This research has therefore conducted an exploratory qualitative analysis with an expert panel to evaluate traditional personalization methods and an experimental study to study the effects of knowledge personalization on customer satisfaction. It was found that the level of conversation detail positively influences customer satisfaction. This relation is moderated by customer product knowledge, creating a personalization opportunity. As the level of product knowledge increases, the effect of level of detail on customer satisfaction decreases. By presenting customers with a level of detail personalized to their level of product knowledge, the average customer satisfaction could increase. The effects of knowledge implementation are case-specific and special attention should be given to the problem complexity, knowledge diversity and customer knowledge assessment.

Management Summary

Due to increasing personalized demands of customers, radically innovating communication channels and decreasing cost of computing power, automated customer support is currently one of the fastest growing industries. Standardization of customer offerings is rapidly changing to mass-customization and mass-personalization. Virtual assistants enable the service industry to give personalized customer support, which is available at any possible time and through any possible channel. Personalization of automated digital customer support through virtual assistants has the potential of simultaneously increasing the efficiency and service quality of the support channel.

Previous research on personalization in customer support has identified the most popular personalization methods for traditional, face-to-face customer support. Furthermore, research on personalization in automated digital customer support mainly focused on general effects. Multiple studies have found a positive effect of personalization on service quality and customer satisfaction. However, distinctive personalization methods in automated digital customer support have not been studied separately. This leaves implementation of personalization methods for virtual assistants in customer support for open interpretation of the businesses. A deeper understanding of the effects of personalization methods on service evaluations would therefore stimulate industries by proposing concrete starting blocks for implementation of personalization in automated digital customer support. This research was conducted to contribute to this deeper understanding by answering the following research question:

How could customer satisfaction about an automated digital customer support conversation be improved through personalization?

The theoretical framework of personalization as proposed by this research is based on analysis of previous studies. Two components of personalization in automated digital customer support can be distinguished: the customer profile and the conversation feature. By adjusting the conversation feature based on the customer profile, personalization occurs. By successfully personalizing the conversation, the goal of increasing customer satisfaction, will be met.

Traditional personalization methods were discussed with an expert panel using a structured Delphi method. The goal of this qualitative study was to evaluate traditional personalization methods on their effectiveness in automated digital customer support, propose new personalization methods and rank the new list of personalization methods based on their effect on customer satisfaction. An expert panel consisting of 14 experts working in research and development of (chat-based) virtual assistants completed the qualitative study in three rounds of structured interviews, collaborative feedback and an internet survey.

The qualitative study resulted in an updated list of personalization methods, specified for their effectiveness in automated digital customer support. The most popular personalization method among the experts was knowledge personalization. Knowledge personalization adjusts the level of detail in a conversation based on the level of product knowledge of the customer. All experts expected a positive effect on customer satisfaction. Secondly, outcome personalization changes the number of options or solutions presented to the customers based on the desire for control or simplicity of the user. Experts predicted a positive effect on personalization when implemented successfully, but a challenge in successfully determining the optimal number of options. Human routing personalization matches the profile of the customer to the profile of a human support agent when the virtual assistant is not sufficient. Whilst this would create potential benefits in emotion management, the expert panel valued selection based on availability higher than selection based on personality. Lastly, language personalization was predicted to have a very limited effect on customer satisfaction.

Due to its predicted positive effect on customer satisfaction, its extension on current personalization research and its relatively easy implementation, knowledge personalization was further analyzed in this research. The two components of knowledge personalization, which are level of conversational detail and level of customer product knowledge, were constructed based on conversational and knowledge studies. Level of detail is based on two sub-variables. First, the difficulty of vocabulary determines the level of intelligence or knowledge necessary to comprehend the vocabulary used. The second sub-variable is the number of distinctive steps in which a solution or response is described. This number of steps is closely related to the cognitive effort needed to understand the action that is requested from or proposed to the customer. A relatively high level of detail can be obtained by a relatively low difficulty of vocabulary and a relatively high number of steps. However, this also causes a relatively high length of the response and conversation. Customer product knowledge is based on product expertise and product familiarity. A personalization opportunity could be hypothesized as customers with a high level of product knowledge are likely to prefer a short solution proposal and customers with a low level of product knowledge are likely to prefer a detailed solution proposal.

To analyze the effect of knowledge personalization, an experimental study was designed. Potential customers of a Bitcoin virtual assistant were asked about their product knowledge in an online survey. After that, three recorded simulated customer support conversations about Bitcoins were shown to the respondents. After each conversation simulation, the respondents were asked to assess the level of detail and their satisfaction about the conversation. Lastly, the respondents were asked to indicate their preferred conversation.

The gathered data was analyzed to evaluate the effectiveness of knowledge personalization and demonstrate how knowledge personalization could improve customer satisfaction. The results showed a positive effect of level of detail on customer satisfaction. Furthermore, the respondents indicated that the length of the conversation, which is directly related to the level of detail, had a negative effect on customer satisfaction. The moderation effect of customer product knowledge showed a personalization opportunity, as the effect of level of detail on customer satisfaction was different for different levels of product knowledge. As the customer product knowledge increases, the effect of level of detail on customer satisfaction decreased to potentially zero or negative values. A prediction of the preferred level of detail based on the level of product knowledge showed a direct improvement of customer satisfaction, as compared to a situation without personalization. This last result indicated and demonstrated an opportunity to improve customer satisfaction of an automated digital customer support channel through personalization. However, the effect sizes should not be interpreted wrongly, as the effects of level of detail, customer product knowledge and knowledge personalization are highly case-specific and different implementations can yield different results.

Businesses are recommended to analyze their customer support channels for personalization opportunities. This research has demonstrated that knowledge personalization can be obtained relatively easy, directly improving average customer satisfaction. However, the actual effect of knowledge personalization is case-specific. Customer support channels processing complex problems for customers with varying levels of product knowledge have the highest probability of having positive effects from implementing knowledge personalization. If a customer support channel is deemed suitable, the next step is adequately assessing product knowledge. This can be done based on explicit questions, behavioral analysis, previous conversations or natural language processing. Then, for each level of customer product knowledge, a suitable level of conversational detail should be determined. Finally, through continuous improvements, a personalized approach will improve the customer support channel based on its efficiency, effectiveness and quality.

Preface

Completing my Master Thesis marks the closing of my time as a student at the Eindhoven University of Technology. It has been a great ride. My study in Eindhoven has led me through intriguing projects about innovation, sustainability and entrepreneurship. Getting my Bachelor Degree in Sustainable Innovation opened my mind for multidisciplinary projects with a perspective on the future. This acquired vision was of great use in my Master Degree in Innovation Management. Working my way through emerging technologies and translating bright ideas into business value sparked my enthusiasm and determination. A Master Thesis at the ITEM-group and Accenture has therefore been a logical choice to complete my study. This project has been the peak of my study and has challenged me further than I thought I could get. I am more than proud of my achievements and for that, I would like to thank a few people.

First, I would like to thank Ed Nijssen, my first supervisor. In the last year, he has challenged me to improve myself and my project. Without his continuous feedback, I would not have been able to get to this result. I have always appreciated the freedom in combination with the guidance on quality. Secondly, I would like to thank Lambèr Royakkers. His continuous enthusiasm and inspiration has been a great motivation and asset to my project. I would like to thank Michel van der Borgh for contributing to my project as third assessor. After following his course ‘Selling New Products’, I am proud to have him in my graduation committee. A major thanks to Peter Ruijten, for advising me in my experimental setup and statistical analysis.

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Lastly, I would like to thank my family and friends, for their support in the last months and during my complete study. Being part of the fraternity ‘STROPDAS’ has given me joy in my thesis and personal development in my study. Completing my Master Thesis whilst living in the ‘Casa Romana’ is awesome, thank you guys for graduating together.

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Tim

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1. Introduction

Automated customer support has experienced a major increase in interest, applications, and investments and is currently one of the fastest growing industries (Panetta, 2016). This growth is due to improved communication technologies like mobile phones and internet availability and the decrease in costs and increase in speed of data storage (Rust & Huang, 2014). Furthermore, customers demand a more personalized service, continuous availability of service companies and quick problem solving, some of the major opportunities of AI-powered technologies. Therefore, the service industry is moving from static and standardized concepts to dynamic and personalized designs, from collective to individual service delivery and from mass marketing to mass customizing. Due to the fundamental nature of the recent changes in the service industry, the findings of old studies diminish in importance and new research on the dynamic industry is essential. Information technologies (IT) advances in the service industry enable a more personalized service offering, which generally results in changing service relations and profitability of customers. New research should therefore regard the end-user as the center of the industry, whereby personalization and customer satisfaction are the main drivers of the service quality and firm profitability (Marinova, de Ruyter, Huang, Meuter, & Challagalla, 2017; Rust & Huang, 2014).

1.1. Virtual Assistant in Customer Support

A virtual assistant is a technology devoted to helping customers with their need of service by simulating a conversation and execute transactions and operations (Manusama, 2016). Implementation of this technology in customer support could potentially decrease the waiting times, increase the efficiency of frontline employees and increase customer satisfaction (Aanhane, 2017). Current applications involve travel agents, insurance advice, financial requests, governmental assistants and even a digital teaching assistant at a university, see for example Figure 1 (Maderer, 2016). All industries combined, the virtual assistant industry was estimated to have a net worth of 350 million US dollars in 2012, but this is expected to rise by almost 1000% to 3 billion US dollars in 2020 (Hexa Research, 2016; Maoz et al., 2016).

1.2. Personalization of Virtual Assistants

The prospect of personalization opportunities of a virtual assistant is the leading force behind the enormous growth in interest and investments in virtual assistants and a core component of a virtual assistant. Personalization improves customer satisfaction and customer loyalty by providing a unique and optimal experience to the end-user through using customer profiling and matching the customer characteristics to the right conversation features (Baker & Dellaert, 2016; Stanford University, 2016). Hereby, personalization is defined as a customer relationship management (CRM) practice that “enables a business to match the right product or service to the right customer, for the right price, at the right time. This gives each customer a unique experience,” (Coner, 2003).

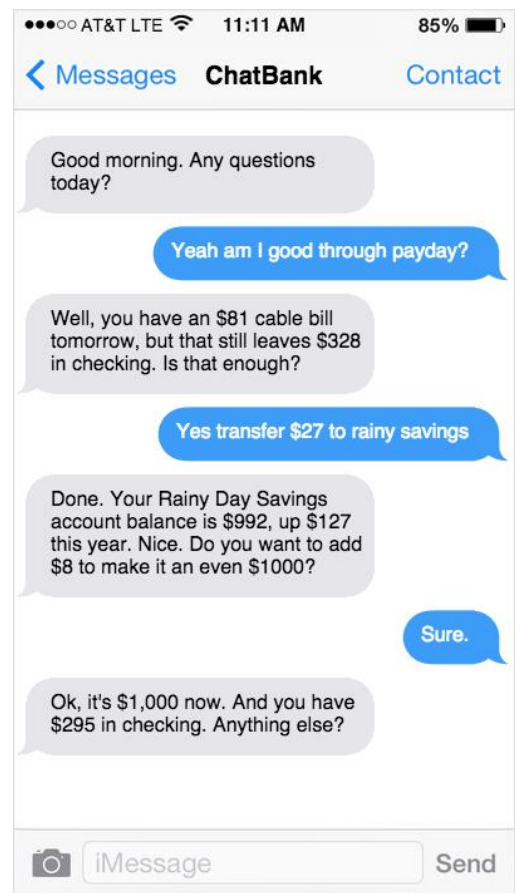


Figure 1: An example conversation with a virtual assistant in retail banking

Personalization could directly affect the evaluation of the customer support and improve sales through enhanced customer relationships (Huang & Lin, 2005; Mittal & Lassar, 1996). The effectiveness and value of virtual assistants is discussed frequently in literature and practice, and this discussion is mainly focused on the personalization abilities of a virtual assistant. Some studies and companies see a virtual assistant as an opportunity to improve customer satisfaction by using customer data to increase the personalization of customer support. Baker & Dellaert (2016) see personalization as a key component of a virtual assistant to create a fully personal offering, resulting in better service quality and increased sales performance. PWC (2015) and Creative Virtual (2016) elaborate in their industry whitepapers how personalization can create a seamless support experience because the customer profile can be used for information retrieval and accelerating customer request solvment. Huang & Rust (2014) point towards the potential increase in profit margin due to personalized and improved service delivery. Lastly, Marinova et al. (2017) explain on how an existing trade-off in the service industry (effectiveness vs efficiency) is eliminated through the use of automated customer support. Due to a personalized conversation, a customer could feel more comfortable interacting with the company and problems could be solved more effectively and efficiently. Other organizations or reviews display virtual assistants as impersonal customer service, increasing the distance between company and customer and decreasing customer satisfaction, which could potentially harm the firm's reputation and competitiveness.

According to Giebelhausen et al. (2014) and Oklopcic (2016), virtual customer support assistants should only be used to solve a problem as quick as possible, without any personal touch. Not many people would like to talk with their bank about the new shoes they bought last week, which the bank knows because of your payment data at the shoe store. Similarly, a pharmaceutical company recommending you a health check based of your frequent Instagram pictures during a holiday romance would rarely be appreciated. Although these examples show the potential positive and negative situations and effects that could occur with a virtual assistant used for customer support, a consensus about the role and effect of personalization in automated customer support lacks in academic literature.

The theoretical background of this research is mainly based upon a relatively small set of explorative studies on the role of personalization in (digital automated) customer support. Marinova et al. (2017) and Ramnarayan et al. (2005) mapped the fundamental relations between service interactions, personalization, technology implementation, and customer evaluation. Michael Ahearne has explored the function of technology in sales situations through multiple studies (Ahearne & Rapp, 2010; Ahearne, Jones, Rapp, & Mathieu, 2008; Ahearne, Hughes, & Schillewaert, 2007). Giebelhausen et al (2014) analyzed the opportunities and barriers of personalization of automated digital customer support agents, and Baker & Dellaert (2016) and Huang & Lin (2005) conducted similar studies specifically focused on the financial sector. Froehle et al. (2004) explored the evaluations and perception measurement methods of automated digital customer support. Overviews of personalization in traditional customer support has been given by Mittal et al. (1996) and Surprenant & Solomon (1987). From an industry perspective, Creative Virtual, PWC, Gartner and MOBGEN have elaborated on the added value of virtual assistants, which is largely based on the added value of personalization, and proposed steps to further develop personalization of virtual assistants. These research and industry papers together provided a highly diverse set of opportunities for virtual assistants, but have not yet been conclusive on what the role of the personalization abilities of a virtual assistant is on the effectivity of that virtual assistant. The nature of the relation between personalization, the main technological driver of the success of a virtual assistant, and the change in customer satisfaction has not yet been studied for the digital customer support industry. Therefore, a deeper understanding on the relation between personalization and customer satisfaction is currently a

gap in the literature. As explained above, further research in this field could contribute highly to the developments of virtual assistants in the future.

This study makes use of, and extends, studies on conversation analysis, customer relationship management and customer experience. The goal of this study is to discuss and rank different methodologies of personalizing digital automated customer support conversations, and analyze and propose one personalization method and its effect on customer satisfaction. To attain this goal, a theoretical framework was created which describes the different components of a personalization method. Multiple personalization methods were discussed with an expert panel using the Delphi method of qualitative research. The results of this qualitative research were used as input for an experimental study on the effect of knowledge personalization on customer satisfaction. Finally, the practical implications of the studies are discussed.

2. Problem Statement

Automated digital customer support through virtual assistants is a new field of industry and study, and which is in continuous development. Personalization of automated webchat support is a potential boost for the effectiveness of this technology and could benefit the company implementing the technology and the customer using it. Although interest and investments in the development and use of virtual assistants are high, personalization is currently implemented very limitedly, as it requires large investments, advanced technical knowledge and a high level of trust from the company in the technology. To improve the technology and provide evidence for the value of personalization in digital customer support, additional research is necessary. By improving the virtual assistants and gathering experiences and evidence on the effects of personalization, an increased level of trust in the technology and more investments can be expected.

Past research on personalization in customer support can be divided into traditional, face-to-face customer support and digital support. Besides that, the previous research can be divided into fundamental and comprehensive research. Fundamental research describes the role and position of virtual assistants and personalization in the customer relation environment on a general level. Comprehensive research analyzes the sub-concepts of personalization and the description and effects of different personalization methods. A lot of research has been conducted on personalization efforts in traditional service delivery, both on a fundamental level to understand the dependencies, as on a comprehensive level aiming to gain a deep understanding on the methods of traditional personalization, the effect and best practices of these methods, and the situational variables related to the personalization activities. Fundamental research on digital technology-generated customer support through a virtual assistant supports the claim that personalization is relevant and, on a general level, effective in digital customer support, but a deep understanding of the effects of different digital personalization methodologies has not yet been created. This deeper, comprehensive research on the properties and methods of digital personalization is limited.

This research aims to contribute to a deeper understanding about the influences of the several methods of digital personalization on customer satisfaction, based on traditional service literature, additional exploratory research in the digital customer support industry and the testing of these findings in a digital customer support environment with a virtual assistant scenario.

This study will serve this goal by doing an explorative qualitative study on potential personalization methods for digital customer support and an experimental quantitative study whereby one proposed personalization method from the first study will be further investigated. Finally, this research aims to recommend a relevant and effective method of personalizing automated digital customer support.

The research question of this master thesis is therefore the following:

How could customer satisfaction about an automated digital customer support conversation be improved through personalization?

To answer this question, this research contributes to developments in personalization research in the field of digital service delivery. By using traditional service industry research and the current limited digital service industry as a starting point for the first study, a connection is proposed between personalization research in face-to-face customer support and digital customer support. Due to changing customer needs and new opportunities in customer profiling and communication methods, the findings of previous studies diminish in importance. This study aims to evaluate findings of previous studies and add new findings about the effect of adjusting the service offering to the customer profile in digital customer support.

2.1. Scope

This study analyzed the effects of personalization in digital customer interactions on customer satisfaction. To adhere to time requirements, the study was limited to the scope described in this chapter. Analyses outside this scope was left for further research.

2.1.1. Customer Support

The study was limited to the virtual assistant as a technology. This technology is often used to automate a part of the customer support, sales or marketing activities of a company. According to Rust & Huang (2014), the personalized interaction can either be that the delivered service is customized to the user's needs with the use of existing customer data or that the customer support activities are personalized to the targeted potential customer, with the use of publicly available social information (Marinova et al., 2017). As this research focuses on customer support only, and not on sales or marketing, this study will focus on a virtual assistant dedicated to customer support in a business-to-consumer (B2C) environment. To adequately study the effect of personalization on customer satisfaction a text-based virtual assistant is the focus of this study. Hereby variables like voice recognition, appearance or environmental attitude are eliminated and thereby background noise in this study is minimized.

2.1.2. Personalization Phases

This study regarded the matching phase of the personalization process. The process of personalization of the customer support experience goes through multiple phases to be successfully executed. First, the preferences of the customers should be obtained and learned by the company and the technology and placed into a customer segment. Secondly, the matching phase links preferences to the service offering and possibilities of the company. Thirdly, the evaluation phase improves the process for future personalization by reflecting upon the segmentation and matching phases (Huang & Lin, 2005; Murthi & Sarkar, 2003). This study focused on the matching phase of the personalization method. This means that personalization was assessed and discussed at the point where the customer profile has already been created. Any practical recommendations on the first phase of customer profile creation and third phase of model improvement are proposed at the end of this thesis but this research mainly analyzed how the customer profile could be matched to conversation features.

2.2. Research Context

This research will be conducted in collaboration with Accenture, a company providing professional services and solutions mainly focused on IT-implementations. Accenture works in a B2B environment to provide and implement technological innovations and thrives to be on the frontline of innovation. Research on the capabilities of virtual assistants is a valuable addition to the service industry and the operations of Accenture. Currently, Accenture aims to generate knowledge on the effectiveness of virtual assistants and the various methods to design and implement virtual assistants, to achieve the best results in different environments. This research, as part of the research efforts of Accenture, contributes to this goal. The main contribution of this master thesis is a set of design guidelines regarding the personalization abilities when developing a virtual assistant. Accenture provides direct support to the master thesis project and is an ideal starting point to connect with experts in the field, both within Accenture as within one of their many partner companies. Recommendations following this research can directly be implemented and tested within one of the virtual assistant solutions of Accenture.

2.3. Research methodology

The methodology of this research was two-folded. This is in line with the goals set for this research. First, an exploratory qualitative study evaluated personalization methods following from a literature review. The list of personalization methods was discussed in an expert panel and other personalization methods were added. Finally, the expert panel ranked the personalization methods relatively from each other on the effectiveness on customer satisfaction. This led to one personalization method which is most likely to affect customer satisfaction positively. This method was chosen by evaluating the expert opinion, value for further research and value for industry.

This one personalization method was further analyzed in an experimental quantitative study. This study showed different scenarios of the personalization method to potential users and measured their satisfaction. The potential effect of the personalization method was hereby demonstrated. The research process is illustrated in Figure 2.

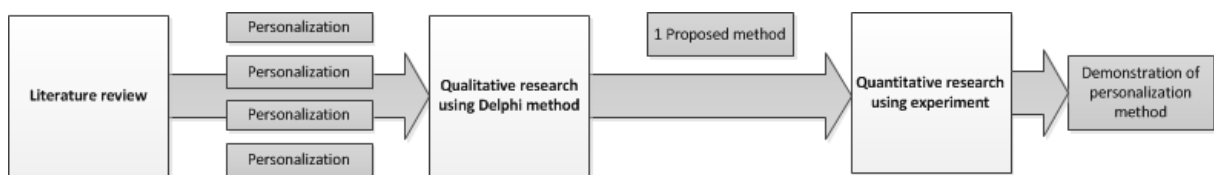


Figure 2: overview of research process

3. Theoretical Framework of Personalization

To understand the role and effect of personalization in automated digital customer support, more information is necessary to be able to describe personalization adequately. An overview on the most relevant technical properties, market and customer influences and goals of virtual assistants are discussed in the preceding literature review (Aanhane, 2017), which resulted in the research opportunity of this thesis. To discuss personalization efforts and methods with experts and measure its effectiveness in an experimental study, the current most relevant personalization should be listed and described. This part of the thesis proposes a framework to describe personalization based on the components of customer profile and conversation features. The first part of this chapter will position personalization in the traditional and digital customer support environment. Then, a short literature review leading up to the personalization process frameworks will be discussed. The theoretical framework will be explained further based on two components, which are the customer profile and conversation features. The main goal of personalization, which is increasing customer satisfaction, is discussed to adequately study the effectiveness of personalization. Lastly, the most relevant and popular personalization methods from previous studies are listed and described according to the proposed framework.

