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Adopting Robotics in Downstream Financial Services

- A study investigating bank customers' readiness, and potential barriers to adopt robotics technology

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Abstract

The financial sector is experiencing great challenges as the world enters the fourth industrial revolution. Changing customer preferences and new companies venturing into the financial sector are forcing banks to shift their focus from upstream to downstream. Traditional banks need to realize that their locus of competitive advantage lies with their customers, who are now demanding that banking services come to them. The purpose of this paper is to imply whether cognitive robotics could be the solution that allows banks to provide their services anywhere, anytime. The implementation of cognitive robotics in direct customer interaction will initiate an adoption process where customers will ultimately accept or reject the technology. This paper aims to identify the potential barriers that need to be overcome in order to successfully implement robotics, and add value to customers. Furthermore, the study aims to uncover whether these barriers differ across various levels of robot interaction.

In an attempt to go beyond traditional constructs in the technology adoption literature, a conceptual model building on basic psychological components to predict adoption intentions will be proposed. The findings in this study give support to the conceptual model, and additionally provides clear evidence of differences in adoption barriers according to the level of robot interaction. Contrary to the majority of research on utilitarian based services, our findings suggest Enjoyment as the critical determinant of adoption intentions. The conclusions drawn from this study have major implications for banks intending to implement cognitive robotics in direct customer interactions.

Preface

This master thesis is one of a series of papers and reports published by the Center for Service Innovation (CSI). Centre for Service Innovation (CSI) is a coordinated effort by NHH to focus on the innovation challenges facing the service sector and involves 15 business and academic partners. It aims to increase the quality, efficiency and commercial success of service innovations and to enhance the innovation capabilities of its business and academic partners. CSI is funded through a significant eight year grant from the Research Council of Norway and has recently obtained status as a Centre for Research-based Innovation (SFI).

This paper was written as part of our M.Sc. in Economics and Business Administration and our five-year long study at the Norwegian School of Economics (NHH).

We would like to express our gratitude to our supervisor, Tor W. Andreassen, for valuable guidance during the research project. We would also like to thank the participating company and the customers who took part in our study. They have been of great help, and raised the quality of this thesis. Additionally, we would like to thank Accenture for their thoughts and ideas regarding the subject in the introductory phase of the research.

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1 Introduction

1.1 Background

Since the introduction of computers in the third industrial revolution, the technological progress in computing power has been tremendous. Automation, robotics and new business models are taking the world into the next industrial revolution, Industry 4.0 (Davies, 2015), forcing both individuals and businesses to rethink the way technology can be used. We now see humans and machines interact in increasingly advanced forms, as "relationships with robots are ramping up; relationships with people are ramping down" (Turkle, 2013, p.19). The last few years have seen technological developments such as cognitive robotics used in health care to diagnose diseases, robots working in elder care and as babysitters, autonomous cars, robot bank tellers, and even hotels run by robots.

The focus area for this thesis within the topic of Industry 4.0 will be cognitive robotics used in direct customer interaction in a retail bank setting. Cognitive robotics involves robots with Artificial Intelligence (AI) and Machine Learning, referring to the simulation of human intelligence, including learning, reasoning and self-correction (Nalpantidis et al., 2015). An example of a cognitive robot that can be used in a bank setting is IPsoft's Amelia, a virtual employee able to identify and respond to human emotions (IPsoft, 2016). Cognitive robots like Amelia could be used to replace, or work alongside human employees in services such as technical support, everyday banking services and even advanced advisory services.

Traditionally, banks have had an upstream focus, where new technology has been implemented primarily to reduce costs (Skinner, 2016). However, according to Dawar (2013), the locus of competitive advantage has shifted downstream. For banks, this implies tilting their strategy to focus on their customers rather than their products and services. To achieve this, banks need to adopt to the era of "anytime, anywhere, and right now" (PwC, 2011, p. 6). Dawar additionally argues that a customer-centric focus will enhance loyalty, and consequently increase the firm value. The rapid technological development following the fourth industrial revolution has resulted in a change in customers' needs, wants and expectations, as they require more innovative and efficient solutions from their banks (Hoemsnes, 2016). Bank customers are increasingly "demanding that banking services come to them, when and where they want them, and they expect to receive an almost immediate response to their requests" (PwC, 2011, p. 6). The implementation of cognitive robotics in banking services has the potential to increase the quality of services by eliminating human errors, increasing accessibility, and providing customers with an immediate response (KPMG, 2016). This thesis aims to uncover whether cognitive robotics could be implemented to meet customers' demands and to increase their perceived value of banking services.

In the discussion of robotics, there are two opposing views: those who celebrate the development, and those who fear it. In the first category you find MIT professors Brynjolfsson and McAfee, known for the book "The Second Machine Age", and in the latter you find Martin Ford, known for the book "Rise of the Robots: Technology and the Threat of a Jobless Future". These opposing views can also be found among consumers. Some consumers embrace new technologies just for the fun associated with the experience itself, while others tend to stick to what is known, skeptical to dive into the unknown and try something new, even when they know it will benefit them. This oxymoron is known as the Technology Paradox (Mick & Fournier, 1998). What is it that prevent these people from adopting new technologies, and how can this resistance be overcome? These are questions we will address in this paper by examining the adoption process following the implementation of cognitive robotics in banking services.

Based on changing customer preferences in the financial sector and the technological progress in cognitive robotics, the following research questions are formulated:

> **RQ1:** *Which factors influence the intention to adopt robotic services by bank customers?*
>
> **RQ2**: *How does the level of robot interaction affect the adoption barriers?*
>
> **RQ3:** *To what extent are bank customers ready to adopt robotic services?*
>
> **RQ4:** *Can robotics be used to add value to customers in banking services?*

1.2 Motivation

> *"Competitive advantage is gained by listening to customers and giving them what they want"* (Dawar, 2013, p. 173).

For the first time, the quality of online banking services is the most important aspect of customer loyalty. In a survey by Accenture (2015a) 81 percent of bank customers claimed they would not switch bank if their local branch closed. If we rewind two years, convenient branch location was the most critical factor for keeping customers loyal. According to

Accenture (2015b, p. 3) "every bank customer is a digital customer" and over 20 percent of customers use online banking services only. This implies a major shift in customer preferences, indicating a digital future of retail banking. Additionally, traditional banks are facing increased competition from companies venturing into the financial industry by investing in financial technology (FinTech). Recent research has revealed that nearly half of bank customers would be willing to bank with non-financial companies such as Apple, Google and Amazon (Accenture, 2015b). To be able to keep their competitive advantage, traditional banks need to become more customer-centric by focusing on customers' needs and enhance the customer experience (PwC, 2011).

Cognitive robotics could be the solution that allows traditional banks to provide all services online, including advisory services, thereby giving customers the flexibility they request. When implementing cognitive robotics, it is crucial for banks to understand the full depth of the adoption process, including the barriers that may arise. This study will examine the adoption process following the implementation of robotics, and aims to indicate customers' readiness to adopt, as well as uncovering the barriers to be overcome. The paper additionally intends to indicate whether a boundary exists for the type of services that successfully could be replaced by robots and simultaneously add value to customers. A comparison of the adoption process associated with high- and low-complexity interaction settings will provide an indication on the level of robotic involvement tolerated by customers, providing valuable insights regarding the potential robotic future of banking.

The academic contribution of this paper is to propose a new theoretical framework for technology adoption, applicable for various levels of customer involvement with the technology. Existing literature regarding technology adoption has a high focus on the Technology Acceptance Model (TAM) (Davis, 1989) and extensions of TAM (which we will elaborate on in Chapter 2.1). Critics claim that this focus is causing researchers to neglect important antecedents of adoption behavior (Bagozzi, 2007). In an attempt to fill this gap, the proposed model will be based on psychological antecedents of adoption intentions.

1.3 The Thesis' Structure

This thesis consists of six chapters, where chapter 1 contains the thesis' background, formulation of research questions, and our motivation for writing it. Chapter 2 presents a literature review of existing theory and studies on automation and self-service technologies in financial services, in addition to present the conceptual model. The methodology used in this thesis, and an evaluation of the data is presented in chapter 3. Chapter 4 introduces the findings from the collected data, and these are discussed further in chapter 5 together with the limitations of the thesis. Chapter 6 provides a conclusion of the thesis, in addition to present suggestions for future research.

2 Literature Review

2.1 Technology Adoption in Financial Services

Innovation adoption has received much attention in the literature. In the case of financial services, the focus throughout the last decade has been on the adoption of self-service technologies (SSTs), particularly adoption of Internet and mobile banking. Cognitive robotics in downstream financial services has, to the authors' best knowledge, yet to receive academic attention, and this literature review will therefore pay attention to what has been researched in the field of SSTs in banking. Hilton, Hughes, Little and Marandi (2013, p.3) defines SSTs as "technologies, provided by an organization, specifically to enable customers to engage in self-service behaviors". Hilton et al. studied adoption of SSTs qualitatively in general, and found that perceived value was one of the most important aspects of an SST, pointing out that the increased effort from the customer must be offset by an equal increase in the perceived value. The possibility to choose from various options is also highlighted as an important aspect, as perceived value may increase due to flexibility in channel options.