3.1. Personalization

“Any customer can have a car painted any color that he wants so long as it is black” (Ford & Crowther, 1922). The quote from Henry Ford while promoting his famous T-Ford car shows no sign of any personalization or customization. The color of one of the first mass-produced cars had only one option, which was black. Now, while most markets experience a transition from mass-standardization to mass-customization, most parts of a car can be adjusted to the needs of the customer. This same transition occurs in technology-generated customer support service. The properties of the conversation can, just like the color of the car, be adjusted to the wishes of the end-user. Personalization is defined by Coner (2003) as a relationship method which “enables a business to match the right product or service to the right customer, for the right price, at the right time. This gives each customer a unique experience,” (Coner, 2003). This definition describes the tailoring of a product or a service, based on the profile of the customer. The price and time of the offering is not regarded in this study.

3.1.1. *Personalization vs Customization*

A distinction between customization and personalization must be made however. Customization describes individual product or service offerings initiated by the customer, like requesting your new car in the color yellow, or using your self-designed pattern to design and order new shoes online. Personalization also describes an individual product or service offering but is initiated by the company based on the customer profile. A customer can thereby receive a different offering than another person due to the personalization activities of the company. For example, a television company can offer a sport-fanatic customer a discount on a sports channel when renewing his or her subscription. Due to this distinction, personalization can only occur when both a process of offering adjustment and consumer profiling is present, whereby customization can already occur with only offering variations (Huang & Lin, 2005). Customization enables the customer to make a choice based on his or her preferences and is therefore based on product needs. On the contrary, personalization offers the choice directly, as the preferences are matched to the available options, and is thus based on the interaction needs of the customer (Ardissono & Goy, 1999).

3.1.2. *Personalization in Traditional Customer Support*

For face-to-face customer support, both fundamental and comprehensive research on the effects of personalization has already been conducted. Fundamental research like that of Mittal & Lassar (1996) describe the value of personalization in traditional customer support, whereby personalization is a method of evaluating service quality or a method to increase customer satisfaction and loyalty. Hereby personalization is seen as a natural, intuitive part of the service delivery. Based on

visual clues like appearance and behavior and linguistic clues like length of the responses the human customer support agent intuitively makes a customer profile and is able to predict the customer needs or goals.

The comprehensive research of the traditional customer support conversation distinguishes multiple methods of personalization. Surprenant & Solomon (1987) recognized three dimensions of personalization within the traditional customer support. First, outcome (or option) personalization adjusts the number of options that an end-user can choose based on the customer profile. Besides this outcome-personalization method, two types of process-personalization methods were recognized. Programmed personalization includes name-calling, small talk and other task-unrelated personalization options. Lastly, customized personalization can transform the service delivery agent into a personal assistant of the customer, adjusting the interaction to the life situation of the end-user and proactively act upon the needs of the customer.

There are important differences between traditional customer support and a digital customer support journey, which make additional research necessary. First, the technology around the digital customer support enables direct customer identification and opportunities to capture customer information and process this information through large databases. A challenge with these opportunities is the danger to the privacy of end-users. Gathering customer data could negatively affect the customer satisfaction when the customers are being confronted by unwanted uses of their information (like promotions) or are losing trust in the protection of their information by third parties (Huang & Lin, 2005).

Secondly, by developing virtual assistants for customer support an important trade-off in the service delivery industry slowly disappears. With traditional customer support a trade-off appeared between the degree of personalization and the efficiency of the service delivery, and therefore between the customer satisfaction about and the efficiency of the process (Surprenant & Solomon, 1987). The development of virtual assistants and other digital service encounters eliminates this trade-off and improves the personalization and the efficiency of the service delivery simultaneously. This is due to the movement from mass-standardization to mass-customization, enabled by artificial intelligence and big data science, the technology behind a virtual assistant.

3.1.3. Personalization in Digital Customer Support

To use personalization in automated digital customer support, intuitive personalization actions should be translated to programmable rules and algorithms. For this, consensus on the personalization effects should appear on both a fundamental as well as a comprehensive level.

On the fundamental research level, multiple studies have researched the general usefulness and effect of personalization in digital customer support. Rust & Huang (2014) analyzed the general effects of personalization on service quality and profit, Varadarajan & Yadav (2002) positioned personalization of interactive technologies in a retail strategy and Creative Virtual (2016) listed multiple positive effects of personalization from an industry perspective, including increased loyalty and cross-selling. These studies concluded that, in general, personalization has a positive influence on customer satisfaction of digital customer support.

For automated digital customer support and technology-generated customer support, comprehensive research on distinctive personalization methods is limited. Ramnarayan & Jose (2005) studied the effectiveness of personalization in a digital customer support environment, and used the dimensions of Surprenant and Solomon (1987) (described in 3.1.2) as the basis for their digital personalization model (Ramnarayan & Jose, 2005). They described personalization as having three

dimensions: one giving explicit choices to the customer, one creating a personal interaction including greetings and small talk, and a last dimension creating an implicit personalized offering. These three dimensions relate highly to the three dimensions of Surprenant and Solomon. However, Ramnarayan & Jose did not find these distinctive personalization methods in digital customer support, but merely used these methods to measure the general effectiveness of personalization.

3.2. Personalization Frameworks

In this section, two approaches are used to create two frameworks to describe personalization practices. The first approach constructs a framework to describe the different activities and phases of personalization, and background activities at companies which are necessary to enable personalization of automated digital customer support. The second approach leads to a framework describing the different components of the matching phase of personalization.

3.2.1. Personalization Phases

Personalization of automated digital customer support generally follows a certain sequence of steps, which is described in different studies. Huang & Lin (2005) and Murthi & Sarkar (2003) described the sequence of personalization going through the phases of segmentation, matching and observation. Appendix A shows a diagram of the personalization sequence. A user profile is constructed based on basic information, previous conversations, behavioral tracking etcetera. Often, a company already has a consumer profile of existing customers and expands this profile with newly acquired information. Based on this profile and the request for customer support, the customer will be placed into a customer segment, which is part of the personalization process. The customer segment will be matched to a specific product or service offering. This matching process is based on a set of rules. Examples of these rules may be that the size of an illustrative image increases with the age of the customer, that the language of a conversation is automatically adjusted to the nationality of the customer or that a printer manufacturer will automatically display a specific brand of printers when the consumer profile indicates that this brand is preferred or previously bought. The evaluation of the customer leads back to an observation function, which records and analyzes the behavior of the consumer. Based on this evaluation, the customer profile and the service offering are adjusted. The personalization sequence of a customer relationship management process therefore consists of three steps. First, the customer is placed into a customer segment based on his or her consumer profile. Secondly, the customer is matched to a personalized service or product offering, based on the company offerings and the customer segment. Lastly, the process is observed, evaluated and improved for future personalization activities. The consumer profile and the company offering, or in this case the technology and conversation of a customer support department of a company, are the main inputs for the personalization process (Huang & Lin, 2005; Murthi & Sarkar, 2003).

Ardissono & Goy (1999) described the personalization through a simpler sequence, involving only two steps. The first step of personalization is the descriptive part. This part creates a user profile based on explicit and implicit inputs, and assigns the user to a stereotypical class. This descriptive part is similar to a combination of the customer profile and segmentation phases of Huang & Lin (2005). The second step of personalization according to Ardissono & Goy is the predictive phase, which is similar to the matching phase of Huang & Lin. The predictive phase uses the stereotypical information of the user to infer the preferences of the user, and adjusts the conversation or system accordingly (Ardissono & Goy, 1999).

Küpper & Kobsa (1999) had a different approach by taking the advice-giving system as starting point of the personalization sequence. Küpper & Kobsa argued that a response of an advice-giving system, like the virtual assistant in this research, can be described as a plan for action. The plan generation is the first phase of the personalization sequence. According to the user problem or request, and the known capabilities and limitations of the user and its environment, a proposed solution, or in this case the plan, is created. The plan should be communicated to the user, which leads to the second

step of the personalization sequence. The second step, plan presentation, tailors the communication of the plan to the customer profile (Küpper & Kobsa, 1999). The plan generation and plan presentation phases are relatively similar to respectively the company offering phase and rule-based matching phase of Huang & Lin (2005).

As the previous descriptions of three personalization sequences show, the personalization sequence is reported using various terminologies by differently studies. However, similarities can be found based on common functions of personalization phases. Figure 3 shows the process flow based on previous studies. By gathering data explicitly and implicitly, a customer profile can be created, which can be placed into a stereotype family through segmentation. The stereotype family is then given a unique experience by using a unique mix of company offerings and conversation features in the matching phase. The personalized response which is created in the matching phase is communicated to the customer. The customer behavior that follows this response, for example direct action or signs of (mis)understanding, is analyzed in the learning phase. Results of the analysis are used in the learning phase to improve the customer profile of the user. This research focuses mainly on the matching phase, and assumes the existence of a customer profile and a diversity of company offerings and conversation features. This process flow can be used to identify the major components of personalization.

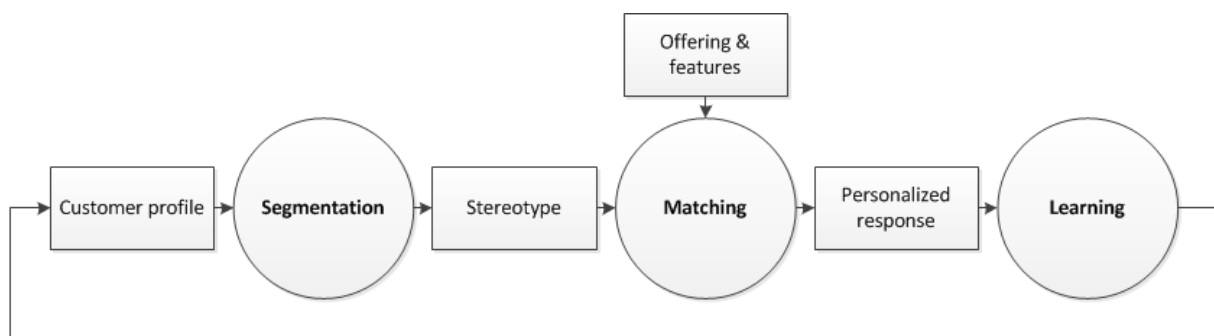


Figure 3: Process flow of personalization

3.2.2. Personalization Components

By analyzing the process flow, and following personalization studies, the main components of the matching phase of personalization can be identified. These components are necessary as inputs for a unique experience to the user. By using the right mix of the personalization components, the service quality will be improved through personalization.

Ardissono & Goy (1999) identified the two main components as the stereotypes or personality traits of the end-user and the product properties. The matching phase uses the stereotype of the end-user to predict the preferences of these users about the product properties, following from matching rules based on other users in the same stereotype family. The stereotype family of an end-user is based on classification data, which describes users based on demographic metrics like gender and age, but also personality traits, preferences and needs (Ardissono & Goy, 1999).

Horvitz & Paek (1999) recognized the stereotype also as a relevant component of personalization in their conversation analysis. They analyzed a traditional, face-to-face customer support conversation to create a rule-based personalization approach to use in automated conversations. People place their conversant in a stereotyping family intuitively by reasoning. This is done based on visual clues and linguistic analysis. For example, a person running towards you asking a short and clear answer can be expected to be in a hurry. Whilst these customer profiles are created automatically and intuitively by people in a face-to-face conversation, the component of customer

profiling and their customer preferences should be programmed in a digital environment. As this thesis analyzes a chat-based virtual assistant, natural language processing technologies could potentially make linguistic analyses and thereby creating direct customer profiles. These profiles should be transformed to stereotypes, which can be done using threshold analysis. Threshold analysis divides values of personality traits into groups, as input for segmentation (Horvitz & Paek, 1999).

To enable a personalized approach, the customer should be identified as an individual person with unique preferences, or be identified as part of a customer segment, in which a group of individuals with similar preferences belong (Ramnarayan & Jose, 2005). The customer data is gathered either explicitly or implicitly. Explicit data gathering is done by asking the customers for information through a questionnaire or registration form, like when a consumer applies for a music event. The downside of this information gathering method is that customers are often unwilling to reveal a lot of information and the basic types of information that are shared has limited usability for personalization. The profile can also be expanded implicitly, by including data from other companies about this user, like when a consumer links his or her social media accounts to their newly acquired account. Another form of implicit customer information gathering is tracking the customer in his or her behavior. By analyzing log files, placing cookies on the computer of the customer, and mapping the interactions with the customer, a behavioral pattern and preference list of the customer can be constructed. The benefit of this method is that it is fast and accurate, and that it does not ask any effort from the customer. The downside is that this method can only be applied in the digital environment of the firm. Any behavior before or after the interaction with the customer cannot be tracked (Huang & Lin, 2005; Murthi & Sarkar, 2003).

Küpper & Kobsa (1999) recognized the properties of the conversation and properties of users as main components of personalization. Hereby the properties of the conversation should adapt to the users, based on their properties like capabilities and knowledge (Küpper & Kobsa, 1999).

Based on the process flow and the stated studies on personalization components, two main components of personalization are used in this thesis. First, the customer profile serves as a description of the user's demographics, behavior and preferences. Secondly, the conversation features describe the product properties of an automated digital customer support journey; see Figure 4. By determining the appearance of a conversation feature based on the customer profile, personalization of a customer support conversation occurs.

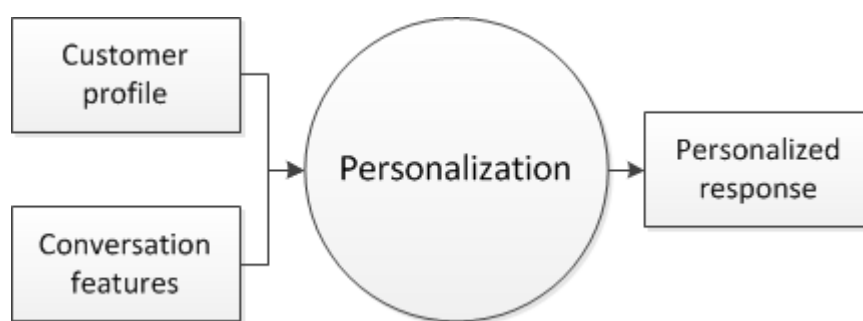


Figure 4: The personalization components customer profile and conversation features

For example, Andres, a Spanish person, requesting assistance on wireless internet set-up could be helped in the Spanish language. In this example, the personalization sequence has seen in the customer profile of Andres that he is from Spain. This information could have gotten into the profile of Andres because his request was in Spanish, at the start of the conversation, Andres has indicated his nationality or any other method of customer data gathering. The personalization sequence could place Andres in the stereotype family 'Spanish nationality' and infers from other customers in the 'Spanish nationality' stereotype family that it is likely that Andres prefers the language, which is a conversation feature, to be Spanish. The matching phase of the personalization process links the nationality of

Andres to the conversation feature of language, thereby creating a personalized response for Andres. A customized response would give Andres the option to change the language of the conversation.

3.3. Customer Satisfaction

To study the effectiveness of personalization, this section briefly discusses the main goal of personalization, which is increasing customer satisfaction. Customer satisfaction is described as a judgement by the customer on the functional, social and psychological values of a product or service relative to competing products or services and resources necessary to obtain the value (Idowu, Zu, & Gupta, 2013). Other goals from the literature study of Aanhane (2017) can be linked to the goal of customer satisfaction, like decreasing the average handling time, improving customer targeting and improving the customer relation. Both academic and practical publications conclude that the increase in customer satisfaction is the most important overarching goal, as this goal contributes most to the long-term growth and reputation of a company. Marinova et al. (2017) indicates that customer satisfaction is one of the key components of success for emerging technologies and MOBGEN (2017) and PWC (2015) indicate that customer satisfaction is the key goal in their business. Other studies relate customer satisfaction to important consequences like loyalty (M. Ahearne & Rapp, 2010; Baker & Dellaert, 2016), happiness (Stanford University, 2016) and performance (Giebelhausen, Robinson, Sirianni, & Brady, 2014; Gremler & Gwinner, 2008).

Customer satisfaction can be measured in three ways (CheckMarket, n.d.). First, the Customer Satisfaction Score (CSAT) measures overall satisfaction, mainly focused on short-term happiness (Kayako, 2016b). Secondly, the Net Promoter Score (NPS), measures long-term satisfaction and loyalty (Kayako, 2016a). Lastly, the Customer Effort Score measures how much effort a consumer must put into an interaction to attain a specified goal (like solving a consumer problem) (Kayako, 2016c). As all measurement methods have their own specialty and therefore complement each other, a combination of these measurements is often the most reliable method of measuring customer satisfaction.

3.4. *Personalization Methods*

Based on fundamental studies on traditional and digital personalization (Ramnarayan & Jose, 2005; Surprenant & Solomon, 1987) and preliminary interviews with technology experts at Accenture, an overview is given of potential personalization methods for digital customer support in Table 1.

Table 1: Popular personalisation methods

Personalization method	Customer profile component	Conversational feature component	Based on:
Outcome personalization	Need for control Need for efficiency/ expected duration Desire for cognitive simplicity	Number of options Number of alterations	Option/outcome personalization (Bell, 1981; Lovelock, 1983; Ramnarayan & Jose, 2005; Surprenant & Solomon, 1987)
Small talk personalization	Desire for cognitive simplicity Desire for personal warmth Empathy	Personal greetings Friendly conversation Non-task related small talk	Programmed personalization (Ramnarayan & Jose, 2005; Surprenant & Solomon, 1987) Personalization construct of service quality (Mittal & Lassar, 1996) Empathy personalization (Parasuraman et al., 1985)
Language personalization	Age Area of residence Speaking in dialect	Use of vocabulary and tone of voice	Preliminary interviews with field experts at Accenture.
Proactive personalization	Desire for cognitive simplicity Need for control IT acceptance Need for privacy	Proactive interventions Moment of conversation	Customized personalization (Ramnarayan & Jose, 2005; Surprenant & Solomon, 1987) Responsiveness personalization (Parasuraman et al., 1985)

4. Qualitative Study

The goal of the qualitative study is to evaluate the value of personalization methods from literature about traditional service delivery, translate traditional personalization methods to digital customer support and expand the set of methodologies to include new, additional personalization methods. As previous research on personalization methodologies has been focusing on traditional customer support or general effects of personalization on customer satisfaction, an exploratory study is necessary to reflect on the list of personalization methods. The methods in Table 1 **Error! Reference source not found.** are studied in traditional customer support or proposed for further research in studies on digital customer support. Furthermore, language personalization is suggested by field experts working at Accenture. To determine the potential value of these proposed personalization methods, a qualitative study has been designed. The study works with an expert panel, composed of people actively working with virtual assistants. A new personalization methodology overview will be created for digital customer support to enable further research. The qualitative study aims to answer the following question:

What are the most relevant personalization methods in automated digital customer support?

At the end of this qualitative study, the relevant personalization methods were adapted to a chat-based virtual assistant. The components of the personalization methods, customer profile and conversation features, were mapped and the personalization methods were ranked based on their potential value. The descriptions and rankings of these personalization methods could be used to further assess how personalization can increase the customer satisfaction of automated digital customer support. On top of that, the descriptions and rankings of the personalization methods will be used as starting point for the quantitative study, which is described in Chapter 6.

4.1. Methodology

The qualitative study will be conducted using the Delphi method. The Delphi method is a qualitative research method which aims to converge expert opinions, create consensus or find patterns on fuzzy environments and work towards a solution designed based on an expert panel (Delbecq, Van de Ven, & Gustafson, 1975; Huang & Lin, 2005). This method is suitable for this study because the list of personalization methods is not fixed; additions or removal of methods is possible if consensus can be reached. Therefore, the personalization methods list can be greatly different from the current list in Table 1. Furthermore, the Delphi method does not require simultaneous or physical encounters, which is preferred as the expert panel consists of 14 experts from various organizations. Still, the Delphi technique enables a form of individual feedback on the collective perspective and ultimately the technique works towards a consensus. Delphi technique works with the current knowledge of experts and participants, instead with old findings in the (related) industry (Delbecq et al., 1975).

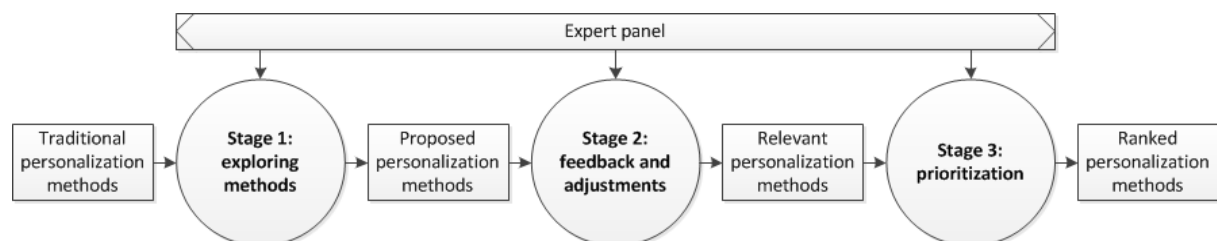


Figure 5: The qualitative study using the Delphi research method

This qualitative analysis followed three stages, related to the Delphi technique. In the first stage, the experts were asked to assess the value of the proposed personalization methods and propose additional methods. The second stage enabled the experts to comment on each other and evaluate the

newly proposed personalization methods. In the third stage, the experts ranked the personalization methods based on the expected effect on customer satisfaction. The first and second stage were conducted by face-to-face and telepresence interviews and analyzed by the project leader. The third stage was conducted using an online survey. See Figure 5 for an overview of the qualitative study.

4.1.1. Panel Selection

The panel consisted of fourteen experts. Of these fourteen experts, ten were working at Accenture on the development and implementation of virtual assistants, three were researchers of the Human-Technology Interaction group at the Eindhoven University of Technology and one experts worked on the development, marketing and implementation of virtual assistants at another organization. The technical background of the expert group varied. The panel consisted of two technology architects (with high level of technical knowledge about virtual assistants), two business analysts, three business developers, four project leaders (relatively low level of technical knowledge) and three researchers in the field of customer experience and technology mediated customer support. Although these functions seem different, they often cooperate or exchange tasks. Besides that, the job functions reflect different levels of management rather than different domains of expertise. The experts worked daily in a diversity of industries, and six experts were not assigned to a single industry, but rather worked cross-industry. See Figure 6 for an overview of the backgrounds of the experts. Although the industry background is diverse, the general expertise of the expert group is focused on development and implementation, which creates a technical expert group. This background should be considered when analyzing the results. The necessary size of the expert panel is related to the homogeneity of the expert panel and the expected results. Apart from the industry background, the expertise of the expert group is quite similar. On top of that, this study aims to get qualitative results. Therefore, the expert panel size of fourteen is considered sufficient (Delbecq et al., 1975; Huang & Lin, 2005)

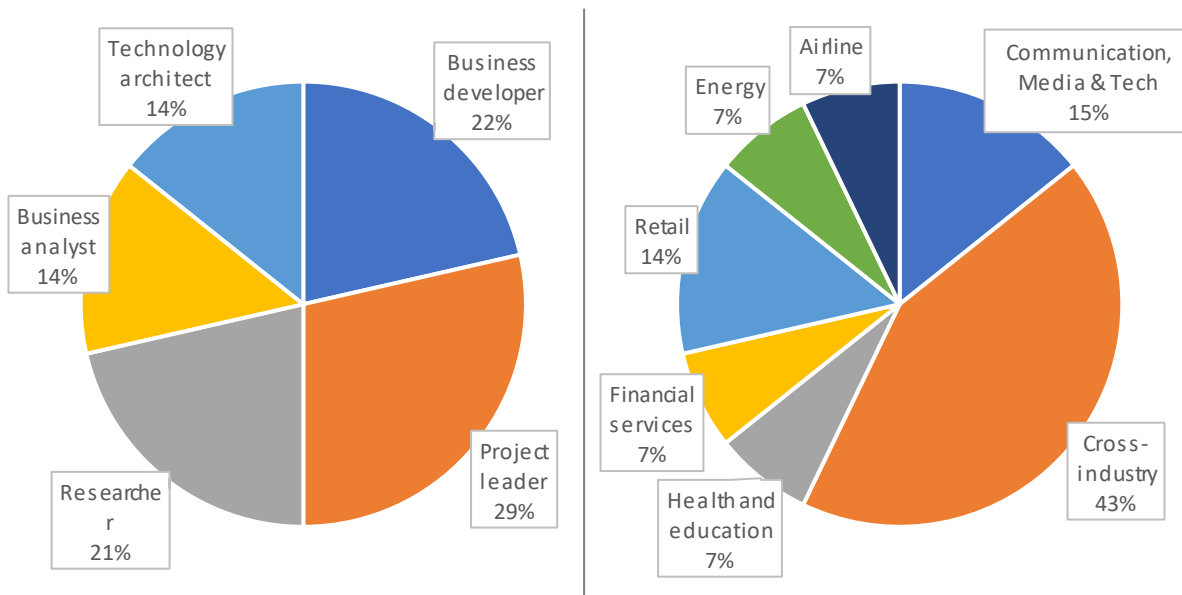


Figure 6: Background description of expert panel

4.1.2. Stage 1: Exploring Personalization Methods

The first stage contained semi-structured interviews with each panel member to discuss the traditional personalization methods and its translation to digital customer support. Semi-structured interviews are a popular methodology in behavioral and service studies and were for example used for

an exploratory analysis to construct a conceptual model to analyze the effect of IT-solutions on service personalization in the hotel industry (Piccoli, Lui, & Grün, 2017) and for generating a behavioral perspective on the traditional service encounter, and the role of personalization in it (Winsted, 1997).

The goal of the first stage was to evaluate the list of personalization methods following from previous research and propose additions to the list. The experts were asked about the expected effects and concrete examples of implementation of the personalization methods. All panel members were interviewed individually for 25 to 35 minutes, using either a virtual interview setting using Skype or a direct face-to-face interview setting. The starting point of the panel interviews was the list of personalization methodologies displayed in Table 1. Each participant is confronted with the list of personalization methods, and asked about their perspective on this method and its effect. Lastly, the participants are asked about the most relevant differences between industries, which can affect the relationship between personalization and customer satisfaction. New or conflicting insights were used as input for the second stage of the qualitative analysis.

4.1.3. Stage 2: Feedback on the Collective

The second stage aimed for consensus among the panel members and consisted of a second round of semi-structured interviews. In this round, the project leader showed the aggregated responses of the expert panel to each panel member. In this way, the experts were able to comment on all the perspectives. The different perspectives on the personalization methods and related variables from the first interview round were discussed. The diverse opinions of the first stage were listed and shown to the panel members, so each panel member could react on the conflicting issues.

4.1.4. Stage 3: Prioritization Survey

The third stage concluded the qualitative study with a short questionnaire, distributed through email. The questionnaire can be found in Appendix B. This questionnaire aimed to prioritize the developed personalization methods and to provide a starting point for further research. In the questionnaire, the list of personalization methods from Stage 2 was displayed, whereby the respondents were asked to mark the methods of which they thought to have a positive effect on customer satisfaction. Furthermore, the experts were asked to indicate which personalization methods they expected to have the largest effect on customer satisfaction. The result of this stage was a short list of relevant personalization methods according to the expert panel, which was used as an input to the second phase of this research, the experimental study.

4.1.5. Analysis of Results

After each stage, the statements of the experts were compared by the project leader. Similar statements were converged to one statements. Statements that had a different or opposing meaning were kept to the next round for further clarification. After the third stage, the personalization methods were discussed based on the statements that the experts gave throughout the study and the relative importance according to the experts. The results should give a deeper understanding of traditional and new personalization methods and their value in automated digital customer support.

4.2. Results

The qualitative analysis resulted in an evaluation of the traditional personalization methods and additional digital personalization methods by experts.

4.2.1. Stage 1: Exploring Personalization Methods

The exploratory interviews resulted in a diverse set of statements. These statements included positive and negative evaluations about the traditional personalization methods from previous

research, but also statements about new types of personalization. All statements developed in the first stage are listed in Appendix C, and discussed shortly below.

The expert panel had diverse perspectives on outcome personalization. 33% of the experts did not agree it was a relevant personalization method, opposing to 50% who agreed that varying the number of given options or solutions based on the customer profile was a relevant personalization method. The experts who did not support outcome personalization argued that the number of options should not be personalized, but that the customer should rather be given one or two options that are very relevant to the customer. Experts supporting outcome personalization argued that some people want a quick fix, and other people want to keep control and know all the available options which are available. There was also not a direct agreement on the effect of outcome personalization on customer satisfaction and the realistic opportunity to find a personalized number of options based on a customer profile.

For personalization of small talk, a distinction was noticeable between two groups within the expert panel. 50% of the experts indicated that the problem-solving function of a customer support function is the most important asset of a virtual assistant. All other functionalities, like the ability to converse in small talk, are subordinate and irrelevant if it increases the time to solve a problem. The other 50% of the experts saw opportunities in small talk, to manage the emotions and comfort level of the end-user. However, a consensus was noticeable in that a virtual assistant should not start small talk, but rather react and follow up on small talk initiative of the customer.

Language personalization appeared to have different applications. Language adjustments regarding slang, dialect and (in)formality were diversely rejected or applauded. These different aspects of language personalization should further be discussed in stage 2. Furthermore, four experts mentioned their concerns that language adjustments greatly increase the risk of inaccurate statements by the virtual assistant.

The experts created immediate consensus about proactive personalization. While proactive customer support can often have a positive effect on customer satisfaction, the situations whereby proactive customer support can be beneficial is dependent on the industry and task, instead of the customer profile. All experts individually indicated that proactive personalization will probably not have the intended effects and should be adjusted to the case and company instead of the customer profile. Due to the unexpected but rather clear statements of all experts, no changing perspectives could be expected further. As consensus was met and no additional statements were expected, proactive personalization was not included in stage 2 and stage 3 of the qualitative research.

A new method of personalization initiated by four experts independently was knowledge personalization. Conversation features are the speed and starting point of the conversation and the amount of information in each step. The customer profile properties where the personalization should be based upon are the (technical) knowledge or computer literacy of the end-user. As multiple experts separately indicated this method as potential for increasing the customer satisfaction, this method will be included in the research.

Another additional personalization method was the personalization of the escalation to a human agent, which was proposed by one expert. The conversation is often routed to a human agent when the virtual assistant is unable to solve the problem of the end-user. While normally the end-user is connected to the human agent which is available first, the end-user can also be connected to a human agent which is best matched to the customer profile. Hereby the conversation feature is the

profile of the human support agent and the customer profile could be tone of voice, area of residence, age or gender.

Collectively, the experts all indicated that it is important to communicate to the end-user that the conversation is executed by a virtual agent, instead of a human agent. As long as the technology is not sufficiently developed and mature enough to make it unable to distinguish it from a human agent, the robotics behind the conversation should be revealed.

Concluding, the personalization methods which followed from literature research and preliminary interviews were evaluated by an expert panel on their value in automated digital customer support. Outcome personalization received opposing perspectives, and the arguments of all experts were used in stage 2 for further clarification and comments. Small talk personalization split the expert panel in two equal groups, whereby the use for emotion management opposed the effect on conversation duration and problem solving. Although the experts agreed that the virtual assistant should not start small talk, the different arguments returned in stage 2. The experts interpreted language personalization differently, as different parts of the language of the conversation appeared to be useful for personalization. Therefore, the language aspects of slang, dialect and formality, as well as the risk of degrading statements due to language adjustments were reflected upon in stage 2. Collectively, the experts argued that proactive personalization did not fit the definition and value of personalization. Proactive actions regarding customer support can be beneficial dependent on industry and task, instead of customer profile. Therefore, proactive personalization will not further be discussed in stage 2. Lastly, two new personalization methods were proposed. Knowledge personalization adjusts the number of steps and speed of the conversation to the technical knowledge of the customer. Human escalation personalization matches the customer profile to a profile of a human support agent. The arguments of stage 1 were summarized in a document which was used as input for stage 2.

4.2.2. Stage 2: Feedback on the Collective

In the second stage, all experts could respond on the diverse statements. Most experts responded in either agreement or disagreement on the statements. Hereby it was possible to make an overview of the position of the expert group regarding each statement. When at least 80% or at most 20% of the experts agreed on a statement, this is regarded as a consensus in the expert panel. The complete overview is included in Appendix D. Below, the most important findings are discussed.

Outcome personalization remained a major discussion point. 64% of the experts saw value in this method for increasing the customer satisfaction, but 36% did not expect any effect on customer satisfaction and 50% of the experts did not define this method as a personalization method. However, a consensus was reached in the statement that it is hard to find a sweet spot, or a right level for the number of options to give to a customer. This indicates that there is discussion about the effects of successfully implementing outcome personalization, but that experts agree that successfully implementing outcome personalization in itself is difficult to do. The discussion was equally diverse for small talk personalization. None of the statements about small talk personalization reached consensus.

All types of language personalization were welcomed by most of the experts, although a formal consensus was not reached on any of the language adjustment methods. The most popular language personalization methods were the use of slang based on the age of the customer (79%) and adjusting the formality of the conversation to the age of the customer (71%). Generally, the expert panel views language personalization as a potential tool to increase the customer satisfaction.

92% of the experts expected knowledge personalization and human routing personalization to have a positive effect on customer satisfaction. A consensus was almost reached on the statement that human routing should be based on both personality and content (75%).

Concluding, knowledge personalization and routing personalization were expected by the panel to have a positive effect on customer satisfaction. The aspects of language personalization were welcomed by the experts, but no consensus was reached here. The experts did not agree on the expected effects of outcome personalization and small talk personalization. To evaluate the relative importances and effects on customer satisfaction, all personalization methods were taken to stage 3.

4.2.3. *Stage 3: Prioritization Survey*

In the last stage of the qualitative analysis, the experts were asked to mark the relevant personalization methods and rank their top 3 in an online survey distributed through e-mail. 13 of the 14 experts responded to this survey.

First, the experts were asked to indicate which personalization methods they expect to have a positive effect on customer satisfaction. The results are displayed in Figure 8. All experts indicated that they expect knowledge personalization to have a positive effect. Furthermore, outcome personalization reached a consensus in this stage, being supported by 85% of the experts. Language formality personalization (62%) and human routing personalization (77%) were also popular among the experts. Most of the experts expected that small talk personalization and personalizing the level of slang or dialect in a conversation would not have a positive effect on customer satisfaction.

Secondly, the experts were asked to indicate which personalization method they expect to have the first, second and third most positive effect on customer satisfaction. The results can be seen in Figure 7. All experts included knowledge personalization in their top 3, and a small majority (54%) of the experts expected that knowledge personalization would have the most effect on customer satisfaction compared to the other personalization methods. 39% of the experts think that outcome personalization has the most positive effect on customer satisfaction and 92% of the experts have include outcome personalization in their top 3. Human routing personalization is expected to do relatively well as 70% of the experts has chosen this method in their top 3.

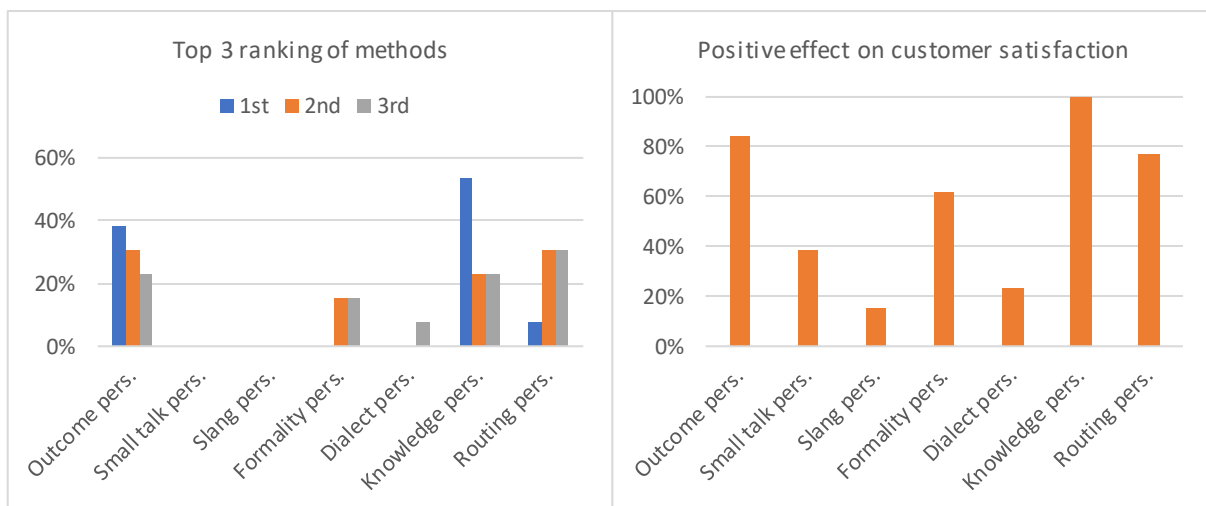


Figure 8: Experts expecting a positive effect on customer satisfaction

Figure 7: Experts expecting the most positive effects on customer satisfaction

4.3. Discussion

Based on the interview stages, an overview of the personalization methods according to the experts was created. This is an updated version of the overview which resulted from the literature review and preliminary interviews as described in Table 1. The new list of personalization methods can be seen in Table 2 **Error! Reference source not found.**

Table 2: Overview of personalization methods for automated digital customer support

Personalization method	Customer profile component	Conversational feature component	Based on	Expert panel result
Outcome personalization	Need for control Need for efficiency/ expected duration Desire for cognitive simplicity	Number of options Number of alterations	Option/outcome personalization (Bell, 1981; Lovelock, 1983; Ramnarayan & Jose, 2005; Surprenant & Solomon, 1987)	Opportunity for increasing customer satisfaction. However, hard to implement due to finding optimal level
Small talk personalization	Desire for cognitive simplicity Desire for personal warmth Empathy	Personal greetings Friendly conversation Non-task related small talk	Programmed personalization (Ramnarayan & Jose, 2005; Surprenant & Solomon, 1987) Personalization construct of service quality (Mittal & Lassar, 1996) Empathy personalization (Parasuraman et al., 1985)	Not expected to have a positive effect on customer satisfaction outside greeting. Could potentially be effective in managing customer emotions. Should not interfere with the goal of quick problem-solving.
Language personalization	Age Area of residence Speaking in dialect	Use of slang Speaking in dialect Formality of responses	Preliminary interviews with field experts at Accenture.	Nice feature, but hard to implement. Formality of conversation can have a positive effect, but slang and dialect are probably irrelevant.
Proactive personalization	Desire for cognitive simplicity Need for control IT acceptance Need for privacy	Proactive interventions Moment of conversation	Customized personalization (Ramnarayan & Jose, 2005; Surprenant & Solomon, 1987) Responsiveness personalization (Parasuraman et al., 1985)	Proactive customer support should not be based on the customer profile, but on the task and industry. Therefore, this is not personalization.
Knowledge personalization	Level of detail and amount of information in the conversation	Technical knowledge Computer literacy	Expert interviews	This is expected to be the most effective personalization method.
Human routing personalization	Human agent profile	Demographics General interests	Expert interviews	Great opportunity for increasing customer satisfaction

The results show that knowledge personalization, human routing personalization and outcome personalization are the most promising personalization methods, according to the experts.

Human routing personalization concerns the moment that the virtual assistant is not able anymore to help the customer any further. Currently, the conversations with the virtual assistants will at that point either stop or repeat itself, or escalate to a human agent which analyzes the request. As normally the first available human agent would take over the conversation, it would be possible to match the customer profile to the profile of the human agent. Regional language, common interests or age-specific vocabulary would therefore be more quickly used commonly, which could increase the customer satisfaction according to most of the experts. However, the same experts doubt the practicality of the personalization method. As not the first available human agents would take over the conversation, but the best matched agents, multiple negative consequences appear. If the number of human agents is limited, this method could seriously increase waiting times as people are waiting for their best matched agent, which in turn decreases customer satisfaction. This can be solved by having a large number of human agents, waiting to be matched based on their profile. This, however, is commercially not preferred or feasible.

Outcome personalization is a personalization method which is expected to have a positive effect on customer satisfaction by the experts, and could potentially be programmed in the virtual assistant. It analyzes the customer profile or stereotype for a need for control, simplicity or quick fix. Dependent on these personality traits, the number of options presented to the user can be limited or extended. A person in a hurry could receive a single solution for his or her problem, whilst e.g. a control-freak would be presented with all the options available. The experts prefer to personalize the content, and therefore presenting one solution which is the most relevant based on the customer profile. The experts see value in adjusting the number of options to the customer profile. However, finding the right number of options is expected to be difficult by the experts. Furthermore, the customer character traits like need for simplicity and need for control are hard to measure. The experts therefore see great theoretical and future potential, but do not expect any current technological success or implementation.

When the results of stage 1 and stage 2 are included, knowledge personalization was clearly the personalization method which was supported most by the expert panel. This personalization method includes the level of detail in the conversation, composed of the number of steps of an explanation and the difficulty of the vocabulary. This has a direct effect on response length. The level of detail could be based on the product knowledge of the customer and the previous experiences of the customer with the product or company. It can be expected that customers with a high level of knowledge or frequent visits, want the conversation to be handled quickly and briefly. The information can therefore be very technical and general, whilst a person with a relatively low level of product knowledge can be expected to prefer more steps to lead to a final solution and details explaining complex terminologies. Personalizing the level of detail could be beneficial to the customers as they get the right amount of information based on their capabilities, and to the company as the conversation of the companies can be shortened or clarified. Furthermore, knowledge personalization extends the personalization methods in the digital customer support. Measuring customer knowledge and computer literacy is difficult in traditional customer support, but could be made possible using natural language processing or historic customer data. The combination of the effects of level of detail and response length on personalization would make knowledge personalization the most potential opportunity for personalization. However, to further analyze the effect of knowledge personalization on customer satisfaction, further research is necessary. Therefore, knowledge personalization will be further analyzed in the quantitative research described in chapter 5 and 6.

5. Theoretical Framework of Knowledge Personalization

This section analyzes knowledge personalization as preparation on the experimental study. The goal of this section is to describe knowledge personalization based on the personalization components and construct hypotheses about the effects of knowledge personalization for the experimental study. The qualitative research proposed knowledge personalization as a potentially effective method of increasing customer satisfaction and an extension to current personalization methodologies and research. This personalization opportunity is further tested in an experimental study. The analysis of knowledge personalization is done using the two components described in 3.2.2, which are customer profile and conversation features. To be able to make recommendations about knowledge personalization, more information is necessary about the two components of knowledge personalization, which are customer product knowledge and level of detail. In preparation for the experimental study, research on personalization, conversation analysis and knowledge assessment are therefore discussed in this chapter. As the relation between the two components of knowledge personalization are analyzed, and the effect of their relation on customer satisfaction is predicted, a customer support conversation can be improved by adjusting the level of detail to the level of customer product knowledge, which is done by the personalization sequence.

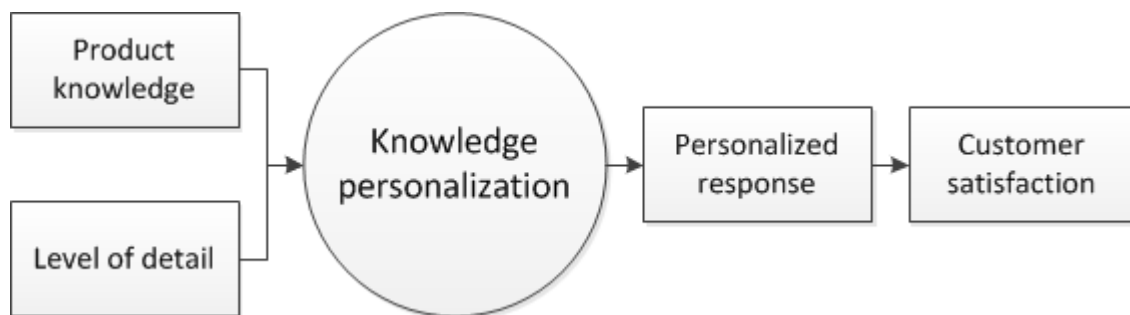


Figure 9: Knowledge personalization and its components

The inputs of the theoretical framework of knowledge personalization consist of two components, as can be seen in Figure 9. First, the conversation feature component is the level of detail. This level of detail is the component in the model that can be adjusted by the firm operating the digital customer support channel. The second component is the product knowledge of the end-user. This customer product knowledge is part of the customer profile and is not adjustable by the company. The goal of knowledge personalization is increasing customer satisfaction, compared to a situation whereby no knowledge personalization occurs.

Research on knowledge personalization in the service industry is limited. Huang & Lin (2005) stated that the knowledge of the end-user is often disregarded in determining the communication strategy. The authors proposed that frontline employees would evaluate the product knowledge of their customers and adjust the conversation accordingly. Hereby jargon should not be used for customers with a low degree of product knowledge, but the conversation can be improved for customers with a high degree of product knowledge by shortening the responses (Huang & Lin, 2005).

While correlational or experimental studies on the concept of knowledge personalization are limited, some explorative studies and conferences have discussed the components of knowledge personalization in the context of digital customer support. Ardisson & Goy (1999) have described the personalization functions of SETA, a tool used for constructing interactive websites. They recognize the opportunity of adjusting the features of product descriptions to the expertise of the users. Experts want short and technical descriptions, where non-experts are expected to prefer fewer features, described in simpler sentences with more intuitive information. If users would want more information,

they would ask themselves (Ardissono & Goy, 1999). Furthermore, Horvitz & Paek (1999) have described knowledge personalization as an intuitive function of people in face-to-face conversations. In traditional customer support, people make intuitive decisions in conversations based on information uncertainty and formulate sentences with a certain level of detail, expected to be appropriate for the conversation and the conversant. If the level of detail does not appear to be appropriate, the conversation intuitively switches to another level of detail (Horvitz & Paek, 1999). Lastly, Küpper & Kobsa (1999) described how automated digital customer support systems generate and present solution plans. They argue that the activity potential, which is described to be similar to the customer product knowledge combined with customer capabilities, determines the level of detail in the conversation. Hereby the length of the conversation and the number of steps in each solution plan is based on the knowledge level of the user (Küpper & Kobsa, 1999).