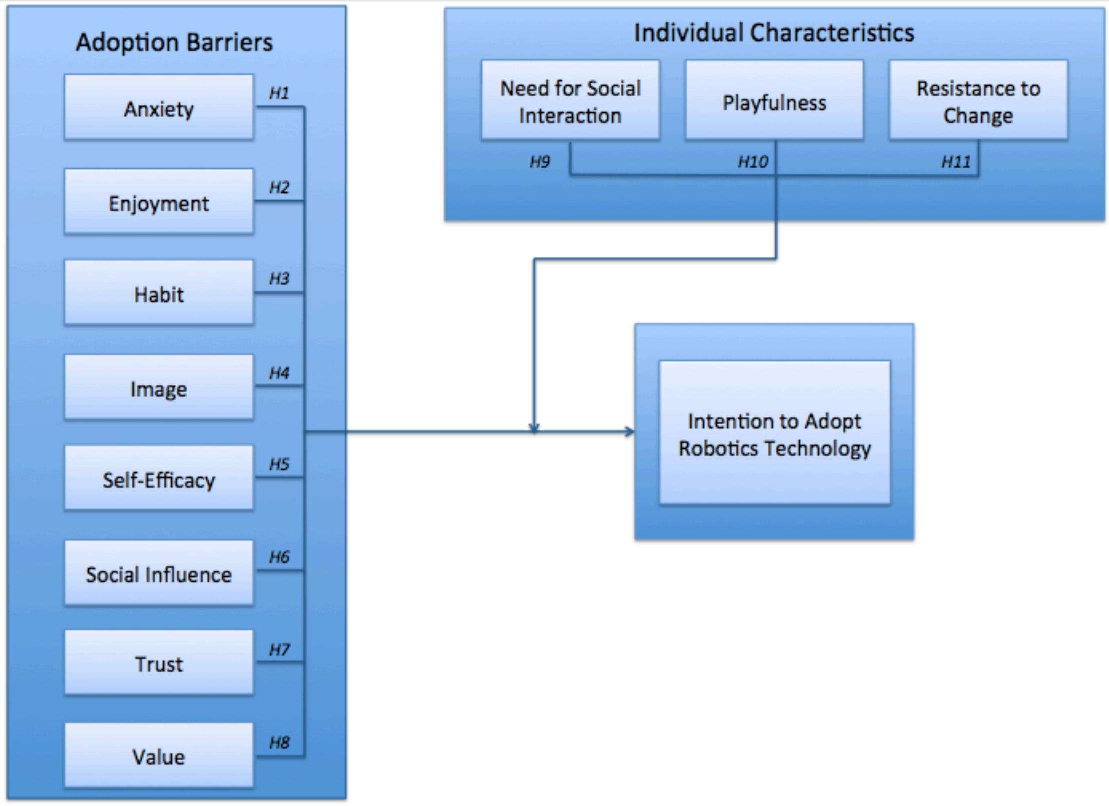
In the banking industry, ATMs, mobile banking and Internet banking are classical examples of SSTs. Cognitive robots in advisory services do to a great extent have the same properties as SSTs, in the sense that customers may interact with the bank at their own convenience, without the need to communicate with bank employees. Shaikh and Karjaluoto (2015) examined the literature on adoption of mobile banking and found that Compatibility, Perceived Usefulness, Trust, Perceived Ease of Use, Credibility, Social Influence, and Self-Efficacy were the recurring antecedents of adoption intentions. These antecedents were the most significant out of 84 antecedents found through 55 studies. An integrative literature review on the adoption of Internet banking, conducted by Hanafizadeh, Keating and Khedmatgozar (2014), found that the dominating psychological theories used to explain the factors affecting adoption were the Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975), the Theory of Planned Behavior (TPB) (Ajzen, 1985), Social Cognitive Theory (SCT) (Bandura, 1986), Commitment-Trust Theory (CTT) (Morgan & Hunt, 1994), and Perceived Risk Theory (PRT) (Roselius, 1971). These theories have been adapted into several new theories trying to explain technology adoption behavior, the most influential being the Innovation Diffusion Theory (IDT) (Rogers, 1983), TAM (Davis, 1989), the Decomposed Theory of Planned Behavior (DTPB) (Taylor & Todd, 1995), the extended Technology Acceptance Model (TAM2) (Venkatesh & Davis, 2000), the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh, Morris, Davis & Davis, 2003) and UTAUT2 (Venkatesh, Thong & Xu, 2012). Common for these models are that they seek to explain actual behavior and usage of the technology in question. Bagozzi (2007) points out two critical gaps in TAM-based research: 1. the intention-behavior link may be weaker than assumed, and 2. the independent variables may fail to capture all factors underlying the intention to adopt the technology. Bagozzi highlights that even the UTAUT model, with 41 independent variables, may not entirely explain intentions because few of the variables are generic and fundamental. Originally, UTAUT was an integration of eight different technology acceptance models, aiming to explain the adoption of technology in an organizational context. UTAUT2 (Venkatesh et al., 2012) attempted to mitigate some of the shortcomings mentioned by Bagozzi (2007), by expanding UTAUT with more variables, and tailoring it to a consumer context. UTAUT2 has been applied in bank settings regarding SSTs such as Internet banking (e.g. Arenas-Gaitán, Peral-Peral & Ramón-Jerónimo, 2015) and mobile banking (e.g. Baptista & Oliveira, 2015), explaining 69 percent and 62 percent of intentions to use, respectively. In Arenas-Gaitán et al.'s (2015) study, focusing on the adoption of Internet banking by people above the age of 55, Habit, Performance Expectancy, Price Value, and Effort Expectancy were found to be the greatest influencers on the intention to use. In Baptista and Oliveira's (2015) study, aiming to explain mobile banking adoption, Performance Expectancy, Hedonic Motivation and Habit were found to be the most significant predictors of adoption intentions.

Technology adoption literature in general has been criticized for only contributing with minor adjustments of existing models, with little progress being made (Venkatesh, Davis & Morris, 2007). Bagozzi (2007) suggests that using more fundamental and generic variables would provide additional insights to the existing body of literature. In line with this, we suggest a model that goes beyond the traditional constructs in the technology acceptance literature, building on psychological antecedents.

2.2 Conceptual Model and Hypotheses

Figure 1 summarizes the conceptual model proposed in this study to explain bank customers' intention to adopt robotics technology. The model aims to uncover the underlying psychological factors that are influencing an individual's intention to adopt, and how these factors are moderated by individual characteristics. The conceptual model builds on existing theory and findings, and proposes eight factors as potential barriers for bank customers' adoption of robotics technology: *Anxiety, Enjoyment, Habit, Image, Self-Efficacy, Social Influence, Trust* and *Value*, in addition to three moderating individual characteristics: *Need for Social Interaction*, *Playfulness* and *Resistance to Change*.

Figure 1: Conceptual model



2.2.1 Adoption Barriers

Anxiety

Mick and Fournier (1998) argue that technology may trigger both positive and negative feelings. While positive feelings, such as enjoyment, have received much attention in the literature, negative feelings have not been incorporated to technology acceptance models to a large extent. Anxiety was found by Igbaria and Parasuraman (1989) to be the strongest predictor of negative attitudes towards usage. Carter, Schaupp and McBride (2011) also found Anxiety to affect the intention to adopt innovations, and Bagozzi and Lee (1999a) additionally note that "for anxiety the action tendency is avoidance or to flee". This implies that individuals experiencing anxiety towards using a technology have a tendency to reject it. Kulviwat, Bruner, Kumar, Nasco and Clark (2007) on the other hand, did not find this relationship to be significant. Despite this, they encourage future research to be conducted concerning the effect of emotions, such as Anxiety, on the intention to use a technology. Based on this, Anxiety is incorporated to the proposed model, referring to the extent to which customers experience negative feelings towards using robotics technology. It is believed that individuals with high levels of robotics anxiety will be less likely to adopt the technology.

> ***H1****: Anxiety of interacting with robots in banking services will have a negative effect on the intention to adopt robotics technology.*

Enjoyment

Davis, Bagozzi and Warshaw (1992) define Enjoyment as the extent to which the activity is perceived to be enjoyable on its own, referring to the value perceived by the customer beyond the pure practical one. In the study by Kulviwat et al. (2007), emotions such as Fun, Joy and Coolness were found to have significant effects on the intention to use technology in a consumer setting. Research on consumer behavior, Information Systems, and SSTs have theorized and found Enjoyment to affect the intention to use a technology (e.g. Holbrook & Hirschman, 1982; Van der Heijden, 2004; Nysveen, Pedersen & Thorbjornsen, 2005; Thong, Hong & Tam, 2006). Venkatesh et al. (2012) found Enjoyment (conceptualized as Hedonic Motivation) to be a critical determinant of behavioral intention, and to be a more important driver than Performance Expectancy (similar to Value in the model used in this thesis) in a consumer setting. In this thesis, Enjoyment will be defined as the extent to which the customer experiences positive feelings of Fun, Joy, Excitement and Coolness associated with the robotic service. Based on previous literature, perceived Enjoyment is thought to have an impact on the intention to adopt robotics technology.

> ***H2****: The perceived Enjoyment by interacting with robots in banking services will have a positive effect on the intention to adopt robotics technology.*

Habit

Habit is defined by Limayem, Hirt and Cheung (2007, p. 705) as "the extent to which people tend to perform behaviors automatically because of learning", and is measured as a self-reported perception. Habit is said to be a reflection of the results of prior experience (Ajzen & Fishbein, 2005), and once a habit has been established, behavior is performed automatically (Orbel, Blair, Sherlock & Conner, 2001). Several studies indicate the effect of Habit on the intention to adopt a technology and on actual usage. Bagozzi and Lee (1999a) found initial resistance of new technology to be a consequence of Habit, while Sheth (1981) claimed Habit to be "the single most powerful determinant in generating resistance" and that people typically strive for consistency and the status quo. A study by Kim and Malhotra (2005) also supports Habit to predict future technology usage. Technology acceptance models such as UTAUT2 (Venkatesh et al., 2012) have been extended with Habit as a factor to influence intentions, and Bagozzi and Warshaw (1990) found Habit to add explanatory power to TRA. Ram and Sheth (1989) define two barriers to adopt new technology similar to Habit: Usage and Tradition. The Usage barrier refers to the perception that an innovation is not compatible with the customer's current habits and routines, while the Tradition barrier refers to psychological resistance caused by requirements to deviate from established norms and traditions. Both Usage and Tradition shows certain similarities with Habit, as they are a result of cognitive rigidity. Due to these similarities, this study will use a definition of Habit that includes elements from the Usage and Tradition barriers, in addition to the aforementioned aspects of habit. Established habits, routines and traditions are therefore thought to have an effect on adoption intentions.

> ***H3****: The extent to which cognitive robots in banking services are compatible with existing habits will have a positive effect on the intention to adopt robotics technology.*

Image

Image is found by researchers to have an influence on decisions to adopt technological innovations (Kleijnen, Ruyter, & Andreassen, 2005). According to Ram (1989), the Image barrier arises out of stereotyped thinking and a lack of information, and if the consumer has an unfavorable impression of the originating country, brand, industry, or other side effects of the innovation, it can be a barrier to adopt the technology (Ram & Sheth, 1989). In this study, the Image barrier will be measured along two distinct dimensions: Brand Image and Self-Image.

A positive image can transfer from a brand to the innovation (Antioco & Kleijnen, 2010), while an unfavorable image can have severe negative effects on consumers' intentions to adopt the innovation (Strebel, O'Donnell, & Meyers, 2004). An individual's perception of brand image is therefore thought to have an influence on adoption intentions.

> ***H4a:*** *The perceived Image of the bank will have a positive effect on the intention to adopt robotics technology in banking services.*

Sirgy (1982; 1985) found that consumers often prefer brands with images that are consistent with their self-image. The phenomenon of the fit between self-image and the image of an innovation is referred to as *Image Congruence* (IC) (Grubb & Grathwohl, 1967). IC is found to play an important role in the consumer adoption process, and an image of a service that fits with the self-image will have a positive impact on both attitude and the intention to use the technology (e.g. Kleijnen et al., 2005; Graeff, 1996; Onkvist & Shaw, 1987). An individual's self-image compared to perceptions of the service's image is therefore thought to have an influence on adoption intentions.

> ***H4b:*** *The fit between self-image and the image of the robotic service will have a positive effect on the intention to adopt robotics technology in banking services.*

Self-Efficacy

Self-Efficacy (SE) refers to an individual's own judgements about one's own knowledge and ability to complete a certain task or a goal (Bandura, 1982). These judgements influence the choice of action, even when they are inaccurate, causing people to avoid activities that they perceive to be difficult to perform (Bandura, 1977). Bagozzi and Lee (1999a) note that SE can influence both the willingness to act as well as the behavioral intention. Hence, SE may be another barrier for individuals to adopt new robotics technology. Research has identified a strong link between SE and individuals' adoption of new technology (e.g. Compeau & Higgins, 1995a). In a study by Compeau, Higgins and Huff (1999), SE explained 18 percent of the variance in usage of new information technology. Perceptions of SE are therefore thought to have an influence on adoption intentions.

> ***H5:*** *Self-Efficacy in robotics technology will have a positive effect on the intention to adopt it in banking services.*

Social Influence

Social Influence (SI), also referred to in the literature as the Bandwagon effect, is the extent to which members of a social network influence one another's behavior (Rice, Grant, Schmitz, & Torobin, 1990). It is measured as the perceived pressure to perform a specific behavior from people who are important to the individual (Fishbein & Ajzen, 1975). This thesis will define SI as the extent to which consumers perceive that important others believe they should use robotics technology. SI is comprised of subjective norms, social factors and image (Carter et al., 2011). Image in this setting must not be confused with the aforementioned Image barrier, as it here refers to the degree to which using the technology is perceived to enhance one's social status (Moore & Benbasat, 1991). Chau (1996) found that the desire to gain social status may be one of the most important motivational factors for a consumer to adopt an innovation, and Brown and Venkatesh (2005) found that perceived status gains had an impact on the intention to adopt technology. SI is found by several researchers to have a significant impact on the intention to use a technology in a voluntary consumer setting (e.g. Schaupp & Carter, 2009; Carter et al., 2011; Venkatesh et al., 2012; Martins, Oliveira & Popovic 2014), and Venkatesh, Thong, Chan, Hu and Brown (2011) found SI to significantly affect the intention to use technology in an SST setting. SI is therefore thought to have an effect on the intention to adopt robotics technology in a bank setting.

> ***H6****: Social Influence will have a positive effect on the intention to adopt robotics technology in banking services.*

Trust

In the literature, Trust has been defined in multiple ways, and no universally accepted definition of the term exists (Rousseau, Sitkin, Burt, & Camerer, 1998). However, in an integrative review of previous literature on Trust, McKnight and Chervany (2002) suggest a conceptualization of Trust described along four dimensions: 1. Competence, one's perception of the other party's ability or power to do what is needed, 2. Benevolence, one's perception of whether or not the other party cares about one and acts in one's best interest, 3. Integrity, one's perception of the extent to which the other party tells the truth and fulfills promises, and 4. Predictability, one's perception of whether or not the other party's actions are consistent over time. The two services examined in this thesis (refinancing and pension plans) are not frequently used by consumers. Hence, it is believed that predictability will have a smaller impact on trusting beliefs in these settings. The thesis will therefore focus on the first three components of Trust, namely Competence, Benevolence and Integrity, consistent with the definition of Trust by Mayer, Davis and Schoorman (1995). Using the same definition, Yousafzai, Pallister and Foxall (2009) found that Trust significantly affects the intention to adopt Internet banking, and Venkatesh et al. (2011) found Trust to affect Intention in an SST setting. Trust is therefore thought to have an effect on the intention to adopt robotics technology.

> ***H7****: Trust in robotics technology will have a positive effect on the intention to adopt it in banking services.*

Value

Value is included in most technology acceptance models, with various definitions, as a predictor of adoption intentions (e.g. TAM; TAM2; UTAUT; UTAUT2). In UTAUT2, Venkatesh et al. (2012) define value (conceptualized as Performance Expectancy) as the extent to which using a technology will provide benefits to the customer in performing an activity. Value is an example of extrinsic motivation, meaning the performance of an activity due to its valued outcome (Davis et al., 1992). Extrinsic motivation can influence an individual's behavior, and therefore function as a barrier if not present. In the article by Ram and Sheth (1989), this functional barrier is defined as the performance-to-price ratio compared to substituting products. If customers perceive the value of an innovation to be low, they will have no incentive to change their behavior (Ram & Sheth, 1989). In banking services, this price-to-quality ratio can be quite difficult for customers to imagine, as there are no direct costs of advisory services. The indirect cost for customers by using these services may be seen as their time spent. The main arguments for implementing robotics technology in banks are lower operating costs for banks, and reduced waiting time and increased efficiency for customers, lowering their indirect cost. Due to this, the focus will be on customers' perceived value of robotics technology. Value will be the only functional barrier in the proposed model, while the aforementioned barriers are psychological ones. Based on previous research Value is thought to have an impact on the intention to adopt robotics technology.

> ***H8**: The perceived Value of robotics technology will have a positive effect on the intention to adopt it in banking services.*

2.2.2 Intention to Adopt Robotics Technology

Intention to Adopt Robotics Technology is the dependent variable in the proposed model. Since the bank studied in this thesis has not yet implemented cognitive robots, our study could not test the model on actual usage of robotics technology. Individuals' intention to adopt technology is, however, found to be a reasonably well predictor of self-reported usage behavior (e.g. Davis, Bagozzi, & Warshaw, 1989; Taylor & Todd, 1995) and of actual behavior (e.g. Morris & Venkatesh, 2000; Venkatesh & Morris 2000; Venkatesh, Morris, & Ackerman, 2000; Venkatesh & Speier, 1999). In an article by Sheppard, Hartwick and Warshaw (1988), a comparison was made between 87 studies, concluding with a correlation of 0.5 between intention and actual behavior. Intention to adopt will therefore be used in this study as a predictor of actual adoption of robotics technology. Bagozzi and Lee (1999a) note that there are four general decisions that can be made regarding technology adoption: 1. adopt the technology, 2. try the technology, 3. keep one's decision open (meaning that you are undecided), or 4. resist adoption of the technology.

2.2.3 Moderating Effects

In this study, three individual characteristics are incorporated to the model as moderators to affect the relationship between the independent variables and the intention to adopt robotics technology. The purpose of including moderator effects is to enhance the explanatory power of the model, as evidenced by research on individuals' decision making (e.g. Agarwal & Prasad, 1998; Dabholkar & Bagozzi, 2002; Liska, 1984; Medsker, Williams & Holahan, 1994). In a study by Andreassen and Streukens (2013), the inclusion of Playfulness (conceptualized as inherent novelty seeking) and Need for Social Interaction provides a more precise understanding of technology adoption. Based on this, these two concepts are added as individual characteristics. Additionally, the proposed model includes Resistance to Change as a moderator to allow for a broader psychological foundation of the model.

Need for Social Interaction

A Need for Social Interaction (NSI) is referred to by Dabholkar (1996) as the importance of human interaction to the customer in service encounters. Human interactions allow for the development of relationships that may be perceived valuable to some customers. Customers with a high NSI will prefer to interact with people rather than technical solutions, and will perceive face-to-face interactions as more valuable (Andreassen & Streukens, 2013). Andreassen and Streukens (2013) argue that people with a high NSI will be less motivated to adopt technology as a replacement for human interactions because "they are psychologically predisposed toward human contact". Researchers have also found that individuals with a high NSI tend to avoid machines (e.g. Forman & Sriram, 1991; Prendergast & Marr, 1994). For these consumers to consider adopting technological solutions, they would have to perceive it as much more reliable, valuable and enjoyable than would individuals with a low NSI (Dabholkar & Bagozzi, 2002). Research has also shown that some customers actively seek to avoid personal interaction with employees, and instead wish to use technological solutions (Meuter, Ostrom, Roundtree & Bitner, 2000). This means that people with a low NSI will find it more valuable to interact with a robot than a human employee, and hence have a higher intention to adopt robotics technology. Based on this we wish to include the NSI as a moderating variable that is thought to have an effect on the relationship between the independent variables and the intention to adopt robotics technology.

> ***H9:*** *The relationships proposed in H1, H2, H3, H4, H5, H6, H7 and H8 will be moderated by the customer's level of Need for Social Interaction when communicating with the bank.*

Playfulness

In a technology context, Playfulness (also conceptualized as Personal Innovativeness in the literature) refers to the willingness of an individual to try new technologies (Agarwal & Prasad, 1998; Rogers, 1995). Playfulness can be considered as a personality trait that is a relatively stable descriptor of individuals, and is consistent across situational contexts (Robinson, Marshall & Stamps, 2005). Consumers with a high Playfulness tend to favor technology and technological solutions, as they enjoy the process of trying new technologies itself (Hirschman 1980; Mehrabian & Russell 1974; Midgley & Dowling 1978). This implies that customers with a high Playfulness would have a higher intention to adopt robotics technology. Andreassen and Streukens (2013) found the similarly defined Inherent Novelty Seeking to display moderating effects on the attitude towards using a technology. Based on this, Playfulness is incorporated to the proposed model as a moderator in the relationships between the independent variables and the intention to adopt robotics technology.

> ***H10:*** *The relationships proposed in H1, H2, H3, H4, H5, H6, H7 and H8 will be moderated by the customer's level of Playfulness with technology.*

Resistance to Change

Oreg (2003) designed The Resistance to Change scale (RTC) to measure an individual's resistance to change based on three dimensions divided into four factors: 1. Routine Seeking, 2. Emotional Reaction to Imposed Change, 3. Cognitive Rigidity, and 4. Short-Term Focus. The scale can be used to compare individual's resistance to change, and to predict reactions to specific change. The behavioral dimension aims to measure people's tendency to adopt routines. The affective dimension consists of two components: Emotional Reaction and Short-Term Focus. Emotional Reaction reflects the amount of stress and uneasiness people experience when confronted with change, while Short-Term Focus reflects the extent to which people are distracted by short-term inconveniences due to change. The cognitive dimension, represented by the Cognitive Rigidity factor, reflects how often and how easy it is for people to change their minds. Oreg (2003) also found that RTC could be used to predict people's resistance to innovations. Based on this, RTC is included as an individual factor to moderate the relationship between the adoption barriers and the intention to adopt robotics technology.

> ***H11:*** *The relationships proposed in H1, H2, H3, H4, H5, H6, H7 and H8 will be moderated by the customer's level of Resistance to Change.*

2.3 Level of Robot Interaction

Little research has been conducted concerning the impact different types of services have on the intention to adopt technology (Dimitriadis & Kyrezis, 2011). However, preliminary evidence suggests that factors such as customers' involvement in the service and the level of complexity in the service influence both attitude and behavior towards using it (Huang, 2006; Koufaris, Kambil & Labarbera, 2001; Park, Lee & Han, 2007). This study aims to uncover whether the level of interaction required in banking services has an effect on the intention to adopt robotics technology. The comparison of two services, with various levels of interaction complexity, will indicate the effect on adoption intentions. Based on the aforementioned preliminary evidence it is believed that the level of interaction required will have an effect on the adoption barriers.

2.4 Added Value to Customers

One of the ideas behind this thesis is to increase focus around the importance of customer-centric thinking. A way to increase customers' value is by improving a metric known as Customer Value Added (CVA). CVA is defined as the difference between the value created by a firm as perceived by its customers, and the cost incurred by the firm in providing this value (Sexton, 2009). CVA is measured by subtracting the variable delivered cost per unit from the Perceived Value per unit. Sexton (2009, p. 90) defines Perceived Value as "the level of performance that the customer believes that they have received on any benefit provided by a product or service". Zeithaml (1988, p. 14) provides a similar definition; "Perceived value is the consumer's overall assessment of the utility of a product based on perceptions of what is received and what is given". Value-driving attributes relate to quantity, quality or convenience, and what customers perceive as given may vary from monetary costs to time and effort. Different perceptions of Perceived Value as a construct may be attributable to differing customer evaluations regarding individual product features (Holbrook, 1981).

Sexton (2009) also distinguishes between the Actual Value and the Perceived Value of a product or service. Actual Value refers to "the level of performance that the customer actually receives on any benefit provided by a product or service" (Sexton, 2009, p. 90), and the discrepancy between Actual and Perceived Value originates from the benefits of a product or service that customers do not realize they have received.

In order to measure CVA accurately, a thorough analysis of variable costs with and without the use of robotics technology would be necessary, which is beyond the scope of this study. This thesis has therefore opted for a different approach by studying what robotics technology can contribute with in added value to the customer. Added value will be measured by comparing different aspects of customers' Perceived Value of the service in a traditional human employee scenario relative to a cognitive robot scenario. As "customers are demanding that banking services come to them, when and where they want them, and they expect to receive an almost immediate response to their requests" (PwC, 2011, p. 6), cognitive robotics is thought to enhance customers' Perceived Value of banking services.

3 Methodology

This chapter presents the methodology used to answer the research questions and to test the hypotheses formulated. As suggested by Bono and McNamara (2011), the methodology is thoughtfully chosen to ensure that the results do not depend on the method used, but rather reflect the reality as accurately as possible. First, the research design will be presented, and the methodology justified. Next, the data collection procedure is explained, followed by a brief explanation of the analyzing techniques used in the thesis. The reliability and validity of the data in addition to research ethics will also be discussed.