5.1. Level of Detail

Level of detail is defined as the level of detail within a customer support conversation that can be adjusted to the knowledge level of the end-user. Ardissono & Goy (1999) described the level of detail in a conversation as a need of a customer. The level of detail can be adjusted by adjusting the linguistic form of the sentences or switching between different templates with different levels of difficulty or technicality. The level of detail is also divided into a number of features (which can be adjusted based on the receptivity of the customer) and the level of detail in the description of the features. As this research regards the level of detail when the meaning

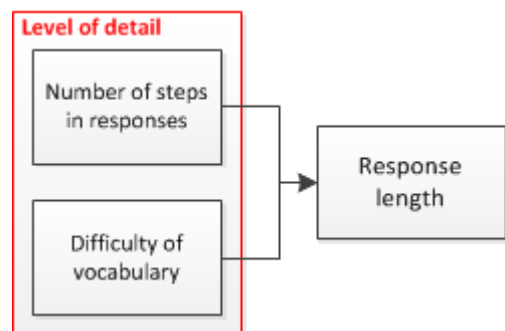


Figure 10: Level of detail

of the responses stays the same, the level of detail components of Ardissono & Goy (1999) are restricted to the technicality of the descriptions and the selection of the linguistic form. Horvitz & Paek (1999) recognized the same construction of level of detail, describing the level of detail in the syntax, length and typicality of the responses. Küpper & Kobsa (1999) add the number of steps in a sequence of a solution plan to the construct. They indicated that concepts within responses can be communicated directly, but also explained into sub-concepts and attributes based on terminological knowledge.

Based on the qualitative study and the discussed studies of Huang & Lin (2005), Ardissono & Goy (1999), Horvitz & Paek (1999) and Küpper & Kobsa (1999), the level of detail in this research describes the number of steps in which one solution, request or direction is described, and the difficulty of vocabulary. See Figure 10. A high number of steps in which a message is communicated means that a single call for action by the virtual assistant is divided into a lot of smaller steps to get to the requested result. A high number of steps gives the customer a detailed description of how to solve the problem and is therefore easiest to understand. However, utilizing unnecessarily detailed descriptions could also wear off customers with a high level of product knowledge.

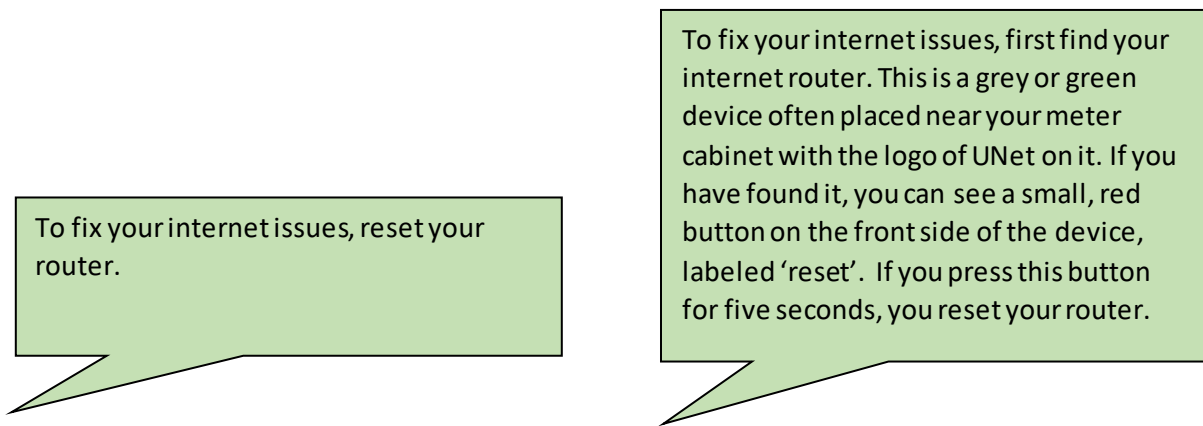


Figure 11: Two example responses with a different level of detail

The solutions given in Figure 11 describe the same action. However, the example response on the right describes the solution in multiple small steps and a high level of detail, where the response on the left gives a quick short response without a lot of detail. Previous studies have related syntactic complexity (linguistic complexity regarding sentences) to the amount of information transferred. Therefore, the amount of information transferred, in this case the level of detail, can be analyzed using the Interactive Alignment model. This model states that, in a conversation, people adjust the level of detail to their conversant. By find a compromise in the level of detail of their conversation, they come to mutual understanding and contribute to a successful conversation. However, this study regards the natural behavior of humans, which virtual assistants do not have. By analyzing the level of detail, we analyze the digital equivalent of the automatic alignment of details done by humans.

The level of detail is closely related to difficulty of vocabulary. Increasing the difficulty of vocabulary is often mentioned in the qualitative study as an example on how to complexify the conversation by exchanging multiple details into one word or phrase. Increasing the difficulty of vocabulary, including the use of jargon (industry- or profession-specific vocabulary), can be used to keep the responses of the digital customer support agent short and to the point. However, it is expected that only when the end-user can understand the meaning of this vocabulary increasing the difficulty of vocabulary can lead to a higher customer satisfaction through a shortened conversation. By using a lot of jargon or otherwise use difficult vocabulary, certain objects or actions explained by the virtual assistant can be indicated precisely and shortly. You can see an example of two responses communicating the same solution, but with a different difficulty of vocabulary and therefore level of detail in Figure 12.

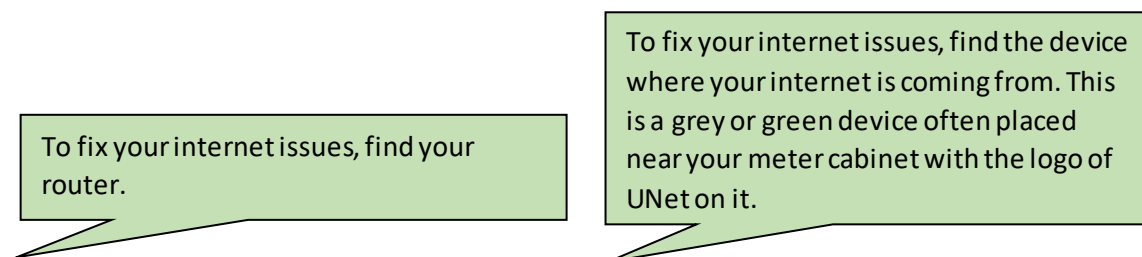


Figure 12: Two example responses with a different degree of vocabulary difficulty

Both text responses ask the customer to find their router. Without using the word 'router', which may not be understandable by customers with a low product knowledge, the response gets longer, but easier to understand. For people who know what a router is, the response on the left is easy to understand and quick in interpretation. If the difficulty of vocabulary decreases, so less jargon is used, more details are necessary to describe the same objects and actions. Difficulty of vocabulary is

therefore inversely related to level of detail. Linguistic studies and theories, like the Interactive Alignment model, have indicated mutual understanding as being very important in making a conversation successful (Xu & Reitter, 2016). Mutually understandable vocabulary is therefore important in the effectiveness of a virtual assistant. Studies in the service industry likewise valued the (limited) use of jargon important in successfully executing a customer support conversation (Huang & Lin, 2005). Mutual understanding could therefore be improved by lowering the difficulty of vocabulary by increasing the level of detail in the responses. This is expected to have a generally positive effect on customer satisfaction, but mostly be effective on customers with a low level of product knowledge whereby mutual understanding is easily obscured.

The length of the responses is also directly related to the level of detail. Logically, a conversation with a high level of detail and vocabulary which is easy to understand, will have longer responses than conversations that describe solutions on a general, undetailed level. Conversely, when a response uses a lot of jargon and explains a solution in a minimal number of steps, the response will automatically be relatively short. Examples of this effect can also be seen in Figure 11 and Figure 12. Linguistic studies also included the response length into their analysis of conversation complexity, partially in the form of sentence length (Xu & Reitter, 2016). Furthermore, Huang & Lin (2005) expected that a high conversation length is the main factor for decreasing satisfaction of people with a high product knowledge.

Due to time restrictions and the limited amount of literature about constructing conversation level of detail, this experiment manipulates the number of distinctive steps in a message at the same time as the difficulty of vocabulary and the response length. These concepts are manipulated simultaneously, but the manipulations will all be checked in the experiment. As these variables are related to each other and in practice often interchangeable, it is not expected to have major implications on the usability of the conclusions about level of detail as a generic variable. The number of distinctive steps in which a message is communicated and the difficulty of vocabulary together form the level of detail, which both affect the response length. Analyzing the effect of vocabulary and steps separately is left for future research.

5.2. Customer Product Knowledge

Customer knowledge is the customer profile part of the model. Customer knowledge is defined by Chang et al. (2006) as knowledge and information about the product or service (Chang, Changchien, & Huang, 2006). Komiak & Benbasat (2012) have also positioned personalization and familiarity in the relevance of technology adoption. Furthermore, Mothersbaugh et al. (1994) have studied the construct of product knowledge, and the difference between subjective and objective knowledge, which can be translated to this study in the form of expertise. Ardissono & Goy (1999) indicated that technical interest or knowledge can be used as a main factor for determining stereotyping families.

Familiarity can be described as the customer's knowledge about a product or service, based on previous experiences. As a customer interacts more often with a certain product, service or channel, it is understandable that the knowledge of the customer about this product, service or channel increases. Furthermore, with an increased familiarity, customers would assess their knowledge higher themselves, as they can recollect more related experiences (Chellappa & Sin, 2005; Mothersbaugh, Feick, & Park, 1994). Increased familiarity can benefit the way how a customer expresses his requests, processes the acquired information and translates the responses to appropriate actions. Furthermore, increased familiarity has a positive effect on the customer's trust in the competence and integrity of the virtual assistant. Lastly, an increased familiarity increases the mutual understanding between virtual assistant and customer (Komiak & Benbasat, 2012).

Expertise is "the ability to perform product-related tasks successfully" (Chang et al., 2006; Mothersbaugh et al., 1994). The most popular studies use a construct of subjective and objective

knowledge. Others also include experience (or familiarity), product-class information (like brands or attributes) or storylines. Expertise can affect decision making and information acquisition in the form of search behavior. Chang et al. (2006) proposed that customer expertise can be a good customer property to personalize service upon. Subjective knowledge has the largest effect on behavior and decision making of all knowledge types and is positively related with stored product knowledge. There is a positive relation between familiarity and expertise (Chang et al., 2006; Mothersbaugh et al., 1994). Therefore, customer product knowledge can be constructed from subjective knowledge and product familiarity.

5.3. Customer Satisfaction

Customer satisfaction has earlier been described in this thesis as a judgement by the customer on the functional, social and psychological values of a product or service relative to competing products or services and resources necessary to obtain the value (Idowu et al., 2013). Customer satisfaction is positively related to cross- and upselling, trust and loyalty (Aanhane, 2017). Customer satisfaction is the most important goal of a customer support journey, as the success of future selling activities largely depend on the general satisfaction of a customer about a company.

Customer satisfaction can be measured using the Customer Satisfaction Score, Net Promoter Score and the Customer Effort Score. (CheckMarket, n.d.; Kayako, 2016a, 2016b, 2016c). A combination of the three different measurement methods gives the most reliable indication of the customer satisfaction.

The effect of the conversation properties on customer satisfaction and the value of customer satisfaction in further customer relationship management and customer behavior can be analyzed using the Theory of Planned Behavior and the Theory of Reasoned Action (Froehle & Roth, 2004). These theories describe the effect of customer beliefs on customer attitude and customer intentions, and are fundamental theories for modern management theories like the Technology Acceptance Model.

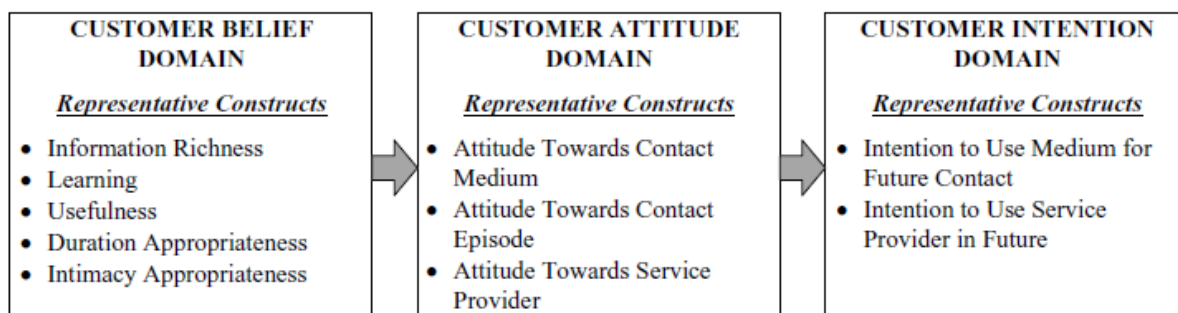


Figure 13: Belief-Attitude-Intention framework by Froehle & Roth (2004)

Figure 13 shows the framework by Froehle & Roth (2004), also used by Komiak & Benbasat (2012) on the interactions between customer beliefs, attitudes and domains in technology-mediated customer support. The attitude towards contact medium, episode and provider together form the overall satisfaction of the customer. This customer satisfaction is important as it determines the customer's intention to use the customer support channel for future contact and the intention of the customer to use the service provider, or the company, in the future. As these customer intentions are central to customer loyalty and therefore the main goal of customer relationship management, a focus on customer satisfaction is relevant for the virtual assistant. Customer satisfaction is stated to be influenced by the customer beliefs, which can be divided by constructs of 'information richness', 'learning', 'usefulness', 'duration appropriateness' and 'intimacy appropriateness'.

The information richness belief describes the vividness of the interaction, and includes the amount of different information streams (for example verbal, non-verbal, textual, etcetera). Learning belief describes the perception that a user has about the difference in product knowledge before and after the conversation. Usefulness belief encompasses the degree in which the wish of a customer is fulfilled or a goal attained. This goal of a conversation with a customer support virtual assistant is to solve a customer problem and this study analyzes *how* the problem is solved. For the goal of analyzing the conversation style instead of the conversation outcome, this study assumes that the customer problem is solved, and therefore maximum usefulness. Duration appropriateness belief describes the evaluation of the duration of the conversation by the customer. Generally, a customer has a certain range of conversation duration that is preferred, and the duration appropriateness belief measures the belief of the customer on how far the actual duration is different from the preferred duration. A very low duration appropriateness belief indicates that the duration of the conversation is much shorter or much longer than preferred. This belief is found to be the most important antecedent for customer satisfaction (Froehle & Roth, 2004). Lastly, the intimacy appropriateness belief describes the level of mutual trust between customer support agent and customer that is gained during the conversation. It is highly related to the empathy-dimension of service quality studies.

5.4. Knowledge Personalization

Following the personalization components framework, the components of product knowledge and level of detail can be used to personalize the conversation, and attain a higher customer satisfaction. When the relationship between the components is understood, the personalization process framework describes the steps to execute knowledge personalization. See Figure 14 for an overview. First, the product knowledge of the customer should be determined. This can be done based on the existing customer profile, historic conversations, natural language processing, explicit questions, etcetera. Based on the product knowledge, the customer will be placed into a stereotype family with similar levels of knowledge. As the preferences of the customer are expected to be similar to the other customers in the same stereotyping group, the preference of the customer regarding the level of detail can be predicted. The matching of the predicted preference of a level of detail to an available level of detail results in a personalized response, which is expected to lead to a higher level of satisfaction on average than a standardized response. To verify the theory and expert perspectives, an experimental study is necessary to further develop the concept of knowledge personalization.

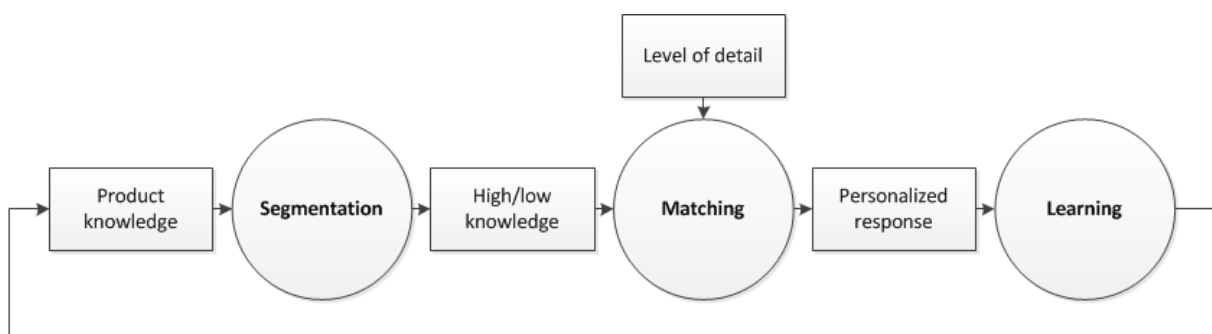


Figure 14: Knowledge personalization process

5.5. Hypotheses

This section will elaborate on the hypotheses derived from previous literature and the qualitative research. The hypotheses will be tested in the quantitative study, which is described in Chapter 6. First, the theoretical model and the related hypotheses are described, also displayed in Figure 15.

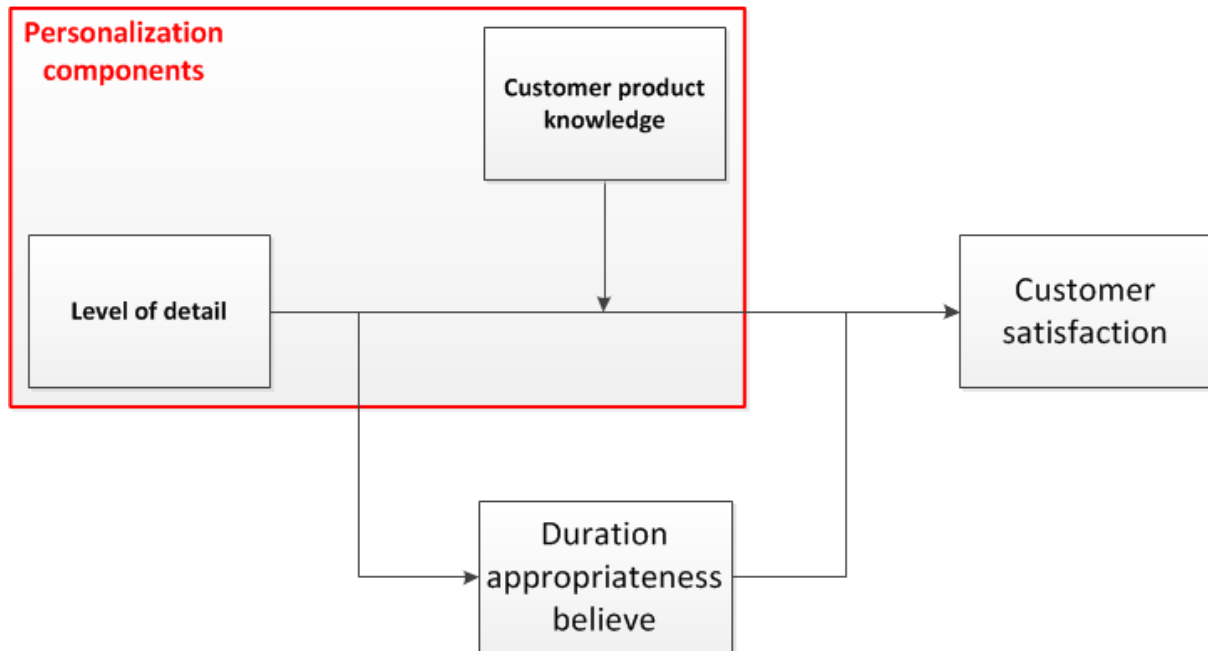


Figure 15: Research model personalized on customer product knowledge

Therefore, the scenarios can be evaluated relatively from each other, analyzing the conversation level of detail as a whole. A lower level of detail requires more cognitive effort to understand the responses by the virtual assistant (Surprenant & Solomon, 1987). Furthermore, a mutual understanding is important for a successful conversation (Huang & Lin, 2005; Xu & Reitter, 2016). It can be expected that a higher level of detail generally causes an increase in customer satisfaction.

H₁: Conversation level of detail has a direct positive effect on customer satisfaction

However, decreasing the level of detail by using less distinctive steps and using difficult vocabulary and jargon instead of elaborate explanations of the components of the problem and solution enables the responses to be shorter. Shorter responses lead to shorter conversations. The qualitative study done earlier found that in customer support, a large majority of the customers want to have their problem solved as quick as possible. We can see the conversation duration as the time it takes to solve a problem. Therefore, most of the customers prefer the conversation with a customer support channel to be as short as possible. As decreasing the level of detail decreases the length of the conversation, it can be expected that customers value the length of the conversation to be preferable if the level of detail decreases. Hereby the duration appropriateness belief can be used as a mediator between level of detail and satisfaction to evaluate the duration effect.

H₂: Conversation level of detail has a negative effect on duration appropriateness belief

H₃: Duration appropriateness belief is positively related to customer satisfaction.

Customer knowledge is expected to have a moderating effect on the relation between conversation level of detail and customer satisfaction. This is because the level of detail in which mutual understanding is possible increases with the customer knowledge. Xu & Reitter (2016) state that mutual understanding is necessary for a successful conversation. If the level of detail lowers, the understanding of the responses by the customer decreases. However, if the customer knowledge increases, it can be expected that the customer is more able to interpret the responses by the virtual assistant. Furthermore, digital customer support also causes a new type of communication. As online webchat is not a natural form of communication, the familiarity and expertise of a webchat channel can have a similar effect as the product knowledge. Expertise and familiarity of the product or service can cause increased abilities to make decisions, interpret the information and translate the information to appropriate actions.

***H₄:** As the value of customer product knowledge increases, the effect of conversation level of detail on customer satisfaction decreases.*

This research regards the balance between the positive and negative effect of conversation level of detail. This balance is affected by the customer knowledge, as this property of the customer profile affects the size of the positive effect of level of detail. As the negative, mediated effect of level of detail on satisfaction is only affected by level of detail itself, personalizing the conversation will keep this constant and positive. Decreasing the level of detail would decrease the understanding and therefore the chance for a successful conversation. It is expected that therefore the positive effect of level of detail on satisfaction has the most impact with a low degree of product knowledge, compared to the negative effect. When the customer knowledge increases, understanding can also be reached at lower levels of detail, and the positive effect of level of detail on satisfaction decreases in size. As the negative effect stays constant, the balance between the positive and the negative effect shifts to the negative effect slowly. Therefore, it is expected that the negative effect of level of detail on satisfaction has the most impact with a high degree of product knowledge.