3.1 Research Method

Research Design

The research design is an overall plan on how to answer the research questions (Ghauri & Grønhaug, 2010), and there are four different designs, namely *exploratory*, *descriptive*, *explanatory* and *evaluative* (Saunders, Lewis & Thornhill, 2015). As mentioned in the introduction, the purpose of this thesis is fourfold: 1. identify the barriers in motion in the adoption process, 2. indicate whether the level of interaction with the cognitive robot affects adoption barriers, 3. uncover bank customer's readiness to adopt robotics technology, and 4. determine whether robotics used in banking services has the potential to increase customers' Perceived Value. The study suggests a combination of a descriptive and explanatory design, known as a descripto-explanatory study (Saunders et al, 2015). Parts one and two of the study require an explanatory study to establish causal relationships between the potential adoption barriers and the intention to adopt robotics technology. For parts three and four on the other hand, a descriptive study aiming to gain an accurate profile of events, persons or situations (Saunders et al., 2015), is well suited.

Research Approach

Saunders et al. (2015) distinguish between three different research approaches: *inductive*, *deductive* and *abductive*. The deductive approach is used when conclusions are drawn from logical reasoning, when existing theory is tested, and when hypotheses are formed and tested (Saunders, Lewis & Thornhill, 2012). In this study, existing theory is used to develop a conceptual model with accompanying hypotheses to be tested, indicating that a deductive approach is suitable.

Research Method

Robotics used in direct interactions with bank customers is a relatively new phenomenon, and to the authors' best knowledge no data regarding adoption barriers and readiness has previously been collected. Hence, primary data was collected straight from the source to test the conceptual model and hypotheses. In addition, collecting data specifically for the research questions assures the relevance for the proposed model. Because of the study's explanatory nature and the objective to examine relationships between variables, quantitative methods were used. When the goal is to generalize findings from a sample to the overall population, which is the case in this study, quantitative methods are well suited (Saunders et al., 2012).

To identify the barriers associated with cognitive robots and to indicate customers' Perceived Value added, an experimental questionnaire was designed. In collaboration with experts from a Northern-European online-bank, two scenarios compatible with actual customer behavior were developed. The scenarios differ in the complexity and level of interaction required between the customer and the financial advisor. Scenario 1 is a high complexity-interaction setting where the customer needs guidance regarding pension plans. Scenario 2 on the other hand, is a low-complexity-interaction setting, in which the customer needs information regarding loan terms and conditions. Both scenarios are presented in full length in the Appendix. Each of the two scenarios has one experiment group (a) and one control group (b), consistent with a classical experiment (Saunders et al, 2015). The only difference between the scenario given to the control group and the experiment group is the financial advisor. The control group receives advisory services from a human agent, while the experiment group interacts with an intelligent robot, exemplified as Amelia. The purpose of the robot manipulation scenario is to uncover the barriers associated with interacting with, and receiving advisory services from a robot. To make sure the questions were answered correctly, all participants were asked to read the scenario carefully. Realism checks were also conducted according to Dabholkar (1996) to ensure that all participants understood the scenario. Table 1 shows that all scenarios were perceived to be realistic by the respondents, as the T-tests are all significantly different from the middle of the five-point Likert scale used. The realism checks are presented in the Appendix together with the questionnaire.

Table 1: Realism Checks

	Realism Check 1 T-Value	Realism Check 2 T-Value
Scenario 1a	16.053***	18.321***
Scenario 1b	9.635***	14.241***
Scenario 2a	16.631***	21.222***
Scenario 2b	12.808***	15.604***

***p < 0.01; **p < 0.05; *p < 0.1

The robotic technology tested in this thesis is not yet implemented in most Northern-European banks, making it difficult to conduct a physical experiment. Due to this, a hypothetical written scenario was given to the respondents, using a self-completed Internet questionnaire, which works well for descriptive and explanatory research (Robson, 2011). Standardized data were collected to allow for easy comparisons between scenarios. All items in the questionnaire associated with the conceptual model, except Intention to Adopt, were administered on a five-point Likert scale anchored by Disagree (1) and Agree (5). Intention to Adopt was also measured on a five-point scale, however using an adaptation of Bagozzi and Lee's (1999a) classification of intention. The questions related to Perceived Value and Retention Rate were measured on an eleven-point Likert scale, in line with Saunders, Lewis and Thornhill's (2007) suggestion of measuring finer shades of opinions and feelings of respondents, which was the objective of these questions. The five-point scale was applied on the questions formed as statements, as it was believed that the respondents would not respond accurately to more than five ratings. Similarly, the eleven-point scale was applied to questions formed as opinions of value, to obtain a more accurate variance in these questions. To ensure flow, the questions were sorted in the most logical order (Saunders et al., 2007). The questionnaire was translated into the respondents' local language before distribution. A parallel translation technique was used where both authors individually translated the questionnaire into the local language before comparing and creating a final version (Saunders et al., 2007). Due to time restrictions a longitudinal study would be of limited value, hence a cross-sectional study that examines a particular phenomenon at a particular point in time was chosen (Saunders et al., 2015).

Sample

The questionnaire was distributed to the customers of a Northern-European Online Bank. The target population consists of bank customers aged between 18-65 years, while the sampling frame consists of the participating bank's customers aged between 18-65 years. Due to the type of services studied in this thesis (pension plans and refinancing), we excluded customers aged 66 years and above, as these services are somewhat irrelevant to this segment. To avoid legal and ethical issues, customers below the age of 18 are also excluded from the study. The population is thus divided into three segments according to age, and stage in the lifecycle (Andreassen, Calabretta & Olsen, 2012): Segment one consists of people aged between 18-30 years, segment two includes adults aged between 31-50 years, and segment three consists of adults between 51-65 years.

The questionnaire was distributed to customers by the participating bank itself, using stratified random sampling. This means that the customers who received an invitation to take part in the study were randomly chosen from their segment. By using this technique, it is possible to generate findings that are statistically representative of the whole population (Saunders et al., 2015). The respondents were also randomly given one of the four scenarios. In each scenario 1500 customers (6000 in total) were asked to participate in the survey, and in total 468 questionnaires were returned, resulting in a response rate of 7.8 percent. Out of the returned questionnaires, 38 were eliminated from the study due to data screening. The screening consisted of three steps: 1. deleting responses with missing values, 2. deleting responses with an unrealistically low response time (Meade & Craig, 2012), considered to be questionnaires completed in 2.5 minutes or less, and 3. deleting long string responses, referring to those with 10 or more equal answers in a row (DeSimone, Harms, & DeSimone, 2015). Table 2 shows the demographic distribution of respondents, where the skewness is partially due to the sampling frame used.

Table 2: Demographic distribution

	Demographics	Total
Completed		468
Used		430
Age	18-30	9 %
	31-50	48 %
	51-65	43 %
Gender	Male	62 %
	Female	38 %
Education	Elementary School	3 %
	High School	24 %
	University (1-3years)	26 %
	University (4-5years)	33 %
	Ph.D./University (> 5 years)	14 %

3.2 Data Analysis

Partial Least Squares Structural Equation Modeling

Due to the relatively low sample size to parameter ratio and non-normality of the data, a least squares estimation approach is preferred over a maximum likelihood approach (Andreassen & Streukens, 2013). The Partial Least Squares (PLS) method, with reflective constructs, was therefore used to analyze the research model, with the statistical software SmartPLS 3. PLS is a components-based structural equation modeling technique, similar to regression, however, it also models the structural and measurement paths (Chin, Marcolin & Newsted, 2003). PLS is a powerful technique for analyzing structural equations with latent variables (Compeau & Higgins, 1995b), and is well suited for testing a great number of moderating effects (Chin et al., 2003). PLS is also capable of performing well under assumptions of non-normality (Chin et al., 2003), and compared to covariance-based structural equation modeling (CB-SEM) PLS is more robust and less dependent on sample size (Hair, Ringle & Sarstedt, 2011). Hair et al. (2011) also point out that PLS is the preferred method when prediction and theory development are the main objectives in the research, and it has a greater statistical power compared to CB-SEM. The aforementioned arguments led to the conclusion that PLS is considered appropriate for this study.

The first step in assessing the PLS model in our study is to examine the measurement model through various reliability and validity checks, which is explained and presented in chapter 3.3. The next step is to examine the structural model. This was done by running the PLS algorithm on responses for scenario 1a and 2a combined to obtain more general results, which are presented in chapter 4.1. To examine differences in interaction levels, PLS was applied separately for the two scenarios. In order to reduce multicollinearity among the interaction terms, the moderator variables were mean-centered (Jaccard, Turrisi & Wan, 1990). Path coefficients were found through PLS, and the significance of these were found through bias-corrected bootstrapping with 5000 subsamples, as recommended by Preacher and Hayes (2008).

Interaction Probing

The moderator effects in the conceptual model will be more closely examined by using a regression based path-analytic framework known as Interaction Probing (Hayes, 2013). The PLS analysis will test whether an interaction effect exists between the moderator and the independent variable in the model to predict adoption intentions. When this relationship is established, the nature of it can be further described and quantified by estimating the independent variable's effect on adoption intentions at different values of the moderator (Hayes, 2013). Using Hayes' (2013) SPSS macro *PROCESS,* the moderator effects will be described using the Johnson-Neyman Technique for probing interactions. The Johnson-Neyman Technique calculates the intervals where the moderator has an effect on the relationship between the independent variable and the intention to adopt robotics, that is significantly different from zero (Hayes, 2013). All tests using this technique will be conducted at a 95 percent significance level, and the results will be discussed in chapter 5.

3.3 Evaluating the Data

3.3.1 Reliability

Reliability refers to the extent to which the questionnaire will provide consistent and replicable findings, whether similar observations and conclusions can be made by other researchers at different times and under various conditions, and whether there is transparency in how conclusions are drawn from the raw data (Saunders et al., 2012). Mitchell (1996) describes three approaches to ensure reliability: Test re-test, Internal Consistency and Alternative Forms. The Test re-test requires respondents to take the questionnaire twice, under as near equivalent conditions as possible, in order to examine the consistency in the answers (Saunders et al., 2012). Due to limitations in the time frame, this was not possible in our study. Internal Consistency, referring to the correlation of responses across either a subgroup of the questions, or all the questions (Saunders et al., 2012), was evaluated using a test for Composite Reliability (CR). When using PLS, CR is preferred to Cronbach's alpha (Bagozzi & Yi , 1988; Hair, Sarstedt, Ringle & Mena, 2012), as Cronbach's alpha is limited by the assumption that all items are equally reliable, and generally tends to underestimate internal consistency reliability (Hair, Sarstedt, Hopkins & Kuppelweiser, 2014). CR however, does not have this assumption. The rule of thumb is that CR should be greater than 0.8 (Peter, 1979), which is the case for all constructs used in this thesis, except Image with a CR of 0.733 (see Table 4 in chapter 3.3.2). CR could however not be measured for the single item constructs of Intention and Playfulness. The alternative form is to include "check questions", meaning more than one question that asks the same thing in various forms (Saunders et al., 2012). Due to the length of the questionnaire, this was not included, as we feared it would result in a low response rate.

3.3.2 Validity

For a questionnaire to be valid, it must be reliable (Saunders et al., 2012). However, reliability alone is not sufficient. Validity is concerned with whether the measures used are appropriate, the accuracy of the analysis of the results, and the generalizability of the findings (Saunders et al., 2007). The validity of a study can be evaluated along two dimensions: internal validity and external validity.

Internal Validity

In experimental research, internal validity refers to whether the study is conducted in an appropriate manner, and how confidently one can conclude that the change in the dependent variable is due to the independent variables in the experiment, and not to other variables outside the model (Weathington, Cunningham & Pittenger, 2012). There are several criteria to use when evaluating the validity of a study, and the first sub form used in this thesis is Face Validity. Face Validity is the degree to which the measure (the questions in the questionnaire) is perceived by the test-takers to reflect the content of the construct we wish to measure (Weathington et al., 2012). To assure Face Validity, a pilot test was conducted on a smaller sample of 25 people with various demographical characteristics, where the respondents provided comments on the questionnaire and the scenarios. In addition, all completed pilot tests were evaluated to ensure all questions were understood.

The second validity concern taken into consideration is Content Validity, referring to the extent to which the questionnaire adequately samples what we are trying to measure (Weathington et al., 2012). Content Validity can be ensured through a careful definition of the research through a literature review, prior discussions with others, or an assessment of the measures by a panel of experts (Saunders et al., 2007). All three methods are used in this thesis to ensure Content Validity. First, a definition of the research was made through the literature review, then an academic expert was consulted before developing the questionnaire, and lastly the questionnaire was assessed by a panel of industry experts who commented on the representativeness and suitability of all questions and the scenarios.

The third step is to establish Construct Validity, referring to the extent to which the questions measure the presence of those constructs we actually intend them to measure (Saunders et al., 2012). Construct Validity can be evaluated along two sub forms: Convergent Validity and Discriminant Validity (Hair et al., 2014). Convergent Validity is concerned with demonstrating that theoretically related items are in fact related in reality (Campbell & Fiske, 1959), while Discriminant Validity demonstrates that theoretically unrelated items are not related in reality (Weathington et al., 2012). To test for Convergent Validity a factor analysis using SmartPLS 3 was conducted. The test indicated that IC loads on both Image and Habit, and this combined with the low score on the CR test led to the exclusion of Image as a construct. Additionally, one of the RTC items (RTC4) were eliminated due to a low factor loading on the RTC construct, and high cross loadings with other constructs. The rerun without Image and RTC4 shows that all factor loadings are above 0.7, supporting Convergent Validity (Hair et al., 2014). In addition the Average Variance Extracted (AVE) was calculated for each construct, and found to be above the threshold of 0.5 (Fornell & Larcker, 1981). Discriminant Validity was first evaluated with the Fornell-Larcker criterion stating that each construct's AVE should be greater than its squared correlation with all other constructs (Fornell & Larcker, 1981). This applies for all constructs, indicating that Discriminant Validity is supported. Investigations of the cross loadings for all items provided increased support for Discriminant Validity. Table 3 displays the factor- and cross loadings, while table 4 shows AVEs and correlation scores. A third and final check of Discriminant Validity is the Heterotrait-Monotrait ratio of correlations (HTMT), as suggested by Henseler, Ringle and Sarstedt (2015). Henseler et al. (2015) point out that HTMT should be able to detect lack of Discriminant Validity in situations where the first two tests do not. A maximum value of 0.85 for any correlation of indicators across different constructs, relative to the average of the monotrait-heteromethod correlations, should suffice to determine that there is no lack of Discriminant Validity. All HTMT-ratios in our study are well below this threshold.

Table 3: PLS factor loadings and cross loadings

Cross Loadings	Anx	Enj	Hab	SE	SI	Tru	Val	NSI	Play	RTC
ANX1	0.902	-0.360	-0.316	-0.346	-0.079	-0.287	-0.306	0.435	-0.260	0.338
ANX2	0.927	-0.472	-0.452	-0.358	-0.157	-0.405	-0.405	0.472	-0.275	0.368
ANX3	0.791	-0.268	-0.274	-0.329	-0.097	-0.270	-0.256	0.308	-0.211	0.343
E1	-0.441	0.885	0.497	0.238	0.380	0.485	0.520	-0.406	0.399	-0.185
E2	-0.378	0.903	0.542	0.233	0.498	0.536	0.562	-0.432	0.304	-0.168
E3	-0.443	0.885	0.589	0.364	0.444	0.562	0.563	-0.449	0.457	-0.228
E4	-0.199	0.763	0.414	0.155	0.576	0.433	0.446	-0.336	0.279	0.000
H1	-0.380	0.559	0.951	0.340	0.453	0.481	0.441	-0.500	0.243	-0.213
H2	-0.403	0.584	0.958	0.328	0.499	0.509	0.477	-0.567	0.258	-0.172
SE1	-0.270	0.171	0.221	0.857	0.175	0.209	0.190	-0.242	0.356	-0.209
SE2	-0.411	0.330	0.379	0.957	0.254	0.351	0.336	-0.345	0.393	-0.228
SI1	-0.138	0.438	0.495	0.260	0.902	0.364	0.406	-0.389	0.146	0.068
SI2	-0.129	0.454	0.410	0.249	0.911	0.382	0.423	-0.258	0.199	0.066
SI3	-0.059	0.502	0.357	0.096	0.718	0.268	0.336	-0.239	0.196	0.049
T1	-0.366	0.528	0.490	0.383	0.376	0.908	0.571	-0.364	0.275	-0.204
T2	-0.373	0.502	0.438	0.291	0.302	0.891	0.506	-0.340	0.258	-0.202
T3	-0.238	0.507	0.423	0.169	0.371	0.807	0.596	-0.272	0.198	-0.044
V1	-0.289	0.518	0.422	0.255	0.425	0.596	0.838	-0.278	0.232	-0.134
V2	-0.371	0.514	0.356	0.278	0.321	0.551	0.848	-0.236	0.260	-0.231
V3	-0.337	0.507	0.463	0.263	0.385	0.453	0.820	-0.342	0.211	-0.172
V4	-0.243	0.460	0.332	0.210	0.377	0.495	0.771	-0.220	0.218	-0.176
NSI1	0.366	-0.353	-0.453	-0.305	-0.315	-0.268	-0.254	0.906	-0.217	0.169
NSI2	0.496	-0.508	-0.572	-0.316	-0.337	-0.409	-0.346	0.951	-0.252	0.276
P	-0.287	0.425	0.263	0.412	0.210	0.281	0.281	-0.254	1	-0.194
RTC1	0.365	-0.222	-0.191	-0.210	0.062	-0.181	-0.227	0.249	-0.230	0.895
RTC2	0.265	-0.085	-0.163	-0.198	0.033	-0.138	-0.162	0.162	-0.073	0.750
RTC3	0.324	-0.045	-0.108	-0.171	0.093	-0.062	-0.081	0.153	-0.104	0.765

Table 4: Construct reliability and validity

	Mean	StDev	CR	VIF	AVE	Anx	Enj	Hab	SE	SI	Tru	Val	NSI	Play	RTC	Int
Anx	2.293	1.256	0.907	2.085	0.766	0.875										
Enj	2.755	1.339	0.919	2.953	0.741	-0.435 ***	0.861									
Hab	3.302	1.406	0.954	2.34	0.911	-0.411 ***	0.599 ***	0.955								
SE	4.333	1.000	0.904	2.16	0.825	-0.392 ***	0.296 ***	0.350 ***	0.908							
SI	2.547	1.068	0.884	1.839	0.719	-0.132 **	0.542 ***	0.499 ***	0.245 ***	0.848						
Tru	3.417	1.266	0.903	2.317	0.757	-0.376 ***	0.589 ***	0.519 ***	0.326 ***	0.402 ***	0.870					
Val	3.310	0.791	0.891	2.449	0.672	-0.379 ***	0.611 ***	0.482 ***	0.308 ***	0.460 ***	0.641 ***	0.820				
NSI	3.564	1.307	0.926	2.205	0.863	0.473 ***	-0.475 ***	-0.560 ***	-0.334 ***	-0.351 ***	-0.375 ***	-0.330 ***	0.929			
Play	4.305	0.931	na	2.347	na	-0.287 ***	0.425 ***	0.263 ***	0.412 ***	0.210 ***	0.281 ***	0.281 ***	-0.254 ***	na		
RTC	1.726	1.011	0.847	1.734	0.650	0.398 ***	-0.179 ***	-0.200 ***	-0.240 ***	0.073 ns	-0.175 ***	-0.216 ***	0.248 ***	-0.194 ***	0.806	
Int	3.268	1.368	na	na	na	-0.436 ***	0.662 ***	0.611 ***	0.297 ***	0.468 ***	0.607 ***	0.569 ***	-0.541 ***	0.333 ***	-0.173 ***	na

Diagonal elements are square roots of AVEs and off-diagonal elements are correlations.
***p < 0.01; **p < 0.05; *p < 0.1

A multicollinearity test was conducted to make sure that the independent variables measure separate effects (Saunders et al., 2012). The rule of thumb is that correlation coefficients should be less than 0.9 (Hair, Black, Babin, Anderson, & Tatham, 2006), and the Variance Inflation Factor (VIF) should be less than 5.0 (Hair et al., 2011), which is the case for all constructs. The VIF scores can also be used to test for Common Method Bias (CMB), which can be caused by the measurement method used in the study (Kock, 2015). Since our study uses the same five-point Likert scale for all questions regarding the model, the presence of CMB was a concern. However, none of the VIF scores are above the proposed threshold of 3.3 (Kock, 2015), suggesting that CMB is not an issue.

Criterion-Related Validity, referring to the ability of the questions to make accurate predictions (Saunders et al., 2012), will not be possible to evaluate until cognitive robots are employed by banks, and comparisons of predictions and actual behavior are made possible.

External Validity

External validity refers to the extent to which the results from the research are generalizable, meaning they can be applied to other research settings (Saunders et al., 2007). When conducting a research study in one organization, or in an organization that differs from the industry standard, one should be cautious generalizing the results (Saunders et al., 2007). As our study includes one bank only, and since this bank is a pure online-bank, the results and conclusions drawn in this thesis may not be generalizable.

3.3.3 Research Ethics

Research ethics refers to the appropriateness of the researchers' behavior in relation to the rights of those who become the subject of the thesis, or those who are affected by the work (Saunders et al., 2007). Ethical issues need to be taken into consideration during the design stage, data collection, analysis and reporting, and when processing and storing the information collected (Saunders et al., 2007). This thesis is developed according to the Norwegian School of Economics' guidelines for research ethics (Norwegian School of Economics, 2015). When collecting data using questionnaires a number of ethical issues may arise, including privacy, respect and volunteerism. To ensure these ethical concerns were avoided, all participation in this study was voluntary, and the respondents had the right to withdraw from the questionnaire at any time without having to state a reason. Anonymity and confidentiality was ensured for the respondents of the questionnaire and the company participating in the study. When collecting data using questionnaires we ensured that no personal data was collected from the participants. To ensure the data was collected objectively, the respondents were selected using probability-sampling techniques. It is also important to ensure that the data we report in this thesis are not a misrepresentation of the data collected (Saunders et al., 2007). This includes not being selective about which data to report.

4 Findings

The findings give support for the proposed model. However, when studying robotic services in general, only four variables are significant: Anxiety, Enjoyment, Habit and Trust. When examining the services according to the level of interaction with the cognitive robot on the other hand, major differences are found in the adoption barriers. Enjoyment is found to be the only common factor to influence adoption intentions in both scenarios, while out of the remaining six factors, five are significant in one scenario each.

Customers are found to be moderately ready to adopt robotics technology in each of the two scenarios. They are equally ready to adopt the service with a cognitive robot as with a human employee in scenario 1, while in scenario 2 they are slightly more ready to adopt the service with a human employee than with a cognitive robot. Perceived Value is found to be lower in both scenarios with the cognitive robot than with a human employee, while customers' Retention Rate increases with the implementation of cognitive robots.