***H₅:** Conversations with a high level of detail are more likely to be preferred by customers with a low customer product knowledge.*

***H₆:** Conversations with a low level of detail are more likely to be preferred by customers with a high customer product knowledge.*

When the relations between the components of the personalization model show significant effects, this knowledge can be used to improve the customer support conversation. By using the gained knowledge and adjusting the level of detail to the expected preference of the customer, the average customer satisfaction should increase.

***H₇:** Personalization of the level of detail in an automated customer support conversation could increase the average customer satisfaction.*

6. Experimental Study

This part of the research describes the experimental study. To analyze the conversation level of detail, three scenarios will be distinguished, with three levels of detail. To create these three levels of detail, the scenario conversations will vary in the number of steps which each response describes, and the difficulty of the vocabulary of the responses. Pre-testing of the scenario's showed different levels of detail, and also different number of steps and difficulty of vocabulary, as experienced by potential test respondents. During the experiment, the scenario manipulation will be checked on the level of detail, but also on the number of steps and the difficulty of vocabulary. For the statistical analysis, the level of detail will be further used, as the manipulation checks indicate an appropriate manipulation and construct of level of detail, see Figure 16.

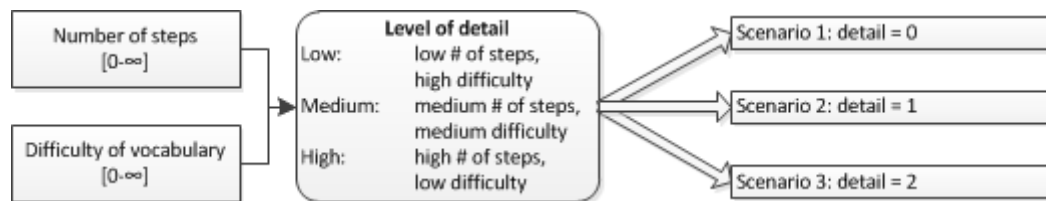


Figure 16: Construction of the scenarios with varying level of detail

6.1. Methodology

The methodology of this study is based on other quantitative studies in (automated) customer support (Giebelhausen et al., 2014; Komiak & Benbasat, 2012; Mittal & Lassar, 1996; Surprenant & Solomon, 1987) and aims to gather and analyze data on the variables described in the model in Figure 15. For this, an experimental study is designed, whereby three scenarios of a financial customer support conversation will be used, with different levels of conversation level of detail (low, medium, high). Furthermore, the product knowledge, channel knowledge, age and level of education of the respondents will be measured.

6.1.1. Sample

Based on preliminary interviews, the population for this study consists of people between the age of 18 and 65. As this study analyses a banking scenario, it can be assumed that this age groups has some kind of responsibility over their own financial situation, and has a minimum level of experience with their financial products to be able to understand the goal of the scenario set. People younger than 18 might have insufficient experience handling their own financial products, and people older than 65 might be affected by digital illiteracy. Furthermore, the use of a computer should not be such a large barrier to the respondents, that it significantly affects the understanding of the respondent about the scenario. Therefore, at least a moderate comfortability with a computer is expected. The experimental model has 3 predictors (level of detail, product knowledge and the interaction effect of level of detail and product knowledge). Furthermore, an error probability of 0.05 and power of 0.8 is used. To find a medium effect size of 0.15, a minimal sample size of 77 respondents is necessary.

6.1.2. Experiment Scenario

The conversation level of detail will be tested with the respondents using three example conversations with a virtual customer support agent, whereby the example conversations have the same problem statement and solution proposed, but differ in conversation level of detail. To simulate a high level of detail, both the vocabulary as the number of steps will be manipulated to create a high level of detail compared to the other scenarios. In other words, the scenario simulating a high level of detail will use a difficult vocabulary and have a low number of distinctive steps in the responses, directly resulting in short responses, compared to the scenarios simulating medium or low level of detail.

The scenarios simulate an actual webchat conversation with a virtual customer support agent. Each scenario is constructed using a short cover story (setting the industry and problem statement) and a video of a conversation with the virtual assistant. This conversation is simulated in Facebook Messenger and the conversation is recorded in a video of maximum 2 minutes. A video is used for this experiment instead of letting the respondents actually communicate with the virtual assistant, because in this way the conversation can be steered towards variable manipulation, and other 'noise' effects, like finding the limits of the virtual assistant or small talk, are minimized.

The video shows a conversation with a virtual customer support agent in retail banking. Retail banking includes all general consumer banking products, like debit- and credit cards, loans and mortgages, customer payments, etcetera. Retail banking is a suitable industry for this experiment because service quality and customer satisfaction are important values for the retail banking, as it is strongly related to trust and loyalty (Baker & Dellaert, 2016; Huang & Lin, 2005; Komiak & Benbasat, 2012; Surprenant & Solomon, 1987). Furthermore, almost everyone has a debit account and therefore has some degree of experience with the retail banking industry. (Surprenant & Solomon, 1987). Lastly, the complexity of the retail banking industry ranges from very low, whereby none to only the basic actions are executed by the end-user, to a very high complexity, whereby the end-user can compose and regulate his/her own financial situation.

To assess further suitability of retail banking for this experiment, some simple preliminary explorative research on retail banking customer support was done. 5 online chat conversations have been started, to try to solve a fictional problem. The conversations were started in different ways, to show either a high product knowledge or a low product knowledge. The diverse reactions, questions and solutions that the human customer support agents proposed, were used to compose the scenario conversation. On top of that, 5 retail banking customer support human agents were contacted, to ask for the most common questions that are asked by customers. Hereby a distinction was made between questions that customers could have solved without the intervention of a customer support agent, the questions that were only solvable by customer support agents and questions that were not solvable by the customer support agent. Furthermore, the customer support agents of the retail banks estimated that approximately 75% of the questions were solvable without intervention by the customer support agent. The range of these questions and the proportion of questions solvable by end-users indicated a wide range of issues with varying complexity, and a range of customers with a varying customer product knowledge.

The scenario conversations follow the same structure, displayed in Table 3. However, the three responses given by the virtual customer support agent are adjusted for the level of detail of the scenario. Underneath is the general structure of the conversation, and the different responses given by the virtual assistant on the indicated positions in the conversation, which are based on the example conversation that real banking con.

The problem statement of the conversation regards a request for more information about paying with Bitcoins. In an earlier stage of this research, a simple payment error was used as scenario. However, preliminary testing of the levels of detail with 10 test respondents of different knowledge levels showed that the highest level of detail in this simple scenario was understandable for all test respondents, regardless of their knowledge level. On top of that, it was hard to differentiate in their product knowledge, as familiarity was almost equal and expertise was interpreted in different ways. It could be expected therefore that a more complex problem statements was necessary to test the model and find significant effects. Pretesting the scenario created the valuable insight that the effect of knowledge personalization appears to be case-specific and the choice of using knowledge personalization depends on the complexity of the problems and the knowledge diversity of the customers. Bitcoins is suitable, because familiarity and expertise with Bitcoins is more variable between people, and can therefore be tested more accurately.

Table 3: General scenario conversation

Customer support agent	Customer
Good day, my name is James, your virtual customer support assistant. How can I help you?	
A	Hi, what is Bitcoin?
B	Yes, how do I get Bitcoins?
C	How do I pay with Bitcoins?

A. What is Bitcoin?

- High level of detail: Good question. Bitcoin is a cryptocurrency and digital payment system. The transactions are verified in a network using blockchains. Can I help you any further?
- Medium level of detail: Good question. Bitcoin is a new type of digital currency and can be used for online payments. All Bitcoin transactions are checked by the Bitcoin network and therefore no bank is necessary to process your transactions and the security is high. Can I help you any further?
- Low level of detail: Good question. Bitcoin is a type of money, just like euros or dollars, but then on the internet. You can use it to pay for products and services, just like the money on your bank or in your wallet. The payments you make are checked by Bitcoin users all around the world, which makes your bank not necessary anymore. Because of the network of Bitcoin users, this type of money is secure, private and independent. Can I help you any further?

B. How do I get Bitcoin?

- High level of detail: Bitcoins can be bought or mined. To buy Bitcoins, you need to create a paper wallet, for example at Electrum. At a Bitcoin Exchange, you can trade Bitcoins directly with a broker and transfer it into your paper wallet. Can I help you any further?
- Medium level of detail: You can either buy Bitcoins or mine them. For you, buying is the most logical option. You will need a Bitcoin wallet, a virtual wallet which you can get for example at Electrum. You can buy Bitcoins directly at a Bitcoin Exchange from the Exchange itself or from other Bitcoin users. After you have bought your Bitcoins, you can transfer your new Bitcoins to your wallet. Can I help you any further?
- Low level of detail: Bitcoins can be bought or created. To create Bitcoins, you need a lot of computers and time, which only works in big factory-like companies. Therefore, I recommend you buy Bitcoins if you want to have any. For this, you need a digital storage of your Bitcoins, which is called a wallet. You can download a wallet, for example from the website of the company Electrum. When you have the wallet, you can buy Bitcoins at a website which sells Bitcoins. Here, you buy Bitcoins from the website or from other people online. If you have bought

Bitcoins, you can send them online to your wallet, which you just created. Can I help you any further?

C.How to pay with Bitcoin?

High level of detail: Request a payment by scanning the public ID of the target organization or person. After your transaction block gets validated by the predetermined number of nodes in the blockchain, your payment is complete. This process can take a couple of minutes Can I help you any further?

Medium level of detail: If your wallet contains sufficient Bitcoins for your payment, you scan the public ID of the person or organization you want to transfer your money to in the form of a QR code or number code. After you requested the payment, your transaction must be checked by several users on the Bitcoins network. The computers of these users receive your payment information, and check if the transaction is correct. After a couple of minutes, your transaction is checked and your payment is complete. Can I help you any further?

Low level of detail: If you want to pay a company or person in Bitcoins, you need to have enough Bitcoins, and the company or person you want to send your Bitcoins to, needs to have a Bitcoin identification code. This identification code is a picture or a number, which you can scan with your smartphone. By scanning the code with your Bitcoin account, you can send the payment. At this point, other Bitcoin users receive your payment details, and automatically check if your payment is correct and legal, just like a bank would automatically do. After a few minutes, your payment has been checked and confirmed. When your payment is confirmed, you have send Bitcoins to the company or person. Can I help you any further?

6.1.3. Measurements

Each respondent will be asked about their product knowledge and channel knowledge. As subjective knowledge is most often used in academic literature, a positive relation has been found between objective and subjective knowledge, and determining the customer product knowledge level on a detailed level is not the main scope of this research, a measurement for subjective knowledge will be used in this research to determine the level of expertise of the respondents (Chang et al., 2006; Mothersbaugh et al., 1994). Familiarity in the form of past experiences will be asked for to complete the customer knowledge part of the customer profile. The customer profile will be complemented with age and education level.

As the goal of this study is to recommend a potentially effective method of personalization, and not to assess the separate components of conversation detail, simultaneous manipulation and analysis of level of detail is sufficient. For the same reason, the correlations between the difficulty of vocabulary, number of distinctive steps and response length do not pose a serious problem. Komiak & Benbasat (2012) used a similar experiment manipulation in their study on the effects of familiarity and personalization on trust. Komiak & Benbasat analyzed the variables familiarity and personalization based on sub-variables and determined their scenarios and samples on relative differences between the sub-variables, without determining the actual value of the sub-variables. Using this method, the conversation level of detail can be analyzed and conclusions can be made, without precisely determining the value of the dimension. Conclusions about the level of detail sub-variables can only be suggestive proposals for future research.

After watching the conversation video, the respondents are asked for their satisfaction regarding the conversation. For adequately measuring the customer satisfaction, a weighted mean of the Customer Satisfaction Score (CSAT) and Net Promoter Score (NPS) is used. The Customer Effort Score measures the time and effort necessary to reach the goal of the customer. As the model assumes that the problem will be solved and therefore the CES is expected to be skewed towards the shortest conversation regardless of the other independent variables, this measurement method does not give an accurate value of the satisfaction and will not be used in this study. The duration appropriateness belief will be measured by asking how the actual conversation duration related to preferred conversation duration. The customer satisfaction will also be measured in the form of most preferred scenario. After the respondent has seen all scenarios, he or she is asked to indicate which scenario was preferred most, and give a reason why this scenario was the favorite.

Furthermore, after each scenario, a manipulation check will be conducted to measure the evaluation of the level of detail sub-variables and the engagement of the respondent in the scenario will be measured. The complete list of measured variables and questionnaire structure can be found in Appendix E.

6.1.4. Data-analysis

In order to evaluate the hypotheses stated in Chapter 5, the gathered data from the questionnaire was analyzed using IBM SPSS Statistics 25 with Hayes PROCESS plugin. The effects of the three levels of detail are analyzed using a Friedman's ANOVA, as the experiment can be regarded as a repeated measure test with three dependent groups (the three levels of detail). Post-hoc analysis will be done using Wilcoxon signed-rank test for not normally distributed mean comparison. The Hayes PROCESS plugin was used to analyze the moderation effect of product knowledge. The Kendall's tau b correlation statistic was used to analyze correlations, as this statistic is applicable for not-normally distributed variables with a lot of similar ranks (like with the Likert-scales used in this research).

6.2. Results and Discussion

This section will discuss the results of the experimental study. The questionnaire was completed by 117 people, of which 116 passed the quality checks of age and computer comfort. Only the relevant statistics for evaluating the hypotheses are discussed, additional statistics can be found in Appendix F to I.

6.2.1. Descriptive Statistics

The results of the experimental study did not contain any missing data or unusual data. This was because of the restricted nature of the questionnaire. The majority of the answer options were possible using a Likert-scale and all questions had to be answered in order to submit the questionnaire response. The sample used was a convenience sample, which was noticeable in the results. 75% of the respondents were 18-30 years old, and 47% were currently studying or have completed a university master, see Figure 17.

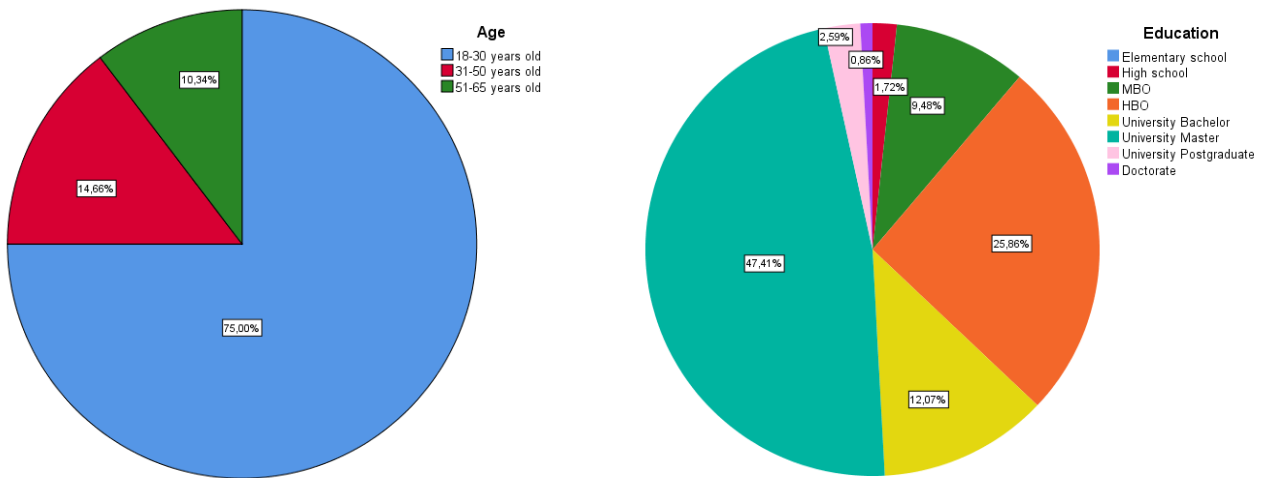


Figure 17: Age and education distributions of the sample

The correlation matrix shows significant correlations between age, education and product knowledge. Furthermore, significant relationships between the dependent and independent variables are noticeable. Further analysis of these correlations will be done in the chapter about hypothesis analysis.

Table 4: Correlation matrix

		Product knowledge	Level of detail	DAB_SL	DAB_RO	CSAT	NPS	Age	Education	Preferred level of detail
Product knowledge	N	348								
Level of detail	Pearson Correlation	,000								
	Sig. (2-tailed)	1,000								
DAB_SL	N	348	348							
	Pearson Correlation	,172	,431							
	Sig. (2-tailed)	,001	,000							
DAB_RO	N	348	348	348						
	Pearson Correlation	-,036	,007	,040						
	Sig. (2-tailed)	,502	,895	,462						
CSAT	N	348	348	348	348					
	Pearson Correlation	,129	,270	,276	-,409					
	Sig. (2-tailed)	,016	,000	,000	,000					
NPS	N	348	348	348	348	348				
	Pearson Correlation	,138	,181	,237	-,367	,741				
	Sig. (2-tailed)	,010	,001	,000	,000	,000				
Age	N	348	348	348	348	348	348			
	Pearson Correlation	-,301	,000	-,109	-,032	-,095	-,203			
	Sig. (2-tailed)	,000	1,000	,042	,550	,075	,000			
Education	N	348	348	348	348	348	348	348		
	Pearson Correlation	,145	,000	,037	,053	,059	,140	-,413		
	Sig. (2-tailed)	,007	1,000	,488	,321	,269	,009	,000		
Preferred level of detail	N	348	348	348	348	348	348	348	348	
	Pearson Correlation	-,301	,000	-,291	-,076	-,216	-,180	,176	-,111	
	Sig. (2-tailed)	,000	1,000	,000	,159	,000	,001	,001	,039	
	N	348	348	348	348	348	348	348	348	348

6.2.2. Manipulation Checks

Level of detail

Friedman's ANOVA shows a significant difference of levels of detail perception of the participants between the scenarios, $\chi^2(2) = 94.4, p < .001$. Wilcoxon rank test shows that the perception of the level of detail is significantly lower for the medium-detail scenario ($M = 4.39$) compared to the high-detail scenario ($M = 4.88$). The perception of the level of detail is also significantly lower for the low-detail scenario ($M = 3.22$) than for the medium-detail or high-detail scenario. This shows that the manipulation of the level of detail of the scenarios have been effective.

Vocabulary

Cronbach's $\alpha = .617$, Friedman's ANOVA shows a significant difference of difficulty of vocabulary between the levels of detail, $\chi^2(2) = 48, p < .001$. Wilcoxon rank test shows that the difficulty of vocabulary is significantly higher for the medium level of detail ($M = 4.22$) compared to the high level of detail ($M = 3.76$). The difficulty of vocabulary is significantly higher for the low level of detail ($M = 5.99$) than for the medium or high level of detail. This shows that the manipulation of the difficulty of vocabulary of the scenarios have been effective.

Number of steps

Friedman's ANOVA shows a significant difference of number of steps between the levels of detail, $\chi^2(2) = 17, p < .001$. Wilcoxon rank test shows that the number of steps is significantly lower for the low level of detail ($M = 3.62$) than for the medium ($M = 4.2$) or high ($M = 4.47$) level of detail. However, the difference in the number of steps between the medium level of detail compared to the high level of detail was not significant. This shows that the manipulation of the number of steps of the scenarios have been effective between the low and medium level of detail, but insufficient between the medium and high level of detail.

6.2.3. Test of Hypotheses

H₁: Conversation level of detail has a direct positive effect on customer satisfaction

To test H₁, the relation between the different levels of detail and the customer satisfaction, in the form of the CSAT and the NPS, is analysed. Extensive results can be found in Appendix F. A Shapiro-Wilk test is used to analyse the distribution of the variables. As a Shapiro-Wilk test shows that both CSAT and NPS are negatively skewed and not normally distributed, a Friedman's ANOVA test will be used to analyse the differences between the satisfaction levels of the levels of detail. A Friedman's ANOVA showed a statistically significant main effect of level of detail on CSAT, $\chi^2(2) = 28.4, p < .001$. Post hoc analyses using a Wilcoxon signed-rank test (with Bonferroni correction) to analyse the levels of detail pairwise indicated that the CSAT scores were lower for a low level of detail ($M = 4.28$) compared to a medium level of detail ($M = 5.14$), $T = 821, p < .001, r = -0.31$. Likewise, the SCAT scores were lower for the low level of detail compared to the high level of detail ($M = 5.19$), $T = 693, p < 0.001, r = -0.29$. The difference between the CSAT scores of the medium and high level of detail was not significant, $T = 1560, p = .767$.

As expected similarly to the CSAT, the Friedman's ANOVA showed a statistically significant main effect of level of detail on NPS, $\chi^2(2) = 28.5, p < .001$. Post hoc analyses using a Wilcoxon signed-rank test (with Bonferroni correction) to analyse the levels of detail pairwise indicated that the NPS scores were lower for a low level of detail ($M = 5.54$) compared to a medium level of detail ($M = 6.54$), $T = 916, p < .001, r = -0.29$. Furthermore, the NPS scores were lower for the low level of detail compared to the high level of detail ($M = 6.47$), $T = 1140, p < 0.001, r = -0.25$. The difference between the NPS scores of the medium and high level of detail was, just like with the CSAT, not significant, $T = 1453, p = .529$.

These results partially support H_1 which states that conversation level of detail has a direct negative effect on customer satisfaction. As a negative effect was found between the lowest level of detail and the other levels of detail, it shows that increasing the level of detail could have a positive effect on customer satisfaction. However, a certain threshold appears to be present, from which point increasing the level of detail does not give a general positive effect on satisfaction. Further increasing the level of detail could even have a negative effect on satisfaction, but this effect was not significant in this study.

H_2 : Conversation level of detail has a negative effect on duration appropriateness belief

To test H_2 , the Duration Appropriateness Belief as a result of the conversation level of detail is considered. The extensive statistical results can be found in Appendix G. Duration Appropriateness Belief is measured in two questions in the experiment; (DAB1: 'I believe the time I spent communicating with the customer support of the bank to solve my problem was... [too short...too long]' and DAB2: 'I believe the overall length of the conversation with the customer support should have been... [much shorter...much longer]') . To use DAB2, it should be reversed, which creates DAB3. DAB1 and DAB3 as subscales of Duration Appropriateness Belief have a sufficiently high reliability of Cronbach's $\alpha = .7$. The construct variable DAB_SL ranges from 2 (conversation was too short) to 14 (conversation was too long) with $M = 7.80$, $SD = 2.02$. A chart of the Duration Appropriateness Belief is shown in Figure 18.

A Shapiro-Wilk test shows that this DAB_SL is not normally distributed. To analyse the effect of conversation level of detail on DAB_SL, a Friedman's ANOVA is used again. This analysis showed a statistically significant main effect of level of detail on DAB_SL, $\chi^2(2) = 76$, $p < .001$. Post hoc analyses using a Wilcoxon signed-rank test (with Bonferroni correction) to analyse the levels of detail pairwise indicated that the DAB_SL scores were lower for a low level of detail ($M = 6.73$) compared to a medium level of detail ($M = 7.82$), $T = 625$, $p < .001$, $r = -0.35$. Furthermore, the DAB_SL scores were lower for the low level of detail compared to the high level of detail ($M = 8.86$), $T = 583$, $p < 0.001$, $r = -0.46$. The DAB_SL scores of the medium level of detail were significantly lower than the high level of detail, $T = 596$, $p < 0.001$, $r = -0.35$.

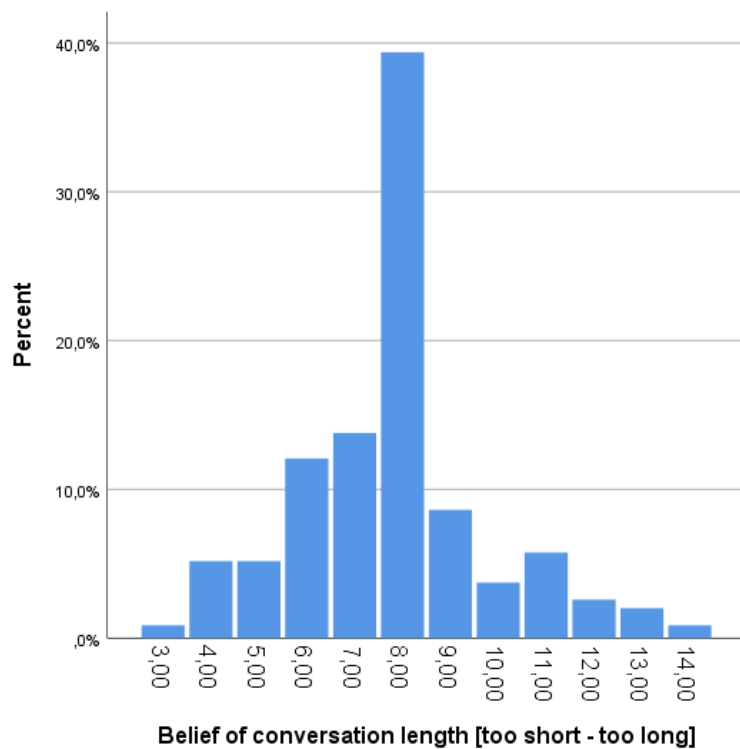


Figure 18: Descriptive statistics about duration appropriateness belief

The results show that by increasing the level of detail, the DAB_SL scores also rises. This is quite logical, as a higher DAB_SL indicates that the conversation is perceived longer. This, however, does not clearly show if the respondents favoured the length of a conversation over other conversations.

An alternative construct of Duration Appropriateness Belief is the difference between the optimal perceived duration (which in the case of DAB_SL is with a value of 8) and the actually

perceived duration. This construct DAB_RO has a range from 0 (just right) to 6 (very far off), $M = 1.37$, $SD = 1.49$. The Friedman's ANOVA shows a statistically significant main effect of level of detail on DAB_RO, $\chi^2(2) = 17.7$, $p < .001$. Post hoc analyses using a Wilcoxon signed-rank test (with Bonferroni correction) to analyse the levels of detail pairwise indicated that the DAB_RO scores were higher for a low level of detail ($M = 1.59$) compared to a medium level of detail ($M = 0.91$), $T = 841$, $p < .001$, $r = -0.25$. The difference between the DAB_RO scores of the low and high level of detail ($M = 1.62$) were not significant, $T = 2522$, $p = .992$. The DAB_RO scores of the medium level of detail were significantly lower than the high level of detail, $T = 715$, $p < 0.001$, $r = -0.28$.

These results do not support H_2 , which states that the level of detail has a negative effect on the Relationship Appropriateness Belief. Analysis of the DAB_RO score shows that the respondents generally appreciated the length of the middle level of detail over the higher or lower level of detail.

H_3 : *Duration appropriateness belief is positively related to customer satisfaction.*

The relationship between Duration Appropriateness Belief and Customer Satisfaction is analysed using bivariate correlation analysis. As the variables DAB_SL, DAB_RO, CSAT and NPS are not normally distributed and there are a lot of equally ranked values of DAB_SL and DAB_RO, the Kendall's tau is a non-parametric correlation coefficient which can indicate a relationship. The results can be seen in Table 5. DAB_SL was positively correlated with CSAT and NPS, respectively Kendall's tau_b(348) = .20, $p < .001$ and Kendall's tau_b(348) = .18, $p < .001$. DAB_RO was positively correlated with CSAT and NPS, respectively Kendall's tau_b(348) = -.34, $p < .001$ and Kendall's tau_b(348) = -.31, $p < .001$. These result support H_3 , which states that Duration Appropriateness Belief is negatively related to customer satisfaction. The DAB_RO variable is hereby indicated as having the largest significant effect on customer satisfaction.

Table 5: Correlation analysis for hypothesis 3

		DAB_SL	DAB_RO	CSAT	NPS	
Kendall's tau_b	DAB_SL	Correlation Coefficient	1,000	-.183**	.203**	.178**
		Sig. (2-tailed)	.	.000	.000	.000
		N	348	348	348	348
DAB_RO	DAB_RO	Correlation Coefficient	-.183**	1,000	-.339**	-.305**
		Sig. (2-tailed)	.000	.	.000	.000
		N	348	348	348	348
CSAT	CSAT	Correlation Coefficient	.203**	-.339**	1,000	.660**
		Sig. (2-tailed)	.000	.000	.	.000
		N	348	348	348	348
NPS	NPS	Correlation Coefficient	.178**	-.305**	.660**	1,000
		Sig. (2-tailed)	.000	.000	.000	.
		N	348	348	348	348

H_4 : *As the value of customer product knowledge increases, the effect of conversation level of detail on customer satisfaction decreases.*

Hypothesis 4 regards the moderating effect of product knowledge on the relationship between level of detail and customer satisfaction. To analyze the effect of product knowledge, the variable product knowledge was first created based on the construct analyzed in the theoretical section of this study. Product knowledge is based on product expertise and product familiarity.

Product expertise is a subjective measure in the experiment, constructed using two questions (PE1 "If someone would ask me, I am able to explain what Bitcoins are and how they work [1 (completely disagree) to 6 (completely agree)]" and PE2 "To what extend do you think you know about cryptocurrencies, like Bitcoin, in general? [1 (I think I know nothing about cryptocurrencies or Bitcoins) to 8 (I think I am an expert in cryptocurrencies or Bitcoins)]"). The two measures are standardized and the Z-scores are further used.

A reliability analysis of Product Expertise variable after standardization shows a Cronbach's $\alpha = .873$, which shows a good reliability. See descriptive statistics in the table below.

Product familiarity is asked in three questions (asking the current and previous ownership of bitcoins and frequency of conversations about bitcoins). Cronbach's Alpha after standardization is

0,66, but by dropping the frequency of discussions, the Cronbach's $\alpha = .84$, which is a good reliability. See the descriptive statistics below.

Product knowledge is composed of product expertise and product familiarity. These two variables have been constructed earlier. As expected and described in earlier research, there is a positive correlation between the product expertise and the product familiarity. Product expertise was positively correlated with product familiarity, Kendall's tau_b(116) = .33, $p < .001$, which indicates a medium sized positive correlation. As earlier research described product knowledge to be equally dependent on product expertise and product familiarity, the final product knowledge variable will be developed by calculating the added

Table 6: Descriptives for product knowledge construct

	N	Range	Minimum	Maximum	Mean	Std. Deviation
BITEXP1	116	5	1	6	3,72	1,311
BITEXP2	116	7	1	8	4,53	1,546
Have Bitcoins	116	1	0	1	,16	,364
Ever had Bitcoins	116	1	0	1	,21	,407
Product familiarity	116	5,21	-,94	4,27	,0000	1,85555
Product expertise	116	7,70	-3,71	3,98	,0000	1,88419
Product knowledge	116	6,89	,00	6,89	2,4736	1,67230
Valid N (listwise)	116					

scores of the standardized versions of expertise and familiarity. A reliability analysis results in Cronbach's $\alpha = .57$, which is not very high, but in combination with the significant correlation can be used to create the variable product knowledge. The minimum of the product knowledge variable is set at 0, as a negative knowledge level is hard to interpret. See the descriptive statistics in Table 6.

The moderating effect of product knowledge on the relationship between level of detail and customer satisfaction is analyzed using the Hayes PROCESS plugin for SPSS. The extensive results can be found in Appendix H. The overall model was found to be significant, $F(3, 344) = 13.98$, $p < .001$, $R^2 = .123$. Also in this model the level of detail had an individual significant effect on customer satisfaction, $b = 0.46$, $t(344) = 5.17$, $p < .001$. This means that for every 1 unit increase in level of detail (1 scenario), we get an increase of 0.46 in CSAT. Product knowledge showed a significant direct effect on customer satisfaction, $b = .11$, $t(344) = 2.62$, $p = .009$. This can be interpreted as a 0.11 increase in CSAT for every 1 unit increase in product knowledge measure. Lastly, the interaction effect, or moderating effect, of level of detail and product knowledge was also significant, $b = -.19$, $t(344) = -3.4272$, $p < .001$. However, this coefficient is harder to interpret and further results show a more elaborate description of the moderation effect.

The relationship between level of detail and CSAT is analysed for three levels of product knowledge by the Hayes PROCESS plugin. These levels of product knowledge correspond with values of product knowledge of one standard deviation under mean, exactly mean and one standard deviation above mean. The low level of product knowledge had the value 0.80, medium level had the value 2.47 and high level of product knowledge had the value 4.14. Based on these low, average and high levels of detail, an indication of the effect of level of detail on customer satisfaction can be given for different levels of product knowledge. For a low level of product knowledge, the level of detail had a significant positive effect, $b = 0.77$, $t(344) = 5.85$, $p < .001$. For an average level of product knowledge, the level of detail also had a positive significant effect, $b = 0.46$, $t(344) = 5.17$, $p < .001$. Lastly, for a high level of product knowledge, the relationship between the level of detail and customer satisfaction was not significant, $b = 0.15$, $t(344) = 1.21$, $p = .23$. The results can be interpreted as an indication of the effect of level of detail on customer satisfaction, at different levels of product knowledge. For low product knowledge, every level of detail higher gives an increase in CSAT of 0.77. For medium product knowledge, every level of detail higher gives an increase in CSAT of 0.46. Although no significant relationship was found at high levels of detail, the results show that the (non-significant) effect becomes smaller and even negative at higher levels of detail. See Figure 19 for the plotted trendline of the different relationships.

The relationship between level of detail and CSAT can be analysed for more levels of detail, which gives an indication at which level of product knowledge the effect between level of detail and CSAT occurs. For a product knowledge of maximum 3.78, level of detail and CSAT are significantly related, $t(344) = 1.97$, $p = .05$, $b = 0.21$. As the product knowledge decreases, the relationship between level of detail and CSAT becomes more positive with the lowest level of product knowledge (which is zero), $b = 0.92$, $t(344) = 5.52$, $p < .001$.

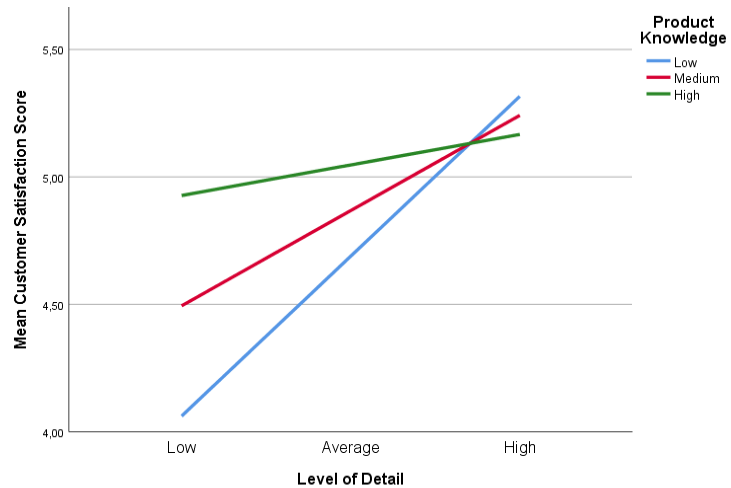


Figure 19: Effect of detail on CSAT at different levels of product knowledge

The results are similar for the relationship between level of detail and Net Promoter Score, however the effects found are smaller, $F(3, 344) = 7.75$, $p < .001$, $R^2 = .063$.

The results show that at lower levels of product knowledge, the effect of level of detail on customer satisfaction is higher compared to the effects at higher levels of product knowledge. Therefore, H_4 is supported.

H_5 : *Conversations with a high level of detail are more likely to be preferred by customers with a low customer product knowledge.*

H_6 : *Conversations with a low level of detail are more likely to be preferred by customers with a high customer product knowledge.*

The relation between product knowledge and preferred level of detail is analysed using bivariate correlation analysis. The extensive results can be found in Appendix I. As the product knowledge is not normally distributed and there are a lot of equally ranked values of product knowledge, the Kendall's tau statistic will be used. The results can be seen below. Product knowledge was negatively correlated with preferred level of detail, Kendall's tau_b(116) = $-.25$, $p = .001$, see Table 7.. These result support H_5 and H_6 , which state that conversations with a high level of detail are more likely to be preferred by customers with a low level of product knowledge and conversations with a low level of detail are more likely to be preferred by customers with a high level of product knowledge.

To analyse the effect size, a Kruskal-Wallis test has been conducted. This test showed that the preferred level of detail is significantly related to product knowledge, $H(2) = 12.4$, $p = .002$. Mann-Whitney U tests were used to follow up this finding with Bonferroni correction (level of significance necessary is 0.0167). The tests show that customers preferring a low level of detail have a higher level of knowledge averagely compared to customers preferring a medium level of detail, ($U = 446$, $r = -.33$). Furthermore, customers preferring a low level of detail significantly have a higher level of product knowledge on average compared to customers preferring a high level of detail ($U = 263$, $r = -.4$). The difference in product knowledge between customers preferring the high level of detail and

customers preferring the medium level of detail was not significant ($U = 799, r = -.12, p = .269$). These results support H_5 and H_6 .

Table 7: Correlation statistics for hypothesis 5 and 6

		Product knowledge	Preferred level of detail
Kendall's tau_b	Product knowledge	Correlation Coefficient	1,000
		Sig. (2-tailed)	.
		N	116
	Preferred level of detail	Correlation Coefficient	-,249**
		Sig. (2-tailed)	,001
		N	116

** . Correlation is significant at the 0.01 level (2-tailed).

H_7 : Personalization of the level of detail in an automated customer support conversation increases the average customer satisfaction.

The knowledge about the relation between level of detail and customer product knowledge could be used to predict the preference of level of detail of customers based on their product knowledge. Using linear regression, a prediction is made of the preferred level of detail. A threshold analysis divided the stereotypes at the level of 1.8 and 2.2 of predicted level of preference. Using these stereotype families, the different scenarios can be assigned and the average customer satisfaction can be compared to the strategy whereby only the medium level of detail is given to the user. Personalizing the level of detail based on customer product knowledge hereby showed an increase in CSAT and NPS, see Table 8.

Table 8: Descriptives for personalization demonstration

	N	Range	Minimum	Maximum	Mean	Std. Deviation
CSAT Low	116	6	1	7	4,28	1,597
CSAT Medium	116	5	2	7	5,14	1,193
CSAT High	116	5	2	7	5,19	1,134
CSAT Personalized	116	5	2	7	5,23	1,281
NPS Low	116	9	1	10	5,54	2,220
NPS Medium	116	9	1	10	6,54	2,019
NPS High	116	9	1	10	6,47	1,867
NPS Personalized	116	9	1	10	6,58	2,119
Valid N (listwise)	116					

7. Conclusion and Implications

To improve the effectiveness of automated digital customer support through personalization, a deeper understanding on the personalization methods and their effect on customer satisfaction was necessary. This research aimed to contribute to this deeper understanding by evaluating traditional and proposed personalization methods in a qualitative study with an expert panel. Furthermore, one personalization method was further analyzed in an experimental study, to assess the relation between the personalization component and its effect on customer satisfaction. Through this methodology, this research aimed to find an answer on the following research question:

How could customer satisfaction about an automated digital customer support conversation be improved through personalization?

As previous studies suggested, a positive relation between the use of personalization and customer satisfaction was expected. However, the relation between specific personalization methods and customer satisfaction was not yet studied for an automated digital customer support channel. Therefore, this study created an overview of the relevant personalization methods for automated digital customer support and analyzed knowledge personalization, a method whereby the level of detail is adjusted to the customer product knowledge.

7.1. Research Implications

The results of the qualitative analysis showed that automated digital customer support enabled new methods for personalization. The expert panel fully supported knowledge personalization, whereby the level of detail of the conversation was adjusted to the customer product knowledge, as a method to improve customer satisfaction. Furthermore, outcome personalization, whereby the number of options presented to the customer is adjusted to the customer's need for control and simplicity, and human routing personalization, whereby the customer is matched to a human support agent based on common interests and backgrounds, were popular among the experts. Traditional personalization methods, like introducing small talk, proactive support delivery or adjusting the language to the residence area or age of the customer, were less likely to positively affect customer satisfaction, according to the experts.

This qualitative study focused the personalization methods for automated digital customer support on a new set of methods, which is different from the personalization methods effective for traditional, face-to-face customer support. The new set of personalization methods, its descriptions through the developed personalization components and its evaluations by experts can provide a starting point for future research, as this research evaluated established traditional personalization methods in a digital customer support environment.

Knowledge personalization was further studied in the experimental study, as this personalization method was expected to have the most positive effect on customer satisfaction, is an extension to the previously studied method of personalization due to its specific applicability in digital customer support and is expected to be relatively easy to implement. Knowledge personalization adjusts the level of detail to the customer product knowledge. Level of detail was defined as the difficulty of vocabulary and the number of distinctive steps in which a solution or response is presented. The components of knowledge personalization, which are level of detail and customer product knowledge, were further studied on their effect on customer satisfaction in an experimental study.

The results of the experimental study showed that the level of detail has a positive direct effect on customer satisfaction. Furthermore, customer product knowledge had a negative moderating effect on the relationship between level of detail and customer satisfaction. Additionally, the customer product knowledge was negatively related to the preferred level of detail, this showed that the respondents preferring a high level of detail had a relatively low level of product knowledge compared

to the respondents preferring a low level of detail. The gained knowledge about the relationship between the personalization components and customer satisfaction could be used to introduce knowledge personalization as a method to increase average customer satisfaction. Linear regression predicted the preferred level of detail of the respondents and threshold analysis divided the respondents in three stereotypical families, based on their preferred level of detail. The customer satisfaction score of the preferred level of detail of each respondent group was used to measure the personalized average satisfaction score. This personalized satisfaction score was higher than the average customer satisfaction of any of the three levels of detail.

The experimental study shows a method of analyzing a personalization method based on its components. Hereby the relation between the components was first measured, before the knowledge about the relations were used to show the effects of using the personalization method. Determining the level of product knowledge, creating templates with varying levels of detail and matching levels of product knowledge to suitable levels of detail is case-specific. Pre-tests with a first scenario regarding a customer banking environment indicated that knowledge personalization would probably have a minimal or no effect on customer satisfaction. This shows that personalization studies are case-specific, and the effects of personalization methods found in a study are no guarantee for any other studies or implementations. However, this study found significant relations between the personalization components, and could translate these relations in a demonstration of a positive effect of knowledge personalization.

7.2. Managerial Implications

The number of businesses using automated digital customer support channels increases, and market predictions show the crucial importance of digital communication channels which are available at any time. Virtual assistants for customer support are a business value as they have 24/7 availability, are cost-effective in the long term compared to a customer support channel fully operated by human agents and create huge opportunities to improve the service quality by using customer data and conversation analytics. Virtual assistants therefore potentially eliminate the trade-off of the service industry between service efficiency and service quality. Traditionally, personalization efforts would require more time to get to know the person and offer a personalized experience. Using virtual assistants, the customer support conversation can be personalized without losing efficiency. However, these positive expectations of virtual assistants are mainly based on a virtual assistant which is able to effectively solve the problems of the customer with a personalized conversation. Whilst industries do have positive predictions on the commercial value of personalization, implementation goes slowly as personalizing the conversation is seen as complicated and risky. This research aimed to provide industry with relevant personalization methods to consider and further analyze one personalization method which is expected to be effective and relatively easy to implement.

First, previous literature and the qualitative and quantitative studies in this research show that business should consider personalization when implementing a virtual assistant for their customer support channels. Personalization of the content enables the customer to get the most relevant answer to their question as quickly as possible. Personalization of the conversation enables the customer to receive a unique experience, tailored to their preference. This potentially increases the customer satisfaction, customer loyalty and further positive effects like cross-selling.

Secondly, the qualitative study shows that multiple personalization methods are applicable and relevant for automated digital support. Knowledge personalization adjusts the level of detail of complex conversation to the product knowledge of the customer. Human routing personalization matches the profile of the customer to the profile of a human support agent. Outcome personalization determines the need for control and/or simplicity of the customer, and adjusts the number of presented options to it. Lastly, the language and vocabulary of the conversation could be personalized. Besides the widely used language selections like English, Dutch or Spanish, also other language traits, like

formality, dialect forms or slang can be personalized. For each personalization methods, businesses should analyze the applicability in their customer support channel.

Thirdly, the effect of knowledge personalization is case-specific. Businesses should analyze their customer support channel on opportunities to personalize their customer support conversations. Knowledge personalization could have a large effect on customer support channels which handles customer problems with a high complexity, a lot of different problem components, a lot of distinctive steps which lead to the final solution or whereby the knowledge of the customer about the subject is highly diverse. The effect of knowledge personalization will probably be small for cases whereby the knowledge levels of the customers are similar, the most complex solutions or explanations are simple to understand for all customers when communicated very briefly or when the solutions to the customer problems involve a simple action with only one or two distinctive steps.

Fourth, customer satisfaction of automated digital customer support could be improved if the customer product knowledge could be determined adequately. Various methods could be used to determine the product knowledge. This research asked respondents explicitly for their belief about their product knowledge. This subjective measurement proved to be directly effective in improving the customer satisfaction through knowledge personalization. However, explicitly asking the customers increases the length of a customer support experience. Another method of determining the product knowledge are based on previous interactions and historic data. The need for more information, complexity of previous problems or speed of understanding the proposed solutions could indicate the general knowledge of customers about the subject. Virtual assistants could be used to gather, document and recall this information. Thirdly, the product knowledge could be determined during the conversation. When the customer asks for more explanation using an 'extra information' button, this could indicate a relatively low level of product knowledge. Finally, natural language processing enables the virtual assistant to analyze the responses of the customer, and determine the level of product knowledge. For example, if the customer uses a lot of industry-specific terminology to described the problem on a highly detailed and specific level, the level of product knowledge can be determined as high. However, determining the level of product knowledge is complicated, case-specific and subject for further research.