4.1 Adoption Barriers

Table 5 presents the standardized path coefficients, significance levels and R^2 for the structural model with and without moderating effects. The results provide some support for the proposed model, as Anxiety, Enjoyment, Habit and Trust are found to have significant effects on intentions to adopt. Self-Efficacy, Social Influence and Value on the other hand, do not display significant effects on Intention. The adjusted R^2 shows that the research model without moderating effects explains 55.7 percent of the variance in adoption intentions. A rerun of the model with the significant variables showed that R^2 decreases with only 0.4 percent.

The inclusion of moderating effects in the model results in an increase in the adjusted R^2 from 55.7 percent to 60.2 percent. All constructs maintain their significance in the direct effect on adoption intentions, except Anxiety. Additionally, Value shows a weak positive effect on adoption intentions (on a 90 percent significance level). Furthermore, NSI displays a significant strengthening effect on the relationship between Enjoyment and Intention, Playfulness exerts a significant attenuating effect on Enjoyment and a strengthening effect on Trust, and RTC has a significant attenuating effect on the relationship between Social Influence and Intention. Finally, an exclusion of all non-significant paths in the moderated model resulted in an increased R^2, from 60.2 percent to 61.4 percent.

Table 5: Path coefficients, complete model

	Model with moderators		Model without moderators	
R^2	0.652		0.570	
R^2 Adj.	0.602		0.557	
	Coefficient	95 % confidence interval	Coefficient	95 % confidence interval
Anxiety	-0.067	[-0.187;0.053]	-0.115**	[-0.208;-0.016]
Enjoyment	0.260***	[0.103;0.418]	0.261***	[0.123;0.407]
Habit	0.166***	[0.029;0.302]	0.219***	[0.095;0.340]
SE	-0.022	[-0.134;0.089]	-0.016	[-0.116;0.078]
SI	0.075	[-0.053;0.203]	0.079	[-0.032;0.193]
Trust	0.168***	[0.041;0.290]	0.206***	[0.084;0.327]
Value	0.133*	[0.005;0.264]	0.099	[-0.029;0.228]
NSI	-0.129*	[-0.272;-0.001]		
NSIxAnx	0.056	[-0.073;0.187]		
NSIxEnj	0.186***	[0.035;0.328]		
NSIxHabit	-0.074	[-0.211;0.072]		
NSIxSE	0.053	[-0.069;0.172]		
NSIxSI	-0.020	[-0.165;0.115]		
NSIxTrust	0.010	[-0.108;0.124]		
NSIxValue	-0.022	[-0.164;0.131]		
Playfulness	-0.013	[-0.149;0.122]		
PlayxAnx	-0.042	[-0.168;0.084]		
PlayxEnj	-0.237***	[-0.416;-0.048]		
PlayxHabit	0.004	[-0.126;0.137]		
PlayxSE	0.036	[-0.051;0.130]		
PlayxSI	-0.025	[-0.178;0.107]		
PlayxTrust	0.190***	[0.032;0.344]		
PlayxValue	0.019	[-0.119;0.144]		
RTC	0.021	[-0.091;0.130]		
RTCxAnx	-0.039	[-0.147;0.071]		
RTCxEnj	-0.043	[-0.194;0.116]		
RTCxHabit	0.010	[-0.124;0.148]		
RTCxSE	-0.068	[-0.175;0.045]		
RTCxSI	-0.131**	[-0.256;-0.012]		
RTCxTrust	0.008	[-0.127;0.136]		
RTCxValue	0.072	[-0.057;0.206]		

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

4.2 Level of Robot Interaction

To answer the second research question of whether the complexity in the interaction level with the cognitive robot will have an impact on the barriers to adopt the technology, the PLS analysis was run separately on both scenarios, with and without moderating effects. For scenario 1a (pension plans) the adjusted R^2 is 54.2 percent without moderators, with Enjoyment, Self-Efficacy, Social Influence and Trust as significant predictors of adoption intentions. The same model applied in scenario 2a (refinancing) has an adjusted R^2 of 61.2 percent, with Anxiety, Enjoyment and Habit as significant variables to predict adoption intentions. A comparison of the model in the two scenarios shows that the barriers to adopt robotics technology are clearly different. The only variable that significantly affects adoption intentions in both scenarios is Enjoyment.

With the inclusion of moderating effects, the adjusted R^2 increases to 59.6 percent in scenario 1a, with Enjoyment, Social Influence and Trust as significant variables. Further, Playfulness is found to have a significant attenuating effect on the relationship between both Anxiety and Enjoyment on the intention to adopt, while NSI displays a significant strengthening effect on the relationship between Enjoyment and Intention. In scenario 2a, the adjusted R^2 is 62.6 percent, meaning an increase of only 1.4 percent with the three moderators. Enjoyment and Habit were the only significant variables, together with a significant moderating effect from Playfulness on the relationship between Trust and Intention. The complete model with moderating effects also shows clear dissimilarities in the barriers to adopt robotics technology in the two scenarios. Enjoyment is once again the only common significant variable to predict adoption intentions.

These results show that for scenario 1a the model with moderating effects has the highest adjusted R^2, and hence has the most accurate prediction of adoption intentions. For scenario 2a on the other hand, the inclusion of moderating effects only improves the explanatory power with 1.4 percent. Additionally, when running the model with significant paths only, the explanatory power is lower for the moderated model in scenario 2a. This indicates that the simple model without moderating effects has the most accurate prediction of adoption intentions in low-complexity services.

Table 6: Path coefficients, separate scenarios

	Model with moderators		Model without moderators	
	Scenario 1a	Scenario 2a	Scenario 1a	Scenario 2a
R^2	0.707	0.715	0.570	0.633
R^2 adj.	0.596	0.626	0.542	0.612
	Coefficient 1a	Coefficient 2a	Coefficient 1a	Coefficient 2a
Anxiety	0.027	-0.150	-0.104	-0.164***
Enjoyment	0.262*	0.291**	0.290***	0.239**
Habit	-0.018	0.319***	0.092	0.318***
SE	-0.068	0.083	-0.152*	0.091
SI	0.217*	-0.048	0.188**	-0.011
Trust	0.242**	0.094	0.292***	0.119
Value	0.181	0.119	0.106	0.110
NSI	-0.181	-0.093		
NSIxAnx	0.100	-0.001		
NSIxEnj	0.306**	0.162		
NSIxHabit	-0.009	-0.109		
NSIxSE	-0.017	0.067		
NSIxSI	-0.006	-0.028		
NSIxTrust	0.044	0.025		
NSIxValue	-0.104	-0.038		
Playfulness	-0.016	-0.041		
PlayxAnx	-0.271*	0.081		
PlayxEnj	-0.273*	-0.303		
PlayxHabit	-0.045	0.046		
PlayxSE	-0.034	0.098		
PlayxSI	-0.011	-0.114		
PlayxTrust	0.105	0.269**		
PlayxValue	0.097	-0.048		
RTC	-0.011	0.107		
RTCxAnx	-0.097	-0.058		
RTCxEnj	-0.065	-0.023		
RTCxHabit	0.080	0.058		
RTCxSE	-0.095	-0.055		
RTCxSI	-0.184*	-0.116		
RTCxTrust	-0.058	-0.010		
RTCxValue	0.080	-0.050		

***p < 0.01; **p < 0.05; *p < 0.1

4.3 Readiness to Adopt Robotics Technology

When asked whether they were ready to adopt robotics technology, 47 percent of customers answered either 4 or 5 on the five-point Likert scale in scenario 1a, while 56 percent of customers answered the same in scenario 2a. However, a descriptive analysis of the intention to adopt robotics technology did not show a significant difference between the two interaction levels. A T-test of the means against the neutral middle-point (3 on the Likert scale, labeled "undecided"), showed that adoption intentions are not significantly different from the middle-point for scenario 1a. For scenario 2a on the other hand, Intention is significantly higher than the middle point of the scale.

For scenario 1 there is no significant difference in the intention to adopt the service with a human than with a robot. However, for scenario 2 there is a significant difference in Intention, as customers are more ready to adopt the service with a human, than with a robot. These findings are summarized in table 7.

Table 7: Intention to Adopt

Scenario	N	Mean	Std. Deviation	F
1a	114	3.15	1.390	
2a	132	3.37	1.345	1.617
1a	114	3.15	1.390	
1b	96	2.90	1.403	1.715
2a	132	3.37	1.345	
2b	88	3.74	1.410	3.792**

***p < 0.01; **p < 0.05; *p < 0.1

4.4 Customers' Perceived Value and Retention Rate

To answer the question of whether cognitive robots can be used to create added value to consumers, two descriptive analyses of variance (ANOVA) were conducted, in which the experiment group (a) and the control group (b) were compared. The results of these are shown in table 8. The ANOVA results from scenario 1 and scenario 2 indicate that customers' Perceived Value would decrease with the use of cognitive robots in both scenarios.

Descriptive analyses of the change in Retention Rate were also conducted. In contrast to the change in Perceived Value, these indicate that customers' Retention Rate will increase in both scenarios with the implementation of cognitive robots. The ANOVA results are shown in table 9.

Table 8: Perceived Value

Scenario	N	Mean	Std. Deviation	F
1a	114	5.906	2.379	
1b	96	6.422	2.115	2.713*
2a	132	6.127	2.740	
2b	88	7.787	1.772	25.237***

***p < 0.01; **p < 0.05; *p < 0.1

Table 9: Retention Rate

Scenario	N	Mean	Std. Deviation	F
1a	114	8.54	2.339	
1b	96	6.89	2.820	21.698***
2a	132	8.66	2.690	
2b	88	6.84	2.852	22.985***
1a+2a	246	8.61	2.529	
1b+2b	184	6.86	2.828	45.093***

***p < 0.01; **p < 0.05; *p < 0.1

4.5 Summary of Findings

Table 10 shows a summary of all the supported hypotheses in each of the scenarios. The findings indicate support for the conceptual model, as all variables, except Value, are found to be significant in at least one of the two scenarios.

Table 10: Summary of Hypotheses

Hypothesis	1a+2a	1a	2a
H1: Anxiety	X	ns	X
H2: Enjoyment	X	X	X
H3: Habit	X	ns	X
H4a: Brand Image	Deleted	Deleted	Deleted
H4b: Image Congruence	Deleted	Deleted	Deleted
H5: Self-Efficacy	ns	X	ns
H6: Social Influence	ns	X	ns
H7: Trust	X	X	ns
H8: Value	ns	ns	ns
H9: Need for Social Interaction	Only for H2	Only for H2	ns
H10: Playfulness	Only for H2 and H7	Only for H1 and H2	Only for H7
H11: Resistance to Change	Only for H6	Only for H6	ns

X: Hypothesis is supported; ns: Hypothesis is not supported.

5 Discussion

This chapter will address theoretical and managerial implications of the findings through in-depth discussions, in addition to clarify the study's limitations.

5.1 Theoretical Implications

5.1.1 Adoption Barriers

The research model was applied to scenarios 1a and 2a together, to identify the potential barriers that robotics technology might face in general. In this chapter, each variable will be discussed separately.

Anxiety

Anxiety is found to have a significant impact on the intention to adopt robotics technology. This is similar to what Carter et al. (2011) found in their study on e-government adoption. As hypothesized, Anxiety displays a negative relationship with Intention, meaning that for individuals sensing a feeling of discomfort when communicating with the cognitive robot, the intention to adopt the service will be considerably weakened. The mean score for Anxiety as a construct is 2.29, indicating relatively low negative feelings among customers. The importance of Anxiety in a robotics setting may be due to the relative newness of the technology, as some people may be afraid of the unknown. New technologies may then provoke feelings of anxiety, as the experience and outcome is uncertain. The significance of Anxiety may be an example of what we referred to as The Technology Paradox in chapter 1.

Enjoyment

This research finds Enjoyment as the strongest antecedent of intentions to adopt robotics technology, with a positive significant influence on Intention. The effect of Enjoyment has been proven throughout the literature on Information Systems. Childers, Carr, Peck & Carson (2001) found in a study of differences between hedonic and utilitarian motives that Enjoyment was a stronger driver of Intention in hedonic settings, than in utilitarian ones. The proposed model adds new elements to this literature by unveiling Enjoyment as the strongest predictor of Intention in a utilitarian setting.

The shift in customer preferences, as mentioned in chapter 1, may serve as an explanation of the importance of Enjoyment found in this study. Customers are increasingly expecting more from their banks, and seem to be very comfortable with trying new technologies, as evidenced by the relatively high mean score on Playfulness (4.31). The findings in this research clearly indicate that Enjoyment is crucial in determining adoption intentions, even in a utilitarian setting. This proves that satisfying the utility needs of the service is not enough, as customers additionally expect to be satisfied hedonically, regardless of the purpose behind the service.

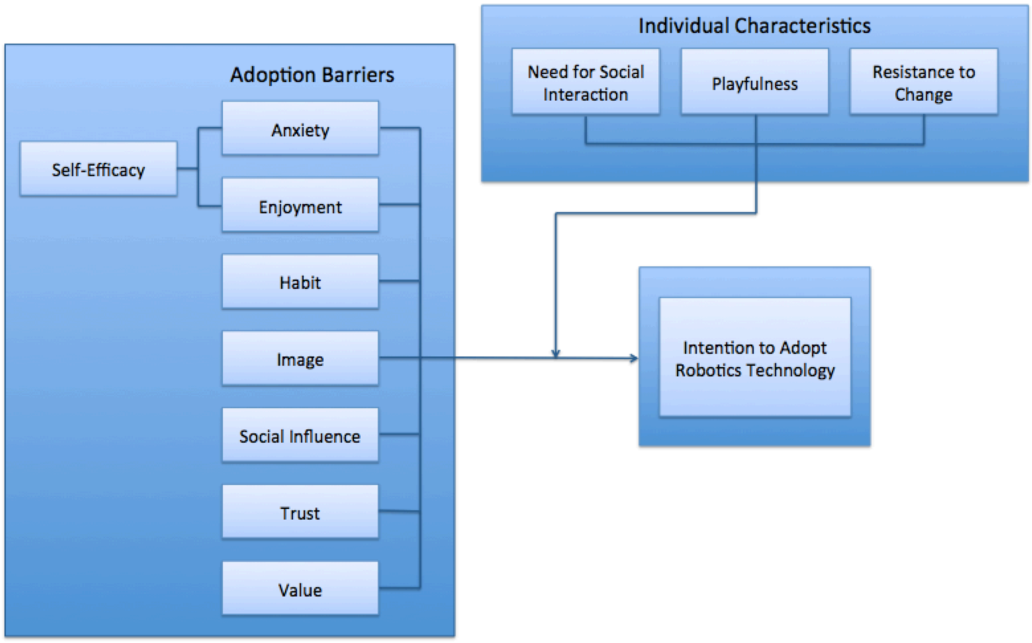
Habit

Habit is found to be the second strongest driver of adoption intentions in this study, with a significant positive effect. The magnitude and importance of Habit is in line with what Venkatesh et al. (2012) found in the UTAUT2 model, where Habit showed the strongest impact on Intention. Habit has a mean score of 3.30 for the services in this study, indicating that robotics technology has a moderate compatibility with existing habits and traditions among the respondents. The relationship with Intention is strong and positive, indicating that customers view the degree of compatibility with existing habits as an important aspect of the service. High compatibility with existing habits will therefore result in a higher intention to use robotics technology. The importance of Habit as a predictor of adoption intentions implies a strive for consistency and the status quo among customers.

Self-Efficacy

Self-Efficacy is not found to have a significant direct effect on the intention to adopt robotics technology in our study. The research also found that customers in general had high levels of perceived SE with the technology, with a mean of 4.33. This could be due to the fact that the study was conducted in a pure online bank, where customers are familiar with using SSTs. Another contributing factor to the overall high SE level could be that the study was conducted in a Northern-European country where the bank sector is already highly automated. In a study by Compeau et al. (1999), where SE did not display significant direct effects on Intention, indirect effects of SE were found. In their study, SE affected Intention through two other variables: Enjoyment and Anxiety. Based on these findings we wished to examine whether similar relationships exist between SE and Anxiety and Enjoyment in our study. The model was therefore tested on the same sample with Anxiety and Enjoyment as mediators of SE on the intention to adopt robotics technology. The results clearly showed that SE has a significant positive effect on Enjoyment (0.30) and a significant negative effect on Anxiety (-0.39) at a 99.9 percent level, and therefore has indirect effects on Intention. This implies a slight modification of the conceptual model, where SE was hypothesized to display direct effects on Intention. Figure 2 shows a new proposed model adjusted for the indirect effects of SE on Intention.

Figure 2: Adjusted model



Social Influence

Social Influence could not be confirmed as a significant predictor of the intention to adopt robotics technology. This indicates that when making decisions about whether to adopt the technology or not, customers are not affected by what other people think they should do. It is however, important to mention that this study was conducted in an independent-based culture, where the primary emphasis typically lies on the individual's own attributes and achievements (Bagozzi & Lee, 1999a). Had the study been conducted in an interdependent-based culture, where memberships in groups are the primary emphasis, the results would most likely be different. More research is therefore needed on SI across different cultures before a conclusion can be made on whether the variable could have significant effects on adoption intentions in a robotics setting. This study does however suggest that in independent-based cultures SI does not have a significant effect on adoption intentions.

Trust

The third most contributing factor to adoption intentions in this study is Trust. A positive and significant relationship with Intention is proved, indicating that trust in the technology underlying this type of services is highly important. The hypothesized effect of Trust on Intention is therefore confirmed. The importance of Trust may be attributed to the consequences that come with misinformation or dysfunctional services in a bank setting. As robotics in a bank setting is a relatively new phenomenon, this may further increase the importance of Trust for adoption intentions. The Mayer et al. (1995) definition of Trust used in this research has also been found to be a predictor of Intention in the literature on Information Systems. Yousafzai et al. (2009), who also studied Trust in an SST bank setting, found Trust to be a significant predictor of Intention. This study therefore supports previous literature by highlighting the significance of Trust in robotics technology in a bank setting.

Value

Value displays a positive path coefficient on adoption intentions, however the effect is only found to be significant when accounting for moderating effects. The hypothesized relationship between Value and Intention can therefore not be confirmed. This research differs from previous TAM-based research in finding that the Value construct is not significant, toning down its importance relative to other constructs.

When interpreting the relationship between Value and Intention, one should simultaneously consider the high importance of Enjoyment as a driver for Intention. The different aspects of Value as a construct may be something that customers have come to take for granted, meaning that customers view the Value attributes as a prerequisite to consider adopting the service. As such, the presence of Value may not be emphasized when making adoption decisions. A lack of Value, however, may result in the rejection of the robotic service. In this setting, Enjoyment may serve as a complement to Value, replacing it in the sense that customers see the Enjoyment aspect as valuable in itself.

Moderating Effects

Need for Social Interaction

To the authors' surprise NSI only displays one significant moderating effect, namely on the relationship between Enjoyment and Intention. NSI and Enjoyment shows clear negative correlations (-0.48), meaning that when NSI increases, the perceived Enjoyment tends to decrease. This coincides with theory and empirical findings, as individuals who prefer to communicate with other people rather than machines (high NSI scores), would experience less enjoyment towards a robot than would individuals with a low NSI. The effect of NSI on the relationship between Enjoyment and Intention is found to be positive in the PLS analysis, with a path coefficient of 0.19. This implies that with increasing values of NSI, Enjoyment becomes more important for customers when making adoption decisions. This coincides with the findings of Dabholkar and Bagozzi's (2002) study on adoption of SSTs. To investigate this effect further, an interaction probing analysis using the Johnson-Neyman Technique was conducted. The test indicated that NSI only has significant effects on the relationship between Enjoyment and Intention for values of NSI above 2.42. In this study, 81 percent of the respondents are above this value of NSI. The analysis also indicated that the positive moderating effect on the relationship between Enjoyment and Intention increases with increasing values of NSI. This means that for people with a moderate to a high need to interact with a human employee when contacting their bank, Enjoyment has a higher effect on the intention to adopt robotics technology. Additionally, NSI correlates negatively with Intention, meaning that people with a high NSI tend to reject robotics technology. For these individuals, who are assumed to have a relatively low perceived Enjoyment with the service, the impact of Enjoyment on the adoption intention is higher. This is explained by the strengthened relationship between Enjoyment and Intention caused by NSI's moderating effect. This coincides with theory, as individuals with a high NSI would prefer to communicate with a human rather than a robot, and this desire would be heightened with increasing values of NSI.

Playfulness

Playfulness displays two significant moderating effects: on Enjoyment and Trust. As anticipated, Enjoyment and Playfulness shows clear positive correlations (0.43). This indicates that individuals who in general find it enjoyable to try new technological solutions also find the cognitive robot used in banking services enjoyable. Individuals who are less playful with technology on the other hand, display lower perceived Enjoyment with the service. The effect of Playfulness on the relationship between Enjoyment and Intention is however negative, with a path coefficient of –0.24. This indicates that with increasing values of Playfulness, the effect of Enjoyment on Intention decreases, meaning that Enjoyment is less important for adoption intentions for individuals with high levels of general technological playfulness. Interaction probing showed that Playfulness displays significant effects on Enjoyment for all values of Playfulness. This is contrary to what was expected, and contradicts previous literature and theory. The literature shows that consumers with high levels of Playfulness tend to have higher intentions to use technology-based services, and that they have a strong intrinsic motivation to use these services as they enjoy trying new technological solutions (Hirschman 1980; Mehrabian & Russell 1974; Midgley & Dowling

1978). The implication from this is that with increasing levels of Playfulness, Enjoyment should be a more important determinant of adoption intentions. In a study by Dabholkar and Bagozzi (2002), Playfulness was found to strengthen the relationship between Enjoyment and Intention. The contradicting finding in this research suggests that Playfulness as a construct should be studied further in order to draw conclusions from the results. Playfulness, as a single item construct, could not be fully evaluated regarding its validity and reliability. Due to this, the effect of Playfulness could be caused by measurement errors.

Playfulness also correlates positively with Trust (0.28), indicating that individuals with a high Playfulness in general have higher trust in the robotic service, while individuals with a low Playfulness display lower levels of Trust. The moderating effect of Playfulness on the relationship between Trust and Intention is positive, with a path coefficient of 0.19. This implies that for increasing values of Playfulness, Trust becomes a more important predictor of Intention. The Johnson-Neyman Technique gives further insight to this effect, and shows that Playfulness has a significant moderating effect on the relationship between Trust and Intention for levels of Playfulness above 3.67. The moderating effect is positive, indicating that for individuals with a high level of Playfulness, Trust has a stronger impact on adoption intentions. In the study, 85 percent of the respondents are above this level of Playfulness. The effect on the relationship between Trust and Intention found in this research contradicts previous literature, similar to what was found on Enjoyment. Dabholkar and Bagozzi (2002) state that individuals with a high level of Playfulness will be less affected by the reliability of the technology when making adoption decisions. This would imply that with increasing levels of Playfulness, the relationship between Trust and Intention should be attenuated. Due to these contradicting results, and the lack of established validity of Playfulness as a construct, further research is encouraged in order to draw precise conclusions.