Fifth, to use knowledge personalization, the level of detail should be adjustable. For this, multiple variations or templates for responses or solutions could be created. When a virtual assistant would communicate a certain response or solution to the customer, the different templates would give the virtual assistant a choice in level of detail to communicate in. These levels of detail can differ in difficulty of vocabulary and number of steps in which the response is communicated.

Lastly, the matching of customer knowledge levels of customers to levels of conversational detail is case-specific and should be tested and developed accurately to ensure the most optimal results. In this research, three random but distinctive levels of detail were used to find an effect of knowledge personalization. While a positive effect of knowledge personalization was demonstrated, the size of the effect is dependent on the case and calibration of the matching phase. In conversation with customers, the two important components of knowledge personalization should be calibrated. First, the levels of product knowledge should be determined through customer segmentation. Analyzing different customer profiles is the first step of knowledge personalization and results in a specific number of different customer segments based on product knowledge. Secondly, the relevant levels of detail should be selected, which can be linked to the customer segments. If three different customer segments based on product knowledge can be distinguished, the levels of detail optimal of these customer segments, or stereotypes, should be determined. If the range of product knowledge and optimal level of detail for each customer segment are mapped, knowledge personalization could improve customer satisfaction by placing individual customers in customer segments and presenting this customer with the optimal level of detail.

7.3. Limitations and Directions for Future Research

The results of this research must be seen in the light of some limitations. The time restrictions of the project created a limited scope, which leaves room for further research. Furthermore, the methodology and results posed interesting insight to be validated in future studies. This section creates an overview of the limitations and recommendations for future research.

First, experimental study used a bitcoin customer support scenario. This scenario was used the financial industry is frequently used for studies on virtual assistants due to its innovative nature and highly involved customers. Furthermore, the subject of bitcoins provides enough complexity and customer knowledge diversity to expect a positive effect of knowledge personalization. To assess the industry and subject properties which indicate a good opportunity for knowledge personalization, more research is necessary to study the effectiveness of knowledge personalization in other industries.

Secondly, the level of detail has been defined in this study as a combination of difficulty of vocabulary and number of distinctive steps in a response, which in turn had a direct effect on the response length. These subordinate variables were inferred from previous research and the qualitative study. However, the individual effects of difficulty of vocabulary and number of steps was not separately studied in this research. Furthermore, the variable of level of detail could be further developed by complimenting it with other conversation characteristics. To further develop knowledge personalization, a study on the sub-variables of knowledge personalization and their effects on response length and customer satisfaction would be valuable.

Thirdly, product knowledge has been measure by explicitly asking the respondents of the experimental study for their subjective belief about their product knowledge. Interviews and studies have proposed other methods of measuring product knowledge, like based on previous conversations or by natural language processing. By improving the assessment of product knowledge, the customer could be better matched to a level of detail. Future research on the methods and impacts of measuring product knowledge is a technological, linguistic and psychological challenge, but would result in necessary insights for implementing knowledge personalization.

Apart from the customer product knowledge, further research could study other customer properties which could be used to predict the level of detail preferred by the customer. Any possible properties could be computer literacy or a desire for a fast solution or cognitive simplicity. Adding other relevant customer profile variables to the process of knowledge personalization would probably improve the effect and reliability of the personalization process.

The qualitative study resulted in multiple potentially relevant personalization methods, according to the expert panel. Of these personalization methods, knowledge personalization was further studied in the experimental study. However, the importance and effect of knowledge personalization relative to the other personalization methods would give industry a complete overview of the personalization opportunities. Whilst the experts in the qualitative studies expected knowledge personalization to have the largest effect on customer satisfaction, this relatively large effect has not yet been supported by data.

Furthermore, the scope of this research was limited to automated digital customer support. Virtual assistants have however also been implemented in sales and marketing. Knowledge personalization and other personalization methods could have similar effects in these other business processes, but to get a deeper understanding of the value of personalization in sales and marketing, additional validating research is necessary. Furthermore, developments in automated customer support reach further than text-based virtual assistants. As the technologies are more and more implemented with voice recognition or connections with other channels, future research in personalization methods in more advanced virtual assistants would create additional business value.

Lastly, the experimental study has been conducted using a convenience sample. Although the product knowledge of the sample is distributed, the age and education of the respondents show a largely skewed distribution. Validating research with a sample which is more representative of the population would strengthen the conclusions of this research.

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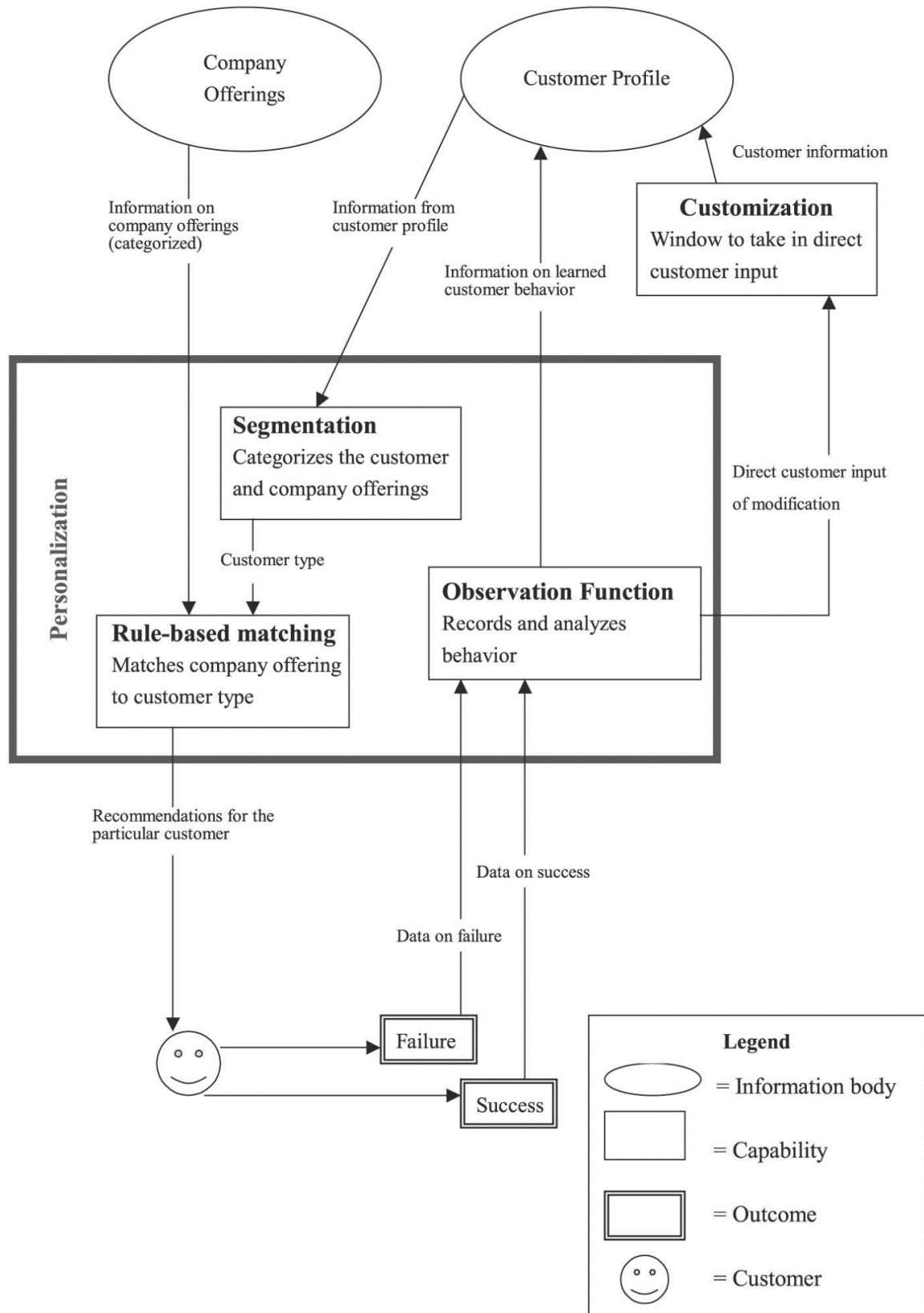
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Appendix A: The Role of Personalization in a Customer-firm Conversation

by Huang & Lin (2005)



Appendix B: Interview Stage 3 Online Questionnaire

Personalization in digital customer support

Thank you for participating in the expert panel of my graduation research. The scope of this research is virtual assistants in customer support, across all industries. This survey is part of the last phase of the expert review and is expected to take around 5 minutes to finish. The results will be processed semi-anonymously, meaning your function or role in the organization and industry will be described in the results on a collective level, to validate the level of expertise of the expert panel. If you have any questions, don't hesitate to contact me through t.r.aanhane@student.tue.nl or +31657933296.

Personalization methods

Different personalization methods have been discussed in the previous rounds.

Outcome personalization

Giving customers a number of solutions to their problem, whereby the number of solutions given depends on the customer profile.

Small talk personalization

Conversing small talk or not, depending on the customer profile.

Language personalization - use of slang

Using 'street language', emoticons or popular abbreviations in the conversation, to target a specific customer segment, based on the customer profile.

Language personalization - informal or formal conversation

Adjusting the vocabulary of the conversation to attain a more formal or informal conversation, based on the customer profile.

Language personalization - dialect vocabulary

Speaking in dialect or not, based on the customer profile.

Knowledge personalization

Adjusting the amount of information in each step of the customer support trajectory and the starting point of the conversation, based on the customer profile.

Human routing personalization

Matching an end-user to a human agent when the virtual assistant is incapable of solving the problem, whereby the end-user is matched to a human agent based on the customer profile (including personality and demographic information), the profile of the human agent and the problem statement.

Which personalization method(s) do you expect to have a positive effect on customer satisfaction? *

Multiple answers are possible

- Outcome personalization
- Small talk personalization
- Language personalization - use of slang
- Language personalization - informal or formal conversation
- Language personalization - dialect vocabulary
- Knowledge personalization
- Human routing personalization

Which personalization method do you think has the most positive effect on customer satisfaction? *

Choose ▼

Which personalization method do you think has the second most positive effect on customer satisfaction? *

Choose ▼

Which personalization method do you think has the third most positive effect on customer satisfaction? *

Choose ▼

Appendix C: Interviews Stage 1 Statements

Subject	Statement
Outcome personalisation	Multiple options are always stressful and complex for the end-user
Outcome personalisation	Let the end-user be in control
Outcome personalisation	More interaction, so that's always better
Outcome personalisation	Personalize the number of outcomes
Outcome personalisation	It's automation, not personalization
Outcome personalisation	It's personalization
Outcome personalisation	Impossible to find sweet spot
Outcome personalisation	Hard to find sweet spot
Outcome personalisation	Easy to find sweet spot
Outcome personalisation	Outcome personalisation can have a positive effect on customer satisfaction
Outcome personalisation	Outcome personalisation will not have a positive effect on customer satisfaction
Small talk personalisation	Customer support should always only be functional, to solve the problem of the end-user
Small talk personalisation	When the users initiates, it is good to react on that. Never let small talk be initiated by the virtual assistant.
Small talk personalisation	It works great for making a connection with the end-user and giving the virtual assistant a soul
Small talk personalisation	Can effectively work to manage the emotions of the end-user
Small talk personalisation	Personalize the small talk
Language personalisation	Language adjustment makes your statements less accurate.
Language personalisation	Language adjustment does not make your statements less accurate.
Language personalisation	You talk differently to friends, colleagues, family, etc. So why not include that in the virtual assistant?
Language personalisation	The relationship between VA and end-user is equal to all customers, so talking differently to different end-users has no value.

Language personalisation	Slang has no added value.
Language personalisation	Slang can help target the right customer segment and therefore be good.
Language personalisation	Adjusting to a formal or informal conversation improves the customer satisfaction.
Language personalisation	Adjusting to a formal or informal conversation does not improve the customer satisfaction.
Language personalisation	The ability to speak in dialect improves the customer satisfaction.
Language personalisation	The ability to speak in dialect does not improve the customer satisfaction.
Language personalisation	Language should be based on the product and company, and not on the customer.
Language personalisation	The VA has a personality and a corresponding vocabulary, you should not change that.
Language personalisation	Language should be based on the customer only
Language personalisation	Language should be based on product, company and customer all together
Customized personalisation	Proactive customer support generally has a positive effect on customer satisfaction
Customized personalisation	The effect of proactive customer support is dependent on the industry and task, not on the customer profile
Knowledge personalisation	Speeding up the process for people with a high product knowledge will increase the customer satisfaction.
Knowledge personalisation	Personalisation based on product/technical knowledge will have no effect on the customer satisfaction.
Routing personalisation	Routing the conversation to a human agent best matched to the customer profile has a positive effect on customer satisfaction
Routing personalisation	Routing the conversation to a human agent best matched to the customer profile does not have a positive effect on customer satisfaction
Routing personalisation	Routing matching should be based on content/problem statement only
Routing personalisation	Routing matching should be based on personality only
Routing personalisation	Routing matching should be based on content and personality

Appendix D: Interviews Stage 2 Statements

Code	Subject	Statement	Agree
1.1.1	Outcome personalisation	Multiple options are always stressful and complex for the end-user	57%
1.1.2	Outcome personalisation	Let the end-user be in control	43%
1.1.3	Outcome personalisation	More interaction, so that's always better	7%
1.1.4	Outcome personalisation	Personalize the number of outcomes	57%
1.2.1	Outcome personalisation	It's automation, not personalization	50%
1.2.2	Outcome personalisation	It's personalization	64%
1.3.1	Outcome personalisation	Impossible to find sweet spot	0%
1.3.2	Outcome personalisation	Hard to find sweet spot	80%
1.3.3	Outcome personalisation	Easy to find sweet spot	20%
1.4.1	Outcome personalisation	Outcome personalisation can have a positive effect on customer satisfaction	64%
1.4.2	Outcome personalisation	Outcome personalisation will not have a positive effect on customer satisfaction	36%
2.1.1	Small talk personalisation	Customer support should always only be functional, to solve the problem of the end-user	23%
2.1.2	Small talk personalisation	When the users initiates, it is good to react on that. Never let small talk be initiated by the virtual assistant.	46%
2.1.3	Small talk personalisation	It works great for making a connection with the end-user and giving the virtual assistant a soul	31%
2.1.4	Small talk personalisation	Can effectively work to manage the emotions of the end-user	23%
2.1.5	Small talk personalisation	Personalize the small talk	62%
3.1.1	Language personalisation	Language adjustment makes your statements less accurate.	44%
3.1.2	Language personalisation	Language adjustment does not make your statements less accurate.	56%
3.1.3	Language personalisation	You talk differently to friends, colleagues, family, etc. So why not include that in the virtual assistant?	69%
3.1.4	Language personalisation	The relationship between VA and end-user is equal to all customers, so talking differently to different end-users has no value.	31%
3.2.1	Language personalisation	Slang has no added value.	21%
3.2.2	Language personalisation	Slang can help target the right customer segment and therefore be good.	79%
3.3.1	Language personalisation	Adjusting to a formal or informal conversation improves the customer satisfaction.	71%
3.3.2	Language personalisation	Adjusting to a formal or informal conversation does not improve the customer satisfaction.	29%
3.4.1	Language personalisation	The ability to speak in dialect improves the customer satisfaction.	58%

3.4.2	Language personalisation	The ability to speak in dialect does not improve the customer satisfaction.	42%
3.5.1	Language personalisation	Language should be based on the product and company, and not on the customer.	14%
3.5.2	Language personalisation	The VA has a personality and a corresponding vocabulary, you should not change that.	21%
3.5.3	Language personalisation	Language should be based on the customer only	29%
3.5.4	Language personalisation	Language should be based on product, company and customer all together	50%
4.1.1	Knowledge personalisation	Speeding up the process for people with a high product knowledge will increase the customer satisfaction.	92%
4.1.2	Knowledge personalisation	Personalisation based on product/technical knowledge will have no effect on the customer satisfaction.	8%
5.1.1	Routing personalisation	Routing the conversation to a human agent best matched to the customer profile has a positive effect on customer satisfaction	92%
5.1.2	Routing personalisation	Routing the conversation to a human agent best matched to the customer profile does not have a positive effect on customer satisfaction	8%
5.1.3	Routing personalisation	Routing matching should be based on content/problem statement only	25%
5.1.4	Routing personalisation	Routing matching should be based on personality only	0%
5.1.5	Routing personalisation	Routing matching should be based on content and personality	75%

Appendix E: Questionnaire Structure

Name	Definition	Construct	(Validating) question
Level of detail	The level of detail within a customer support conversation that can be adjusted to the knowledge level of the end-user.	Difficulty of vocabulary Number of steps	
Difficulty of vocabulary	Level of expertise necessary to understand the vocabulary used by the customer support agent. (Huang & Lin, 2005; Xu & Reitter, 2016)		I was able to comprehend all words and sentences that the customer support agents sent [1-6] The customer support agent used difficult words or terminology [1-6]
Number of steps	Number of distinct steps and level of detail that are recognizable in the directions and solutions given by the customer support agent. (Huang & Lin, 2005; Xu & Reitter, 2016)		The solution given by the customer support agent was explained to me in multiple small, distinctive steps [1-6] The virtual assistant explained and responded with a lot of detail [1-6]
Customer product knowledge	Knowledge and information about the product or service (Chang et al., 2006)	Familiarity Expertise	
Familiarity	Customers understanding of a product, based on previous interactions and experiences (Chang et al., 2006; Chellappa & Sin, 2005; Komiak & Benbasat, 2012; Mothersbaugh et al., 1994)		Do you currently own or trade a cryptocurrency, like Bitcoin? [yes,no] Have you ever owned and/or traded a cryptocurrency, like Bitcoin? [yes,no] In the last year, how often have you read, discussed or heard about cryptocurrencies, like Bitcoin? [Every day, a couple of times per week, every week, a couple of times per month, every month, a couple of times per year, every year, never]
Expertise	Ability to perform product-related tasks successfully (Chang et al., 2006; Mothersbaugh et al., 1994). The most popular studies use a construct of subjective and objective knowledge. Others also include experience (or familiarity), product-class information (like brands or attributes) or storylines. As	Subjective knowledge Objective knowledge <i>Product-related experience</i> <i>Stored product-class</i>	If someone would ask me, I am able to explain what Bitcoins are and how they work. [1-6] To what extent do you think you know about cryptocurrencies, like Bitcoin, in general? [1-

	subjective knowledge is most often used, a positive relation has been found between objective and subjective knowledge, and determining the customer product knowledge level on a detailed level is not the main scope of this research, a measurement for subjective knowledge will be used in this research to determine the level of expertise of the respondents. (Chang et al., 2006; Chellappa & Sin, 2005; Huang & Lin, 2005; Komiak & Benbasat, 2012; Mothersbaugh et al., 1994)	<i>information Reasons data</i>	6] <i>Added to these questions will be examples, which will be linked to certain scores. Hereby labels will be used like 'I have never heard of cryptocurrencies or Bitcoin', 'I know what it is', 'I know what it is and how I can use it', 'I know what it is, how I can use it, and how it technically works'</i>
Customer channel knowledge	Knowledge and information about the channel used for customer support	Familiarity Expertise	
Familiarity	Customers understanding of a channel, based on previous interactions and experiences (Chang et al., 2006; Chellappa & Sin, 2005; Komiak & Benbasat, 2012; Mothersbaugh et al., 1994)		In the last year, how often have you used an online web-chat service (communicating online using text-messages) for customer support (via your web-browser, smartphone application, social media, etcetera)? [never, once, 2-4 times, 5-8 times, 9-15 times, more than 15 times] I am comfortable using a computer [1-6] I am comfortable communicating online using a text-chat. [1-6]
Expertise	Ability to perform channel-related tasks successfully (Chang et al., 2006; Chellappa & Sin, 2005; Huang & Lin, 2005; Komiak & Benbasat, 2012; Mothersbaugh et al., 1994)		To what extend do you think you know about virtual customer support agent in general? [1-6] <i>Added to this are examples to steer the respondent. Examples are 'I have no idea how to use online webchats', 'I know how to communicate with an online webchat and how to interpret the responses of the virtual customer support agent', 'I have a lot of technical knowledge about how the virtual customer support agent works'</i>
Customer satisfaction	Measures how well the expectations of a customer concerning a product or service provided by your company have been met. (CheckMarket, n.d.; Kayako, 2016a, 2016b, 2016c)	CSAT NPS	
Customer satisfaction score	A customer satisfaction score indicates how satisfied your current customers are with your product or service.		How would you rate your overall satisfaction with the service you received? [1-7]

(CSAT)	(CheckMarket, n.d.; Kayako, 2016a, 2016b, 2016c)		
Net promoter score (NPS)	a customer loyalty metric to determine a customer satisfaction score which can be compared over time or between different industries. (CheckMarket, n.d.; Kayako, 2016a, 2016b, 2016c)		How likely is it that you would recommend this company to a friend or colleague? [1-10]
Reasons data	Open field to let respondents explain shortly why they answer in the way they did. (Mothersbaugh, Feick, & Park, 1994)		Could you explain very briefly the reason(s) for the answers you gave in the last two questions above? [open question]
Scenario choice			You have now seen three conversations of an online customer support service chat. Please imagine yourself in the situation of the customer Which conversation do you prefer the most? [A, B, C] Why? [open question] Which conversation do you prefer the least? [A, B, C] Why? [open question]
Duration appropriateness believe	A customer's believe about the appropriateness of the length of the conversation. (Froehle & Roth, 2004; Komiak & Benbasat, 2012)		I believe the time I spent actively communicating (talking to someone, reading or writing emails, chatting) with the digital customer support should have been [Much longer, much shorter] I believe the overall length of time I spent actively communicating (talking to someone, reading or writing emails, chatting) with the digital customer support was [too long, too short]
Final question	Check if the videos have been seen		Have you watched the videos with the customer support conversations completely? [yes/no]
	Final comments		Do you have any final comments?

Section	Subject	Question
1	Introduction	Introduction
2	Demographic	Age
2	Demographic	Education
2	Product familiarity	Currently own
2	Product familiarity	Ever owned
2	Product familiarity	Heard about
2	Product expertise	Explain Bitcoin
2	Product expertise	Subjective knowledge
2	Channel familiarity	How often used webchat
2	Channel familiarity	Comfortable using computer
2	Channel familiarity	Comfortable using web-chat
2	Channel expertise	General knowledge
3	Scenario 1	Scenario 1
4	Difficulty of vocabulary	Comprehension
4	Difficulty of vocabulary	Difficult words
4	Number of steps	Distinctive steps
4	Number of steps	Detail
4	Understanding	Easy to understand
4	Understanding	Understand everything
4	Duration appropriateness belief	Duration was
4	Duration appropriateness belief	Duration should have been
4	Customer satisfaction	Customer satisfaction score
4	Customer satisfaction	Net Promoter Score
4	Customer satisfaction	Reason answers
4	Scenario believability	Realistic
4	Scenario believability	Imagination
5	Scenario 2	Scenario 2
6	<i>Same as section 4, but for scenario 2</i>	<i>Same as section 4, but for scenario 2</i>
7	Scenario 3	Scenario 3
8	<i>Same as section 4, but for scenario 3</i>	<i>Same as section 4, but for scenario 3</i>
9	Scenario preference	Preferred the most
9	Scenario preference	Reason
9	Scenario preference	Preferred the least
9	Scenario preference	Reason
10	Effort check	Checked video's
10	Final remarks	Final remarks
11	Finalize	Thank you note

Appendix F: H₁ Statistical Analysis Results

Descriptives

		Statistic	Std. Error	
CSAT	Mean	4,87	,074	
	95% Confidence Interval for Mean	Lower Bound	4,72	
		Upper Bound	5,01	
	5% Trimmed Mean	4,92		
	Median	5,00		
	Variance	1,919		
	Std. Deviation	1,385		
	Minimum	1		
	Maximum	7		
	Range	6		
	Interquartile Range	2		
	Skewness	-,644	,131	
Kurtosis	-,283	,261		
NPS	Mean	6,18	,112	
	95% Confidence Interval for Mean	Lower Bound	5,96	
		Upper Bound	6,40	
	5% Trimmed Mean	6,27		
	Median	7,00		
	Variance	4,346		
	Std. Deviation	2,085		
	Minimum	1		
	Maximum	10		
	Range	9		
	Interquartile Range	3		
	Skewness	-,634	,131	
Kurtosis	-,101	,261		

	N	Minimum	Maximum	Mean	Std. Deviation
CSAT Low	116	1	7	4,28	1,597
CSAT Medium	116	2	7	5,14	1,193
CSAT High	116	2	7	5,19	1,134
NPS Low	116	1	10	5,54	2,220
NPS Medium	116	1	10	6,54	2,019
NPS High	116	1	10	6,47	1,867
Valid N (listwise)	116				

Tests of Normality

	Kolmogorov-Smirnov ^a			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
CSAT	,236	348	,000	,902	348	,000
NPS	,172	348	,000	,940	348	,000

a. Lilliefors Significance Correction

Friedman's ANOVA & Wilcoxon rank test

Ranks	Test Statistics ^a	
	Mean Rank	N
CSAT Low	1,65	116
CSAT Medium	2,19	116
CSAT High	2,16	116
		Chi-Square
		28,398
		df
		2
		Asymp. Sig.
		,000

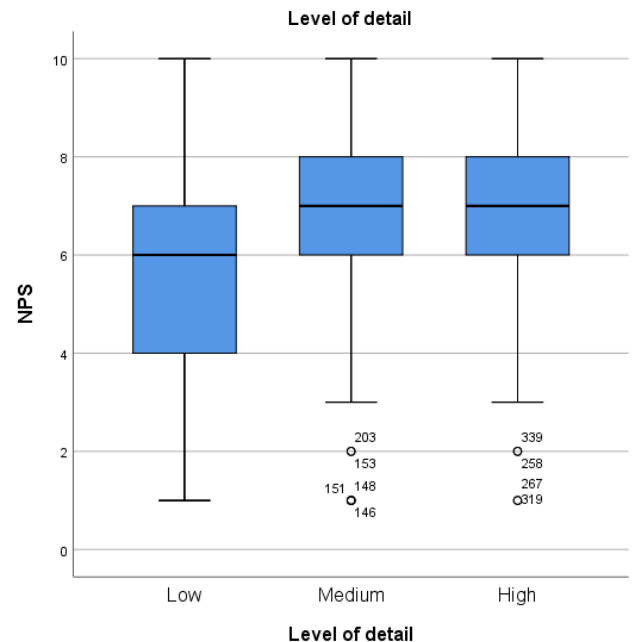
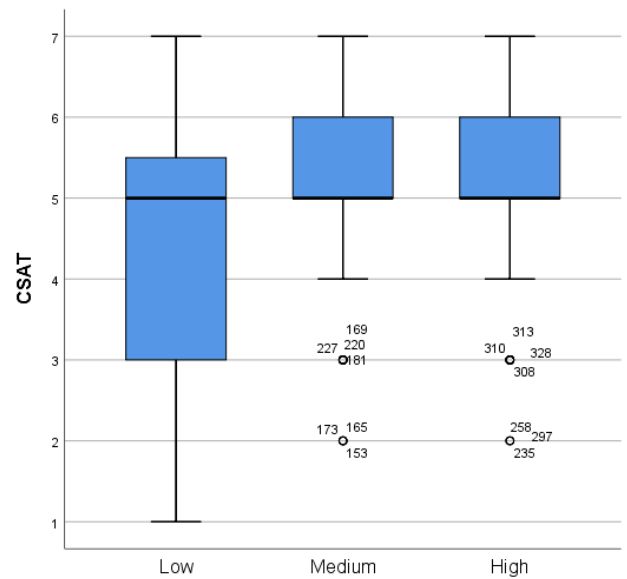
Ranks	Test Statistics ^a	
	Mean Rank	N
NPS Low	1,66	116
NPS Medium	2,25	116
NPS High	2,09	116
		Chi-Square
		28,467
		df
		2
		Asymp. Sig.
		,000

	CSAT Medium - CSAT Low	CSAT High - CSAT Medium	CSAT High - CSAT Low	NPS Medium - NPS Low	NPS High - NPS Medium	NPS High - NPS Low
Z	-4,682 ^b	-,296 ^b	-4,486 ^b	-4,491 ^b	-,629 ^c	-3,802 ^b
Asymp. Sig. (2-tailed)	,000	,767	,000	,000	,529	,000

a. Wilcoxon Signed Ranks Test

b. Based on negative ranks.

c. Based on positive ranks.



Appendix G: H₂ Statistical Analysis Results

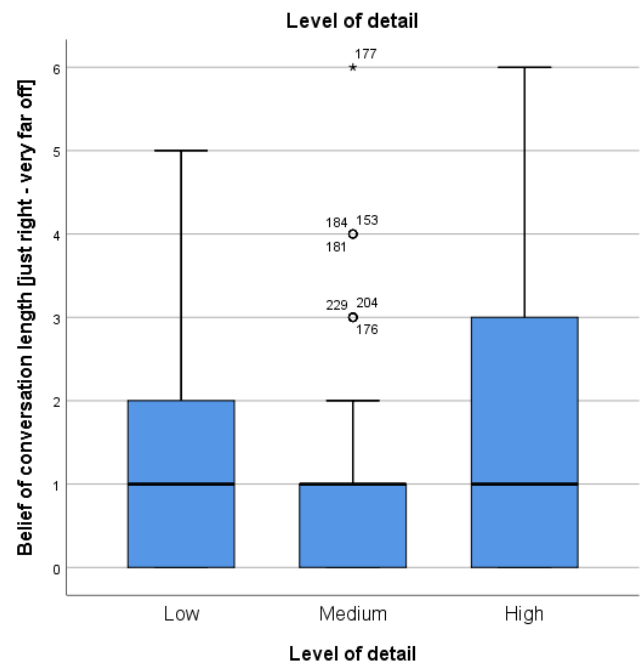
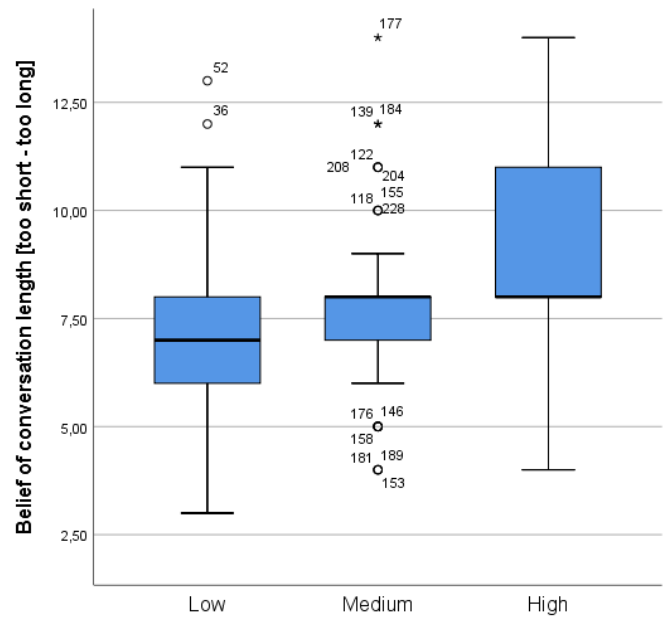
Descriptives

		Statistic	Std. Error	
DAB_SL	Mean	7,80	,108	
	95% Confidence Interval for Mean	Lower Bound	7,59	
		Upper Bound	8,02	
	5% Trimmed Mean	7,75		
	Median	8,00		
	Variance	4,083		
	Std. Deviation	2,021		
	Minimum	3		
	Maximum	14		
	Range	11		
	Interquartile Range	1		
	Skewness	,425	,131	
	Kurtosis	,792	,261	
DAB_RO	Mean	1,37	,080	
	95% Confidence Interval for Mean	Lower Bound	1,22	
		Upper Bound	1,53	
	5% Trimmed Mean	1,25		
	Median	1,00		
	Variance	2,229		
	Std. Deviation	1,493		
	Minimum	0		
	Maximum	6		
	Range	6		
	Interquartile Range	2		
	Skewness	,942	,131	
	Kurtosis	,015	,261	

	N	Minimum	Maximum	Mean	Std. Deviation
DAB_SL Low	116	3	13	6,73	1,756
DAB_SL Medium	116	4	14	7,82	1,501
DAB_SL High	116	4	14	8,86	2,167
DAB_RO Low	116	0	5	1,59	1,462
DAB_RO Medium	116	0	6	,91	1,209
DAB_RO High	116	0	6	1,62	1,672
Valid N (listwise)	116				

Tests of Normality

	Kolmogorov-Smirnov ^a			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
DAB_SL	,226	348	,000	,932	348	,000
DAB_RO	,217	348	,000	,837	348	,000



Friedman's ANOVA & Wilcoxon rank test

Ranks		Test Statistics ^a		Ranks		Test Statistics ^a	
	Mean Rank	N		Mean Rank	N		
DAB_SL Low	1,47	116	Chi-Square	DAB_RO Low	2,17	116	Chi-Square
DAB_SL Medium	2,03		df	DAB_RO Medium	1,72		df
DAB_SL High	2,50		Asymp. Sig.	DAB_RO High	2,11		Asymp. Sig.
			,000				,000

Test Statistics ^a						
Z	DAB_SL Medium - DAB_SL Low	DAB_SL High - DAB_SL Medium	DAB_SL High - DAB_SL Low	DAB_RO Medium - DAB_RO Low	DAB_RO High - DAB_RO Medium	DAB_RO High - DAB_RO Low
	-5,314 ^b	-5,260 ^b	-7,064 ^b	-3,779 ^c	-4,288 ^b	-,010 ^b
Asymp. Sig. (2-tailed)	,000	,000	,000	,000	,000	,992

a. Wilcoxon Signed Ranks Test

b. Based on negative ranks.

c. Based on positive ranks.

Appendix H: H₄ Statistical Analysis Results

Run MATRIX procedure:

***** PROCESS Procedure for SPSS Version 3.00 *****

Written by Andrew F. Hayes, Ph.D. www.afhayes.com
 Documentation available in Hayes (2018). www.guilford.com/p/hayes3

Model : 1
 Y : CSAT
 X : DET
 W : PK

Sample
 Size: 348

OUTCOME VARIABLE:
 CSAT

Model Summary

R	R-sq	MSE	F (HC4)	df1	df2	p
,3505	,1229	1,6980	13,9807	3,0000	344,0000	,0000

Model

	coeff	se (HC4)	t	p	LLCI	ULCI
constant	4,8678	,0701	69,4153	,0000	4,7299	5,0057
DET	,4569	,0884	5,1699	,0000	,2831	,6307
PK	,1074	,0410	2,6212	,0092	,0268	,1880
Int_1	-,1860	,0543	-3,4272	,0007	-,2928	-,0793

Product terms key:

Int_1 : DET x PK

Test(s) of highest order unconditional interaction(s):

	R2-chng	F (HC4)	df1	df2	p
X*W	,0334	11,7459	1,0000	344,0000	,0007

Focal predict: DET (X)
 Mod var: PK (W)

Conditional effects of the focal predictor at values of the moderator(s):

PK	Effect	se (HC4)	t	p	LLCI	ULCI
-1,6675	,7671	,1311	5,8491	,0000	,5091	1,0250
,0000	,4569	,0884	5,1699	,0000	,2831	,6307
1,6675	,1467	,1217	1,2057	,2288	-,0926	,3860

Moderator value(s) defining Johnson-Neyman significance region(s):

Value	% below	% above
1,3036	81,8966	18,1034

Conditional effect of focal predictor at values of the moderator:

PK	Effect	se (HC4)	t	p	LLCI	ULCI
-2,4736	,9170	,1662	5,5187	,0000	,5902	1,2439
-2,1290	,8529	,1506	5,6621	,0000	,5567	1,1492
-1,7845	,7889	,1359	5,8040	,0000	,5215	1,0562
-1,4399	,7248	,1223	5,9270	,0000	,4842	,9653
-1,0954	,6607	,1101	5,9982	,0000	,4440	,8773
-,7508	,5966	,1001	5,9626	,0000	,3998	,7934
-,4063	,5325	,0927	5,7457	,0000	,3502	,7148
-,0618	,4684	,0887	5,2811	,0000	,2939	,6428
,2828	,4043	,0886	4,5651	,0000	,2301	,5785
,6273	,3402	,0923	3,6858	,0003	,1587	,5217
,9719	,2761	,0995	2,7756	,0058	,0804	,4718
1,3036	,2144	,1090	1,9669	,0500	,0000	,4288
1,3164	,2120	,1094	1,9378	,0535	-,0032	,4272
1,6609	,1479	,1214	1,2181	,2240	-,0909	,3868
2,0055	,0838	,1350	,6210	,5350	-,1817	,3493
2,3500	,0197	,1496	,1319	,8952	-,2746	,3141
2,6946	-,0444	,1651	-,2686	,7884	-,3691	,2804
3,0391	-,1085	,1812	-,5985	,5499	-,4649	,2480
3,3836	-,1725	,1978	-,8725	,3836	-,5615	,2164
3,7282	-,2366	,2147	-1,1023	,2711	-,6589	,1856
4,0727	-,3007	,2319	-1,2971	,1955	-,7568	,1553
4,4173	-,3648	,2492	-1,4637	,1442	-,8551	,1254

Data for visualizing the conditional effect of the focal predictor:
 Paste text below into a SPSS syntax window and execute to produce plot.

```

DATA LIST FREE/
  DET      PK      CSAT      .
BEGIN DATA.
  -,8177   -1,6675   4,0615
  ,0000   -1,6675   4,6887
  ,8177   -1,6675   5,3159
  -,8177   ,0000    4,4942
  ,0000   ,0000    4,8678
  ,8177   ,0000    5,2414
  -,8177   1,6675   4,9270
  ,0000   1,6675   5,0469
  ,8177   1,6675   5,1669
END DATA.
GRAPH/SCATTERPLOT=
  DET      WITH      CSAT      BY      PK      .

***** ANALYSIS NOTES AND ERRORS *****

Level of confidence for all confidence intervals in output:
  95,0000

W values in conditional tables are the mean and +/- SD from the mean.

NOTE: A heteroscedasticity consistent standard error and covariance matrix
estimator was used.

NOTE: The following variables were mean centered prior to analysis:
      PK      DET

----- END MATRIX -----
  
```

Run MATRIX procedure:

***** PROCESS Procedure for SPSS Version 3.00 *****

Written by Andrew F. Hayes, Ph.D. www.afhayes.com
Documentation available in Hayes (2018). www.guilford.com/p/hayes3

Model : 1
Y : NPS
X : DET
W : PK

Sample
Size: 348

OUTCOME VARIABLE:

NPS

Model Summary

R	R-sq	MSE	F(HC4)	df1	df2	p
,2512	,0631	4,1078	7,7476	3,0000	344,0000	,0001

Model

	coeff	se(HC4)	t	p	LLCI	ULCI
constant	6,1839	,1090	56,7324	,0000	5,9695	6,3983
DET	,4612	,1331	3,4659	,0006	,1995	,7229
PK	,1731	,0642	2,6959	,0074	,0468	,2993
Int_1	-,1621	,0828	-1,9581	,0510	-,3249	,0007

Product terms key:

Int_1 : DET x PK

Test(s) of highest order unconditional interaction(s):

	R2-chng	F(HC4)	df1	df2	p
X*W	,0112	3,8343	1,0000	344,0000	,0510

Focal predict: DET (X)
Mod var: PK (W)

Conditional effects of the focal predictor at values of the moderator(s):

PK	Effect	se(HC4)	t	p	LLCI	ULCI
-1,6675	,7315	,1951	3,7500	,0002	,3478	1,1152
,0000	,4612	,1331	3,4659	,0006	,1995	,7229
1,6675	,1909	,1883	1,0137	,3114	-,1795	,5614

Moderator value(s) defining Johnson-Neyman significance region(s):

Value	% below	% above
,9826	78,4483	21,5517

Conditional effect of focal predictor at values of the moderator:

PK	Effect	se(HC4)	t	p	LLCI	ULCI
----	--------	---------	---	---	------	------

-2,4736	,8622	,2481	3,4752	,0006	,3742	1,3501
-2,1290	,8063	,2245	3,5911	,0004	,3647	1,2479
-1,7845	,7505	,2023	3,7104	,0002	,3526	1,1483
-1,4399	,6946	,1817	3,8220	,0002	,3372	1,0521
-1,0954	,6388	,1636	3,9036	,0001	,3169	,9606
-,7508	,5829	,1488	3,9166	,0001	,2902	,8757
-,4063	,5271	,1384	3,8084	,0002	,2549	,7993
-,0618	,4712	,1333	3,5338	,0005	,2089	,7335
,2828	,4154	,1343	3,0928	,0021	,1512	,6795
,6273	,3595	,1411	2,5474	,0113	,0819	,6371
,9719	,3037	,1531	1,9840	,0481	,0026	,6047
,9826	,3019	,1535	1,9669	,0500	,0000	,6039
1,3164	,2478	,1690	1,4663	,1435	-,0846	,5802
1,6609	,1920	,1880	1,0214	,3078	-,1777	,5617
2,0055	,1361	,2091	,6511	,5154	-,2751	,5474
2,3500	,0803	,2318	,3463	,7293	-,3757	,5362
2,6946	,0244	,2557	,0956	,9239	-,4785	,5273
3,0391	-,0314	,2804	-,1120	,9109	-,5830	,5202
3,3836	-,0873	,3059	-,2853	,7756	-,6888	,5143
3,7282	-,1431	,3318	-,4314	,6665	-,7957	,5094
4,0727	-,1990	,3581	-,5556	,5788	-,9033	,5053
4,4173	-,2548	,3847	-,6623	,5082	-1,0115	,5019

Data for visualizing the conditional effect of the focal predictor:
 Paste text below into a SPSS syntax window and execute to produce plot.

DATA LIST FREE/

DET	PK	NPS	.
-,8177	-1,6675	5,2972	
,0000	-1,6675	5,8953	
,8177	-1,6675	6,4934	
-,8177	,0000	5,8068	
,0000	,0000	6,1839	
,8177	,0000	6,5610	
-,8177	1,6675	6,3164	
,0000	1,6675	6,4725	
,8177	1,6675	6,6286	

END DATA.

GRAPH/SCATTERPLOT=

DET	WITH	NPS	BY	PK	.
-----	------	-----	----	----	---

***** ANALYSIS NOTES AND ERRORS *****

Level of confidence for all confidence intervals in output:

95,0000

W values in conditional tables are the mean and +/- SD from the mean.

NOTE: A heteroscedasticity consistent standard error and covariance matrix estimator was used.

NOTE: The following variables were mean centered prior to analysis:

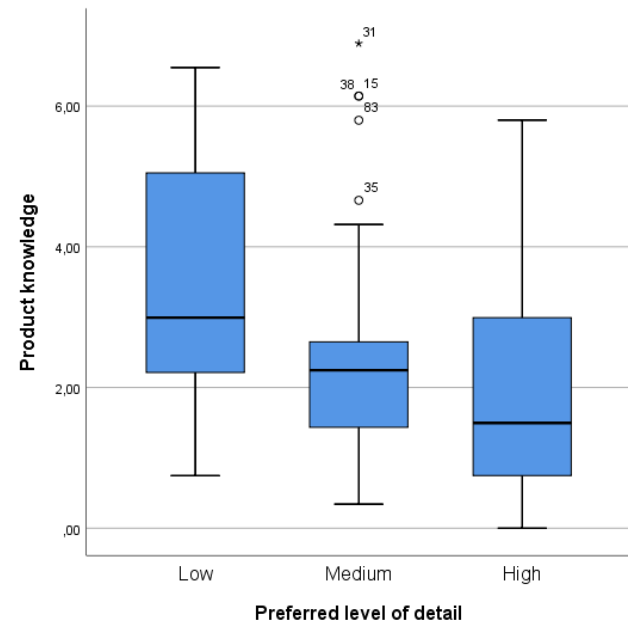
PK	DET
----	-----

----- END MATRIX -----

Appendix I: H₅ Statistical Analysis Results

Kruskal-Wallis Test

		Ranks		
		Preferred level of detail	N	Mean Rank
Product knowledge	Low		28	77,20
	Medium		53	55,35
	High		35	48,31
	Total		116	



Test Statistics^{a,b}

		Product knowledge
Kruskal-Wallis H		12,395
df		2
Asymp. Sig.		,002

a. Kruskal Wallis Test

b. Grouping Variable:
Preferred level of detail

Descriptive Statistics

	N	Mean	Std. Deviation	Minimum	Maximum
Product knowledge	116	2,4736	1,67230	,00	6,89
Preferred level of detail	116	2,06	,738	1	3

Mann-Whitney Test

		Ranks			
		Preferred level of detail	N	Mean Rank	Sum of Ranks
Product knowledge	Low		28	51,57	1444,00
	Medium		53	35,42	1877,00
	Total		81		

		Ranks			
		Preferred level of detail	N	Mean Rank	Sum of Ranks
Product knowledge	Medium		53	46,93	2487,50
	High		35	40,81	1428,50
	Total		88		

		Ranks			
		Preferred level of detail	N	Mean Rank	Sum of Ranks
Product knowledge	Low		28	40,13	1123,50
	High		35	25,50	892,50
	Total		63		

Test Statistics^a

		Product knowledge
Mann-Whitney U		446,000
Wilcoxon W		1877,000
Z		-2,949
Asymp. Sig. (2-tailed)		,003

		Product knowledge
Mann-Whitney U		798,500
Wilcoxon W		1428,500
Z		-1,104
Asymp. Sig. (2-tailed)		,269

		Product knowledge
Mann-Whitney U		262,500
Wilcoxon W		892,500
Z		-3,153
Asymp. Sig. (2-tailed)		,002

a. Grouping Variable: Preferred level of detail