The two moderating effects of Playfulness found in this research clearly contradicts theory and previous literature. Due to this, and the limited validity of the construct, the effects of Playfulness in the general model will not be further discussed. Similar contradicting effects of Playfulness are also found when applying the model across different levels of robot interaction, and due to the same limitations of Playfulness, these will not be analyzed.

Resistance to Change

RTC only displays a moderating effect on the relationship between Social Influence and the intention to adopt robotics technology. The moderating effect of RTC on the relationship between SI and Intention is found to be negative (-0.13). This implies that for individuals who score high on RTC, SI has a lower impact on adoption intentions. Individuals who are resistant to change are less influenced by what other people important to them think they should do, while individuals who score low on RTC are typically more influenced by the opinions of other people. The Johnson-Neyman Technique found that RTC only has a significant moderating effect on the relationship between SI and Intention for values of RTC below 1.40. The moderating effect in this interval is positive, but diminishing with increasing values of RTC. In this study, 50 percent of customers are in the significant interval of RTC scores. An important conclusion to draw from this is that SI will only have an effect on adoption intentions for customers with an extremely low level of RTC. An explanation of this may be that individuals with a high score on RTC by definition do not wish to change their behavior, and are therefore not affected by what other people think they should do. Individuals with a low score on RTC on the other hand, may be more open to suggestions from other people important to them, making SI a more important predictor of adoption intentions.

5.1.2 Level of Robot Interaction

When running the model separately for each of the two scenarios, the results are clearly different. The only common factor that significantly affects the intention to adopt robotics technology is Enjoyment, further supporting the importance of Enjoyment in the complete model. Enjoyment is found to be the second most important predictor of adoption intentions in both scenarios. In the high-complexity interaction setting (pension plans) SE, SI and Trust displays additional significant effects on Intention, while in the low-complexity interaction setting (refinancing) Anxiety and Habit has additional significant effects on Intention.

High-Complexity Interaction Services

In the scenario where cognitive robots are used as advisors regarding pension plans, the relationship between Enjoyment and Intention is found to be moderated by two factors: NSI and Playfulness. NSI and Enjoyment are negatively correlated (-0.42), indicating that in scenario 1a people with high levels of NSI tend to have low levels of perceived Enjoyment with the cognitive robot. The path coefficient of NSI on the relationship between Enjoyment and Intention is positive, and by using the Johnson-Neyman Technique, it is found to be significant for values of NSI above 1.88. In scenario 1a, 92 percent of the respondents have levels of NSI above this threshold. The strengthening effect from NSI on the importance of

Enjoyment increases with increasing values of NSI. This implies that for individuals who score high on NSI, Enjoyment is a stronger predictor of adoption intentions than for those who score low on NSI. Due to the aforementioned limitations of Playfulness as a construct, its moderating effect on the relationship between Enjoyment and Intention will not be discussed.

Further, SE is found to display a small negative effect on adoption intentions when using the original proposed model. This would indicate that with increasing SE, the intention to adopt would decrease, which is contrary to what previous literature has found. However, when including the mediating effects of Anxiety and Enjoyment, the results are more meaningful. SE displays a positive significant effect on Enjoyment (0.29), and a negative significant effect on Anxiety (-0.53) at a 99.9 percent significance level, indicating an indirect effect from SE on adoption intentions. When correcting the model for these effects, the direct effect from SE on Intention is no longer significant. The same theoretical implications applied in the low-complexity interaction service, found SE to display a significant positive effect on Enjoyment (0.30) and a significant negative effect on Anxiety (-0.28). These findings indicate that SE displays the same effect on Enjoyment in each of the two scenarios. Individuals with a high SE will experience more Enjoyment with the cognitive robot, than individuals with a low SE. The impact of SE on Anxiety on the other hand, is greater in the high-complexity interaction service, than in the low-complexity interaction service. The effect on Anxiety seems plausible, as scenario 1a requires a higher level of interaction with the cognitive robot, requiring a higher SE to avoid feelings of anxiety. Individuals with a high SE would experience less robotics anxiety, than would individuals with a low SE, and this effect will be greater for high-complexity interaction services.

SI displays a significant positive effect on the intention to adopt robotics technology in scenario 1a. This implies that for services of high interaction complexity, individuals are more affected by what other people important to them think they should do, whereas in low-complexity interaction services SI is not a significant predictor of adoption intentions. This could be due to the higher complexity of the service, making the customers more uncertain regarding their own judgements, leading them to seek advice from their peers. The effect of SI on Intention is further moderated by the customer's level of RTC. The path coefficient of this moderating effect is negative, implying that with increasing values of RTC, SI will have a diminishing impact on adoption intentions. The effect is however, only significant for values of RTC below 1.64, applying for 57 percent of the customers. In this interval of RTC, the effect on SI is positive, but diminishing. These findings imply that customers with a low RTC are more receptive to the opinions of others when making adoption decisions, than are customers with a high RTC.

The most important factor to influence adoption intentions in the high-complexity interaction service is Trust. Trust displays significant positive effects on Intention, indicating that Trust is an extremely important factor when deciding to adopt or reject the technology. The reason why Trust only displays a significant effect on Intention in scenario 1a could be due to the high complexity of the interaction between the individual and the cognitive robot in this service. The interaction between the customer and the robot in the refinancing scenario on the other hand, is less complex and more standardized, making it easier to validate the advice given by the robot. This could make Trust a less important factor for adoption intentions in low-complexity interaction services.

Low-Complexity Interaction Services

Surprisingly, Anxiety only displays a significant impact on adoption intentions in the low-complexity interaction service. Anxiety was believed to have an effect in both scenarios. However, the results suggest that in the high-complexity scenario, Anxiety is replaced by other variables displaying higher relative importance.

Habit is the single most important factor to influence adoption intentions in scenario 2a. This implies that the extent to which the service is compatible with existing habits and traditions is extremely important for customers when making adoption decisions in low-complexity interaction services. The importance of Habit could be due to the fact that these services are less complex, and that customers use them more frequently than services of higher complexity (Finans Norge, 2016). When the service is used more frequently, habits can be established, and hence have an impact on adoption decisions. Advisory services of higher interaction complexity, such as pension plans, require a more comprehensive dialogue with the advisor, which could lead to less routine communication, resulting in a lower impact of Habit on adoption intentions.

Interestingly, Value is not a significant variable in either of the two scenarios. This contradicts what previous research on technology adoption has found. A possible explanation of this is that customers' expectations are changing, and that they are increasingly driven by the emotional aspects of services, making hedonic motivation the important driver. This has important implications for banks intending to implement robotics technology, which will be addressed in chapter 5.2.

5.1.3 Readiness to Adopt Robotics Technology

As shown in table 7 in chapter 4.3, the mean score of the intention to adopt the robotic service in scenario 1a is 3.15, indicating a moderate readiness to adopt, while with a human employee the mean is 2.90. There are, however, no significant differences found between the control group and the experiment group in the intention to adopt the service when using an ANOVA analysis. This implies that bank customers are equally ready to adopt the service regarding pension plans with a human employee as with a cognitive robot, indicating that cognitive robotics has potential in high-complexity interaction services.

To examine this further, ANOVA analyses were conducted for all items across all independent variables, as this would uncover potential differences between the control group and the experiment group. Table 11 shows the items that display significant differences. The analysis reveals that even though there are no differences in adoption intentions, several discrepancies are found across the measurement items. The respondents clearly have higher Anxiety towards the service when communicating with a cognitive robot than with a human employee. Trust in the service agent is also found to be significantly lower towards the cognitive robot than towards the human employee. The service is also perceived as less valuable with the cognitive robot. These effects contributes to lowering the intention to adopt the robotic service. Bank customers do however find the service to be more exiting with the cognitive robot than with a human employee, shown by the significantly higher value of the third Enjoyment statement. To the authors' surprise, SE is also found to be significantly higher when communicating with the cognitive robot than with the human employee. This could be a result of the high level of general playfulness with technology among the respondents. The high level of SE additionally indicates that there may be substance to Turkle's (2013) view that people are becoming more comfortable with technology than with other people. Moreover, high levels of Enjoyment and SE contributes to increasing the readiness to adopt the robotic service. Despite these differences, the readiness to adopt the robotic service is equal, indicating that the positive and negative effects cancel each other out.

In scenario 2, the mean score of Intention is 3.37 with the cognitive robot, and 3.74 with the human employee. Using ANOVA, these are found to be significantly different, implying that customers are more ready to use the service when communicating with a human than with a robot. Further ANOVA analyses of the differences in the measurement items once again shows that customers have more Anxiety regarding the cognitive robot, than the human employee. The robotic service also scores lower in compatibility with existing habits. Additionally, all items across the constructs of Value, Trust and SE score lower with the cognitive robot. Customers would also experience less joy with the cognitive robot (E2), though they did find the service more exiting when communicating with the robot (E3). These findings explain why customers are more ready to adopt the service with a human employee than with a cognitive robot.

Table 11: Significant item differences

ANOVA 2a vs. 2b			ANOVA 1a vs. 1b		
	Mean	**P-value**		**Mean**	**P-value**
ANX1	2.45		**ANX1**	2.30	
	1.68	0.000***		1.71	0.001***
ANX2	2.64		**ANX2**	2.35	
	1.64	0.000***		1.60	0.000***
ANX3	2.02		**ANX3**	1.75	
	1.42	0.000***		1.47	0.048**
E2	2.45		**E3**	3.46	
	3.01	0.002***		2.93	0.003***
E3	3.39		**SE1**	4.42	
	3.08	0.094*		4.14	0.043**
H1	3.42		**T1**	3.31	
	4.11	0.000***		3.69	0.019**
H2	3.13		**T2**	3.46	
	3.98	0.000***		3.80	0.034**
SE1	4.39		**T3**	2.90	
	4.60	0.069*		3.31	0.022**
SE2	4.24		**V1**	3.22	
	4.60	0.008***		3.56	0.014**
SI2	2.83		**V2**	3.66	
	3.13	0.066*		3.91	0.078*
T1	3.71		**V4**	2.80	
	4.35	0.000***		3.21	0.001***
T2	3.88				
	4.45	0.000***			
T3	3.06				
	3.77	0.000***			
V1	3.39				
	3.98	0.000***			
V2	3.65				
	4.31	0.000***			
V3	3.38				
	3.83	0.005***			
V4	2.93				
	3.47	0.000***			

***p < 0.01; **p < 0.05; *p < 0.1

Darker shaded cells are robot scenarios; Lighter shaded cells are human employee scenarios.

When interpreting the results, it is important to keep in mind that cognitive robotics used in a bank setting is a relatively new phenomenon that has yet to be brought to market. Due to this, customers' information level regarding the technology may be low, resulting in uncertainty and ultimately rejection of cognitive robotics. This can be modeled using Roberts and Lattin's (2000) approach, where decisions are made based on a utility function, which in turn is based on the level of information available. As new information becomes accessible, the utility function needs to be updated. Several researchers (e.g. Ajzen & Fishbein, 1975, Ferreira & Lee, 2014) have suggested Bayesian learning as a good approximation for stepwise integration of the acquired information, thereby updating the utility function (for a thorough explanation, see Roberts & Urban, 1988). In this setting Bayesian learning relates to the updating of the probability of adopting robotics, as new information becomes available (Slovic & Lichtenstein, 1971). Relating this to the findings in this study, the moderate readiness to adopt robotics technology may be a consequence of the presence of Bayesian learning. A typical adoption pattern would then be a low adoption rate in the introductory phase, followed by increasing readiness as information becomes available and benefits are manifested.

5.1.4 Customers' Perceived Value and Retention Rate

Perceived Value scores are significantly higher for the scenarios involving a human employee, than for the scenarios with a cognitive robot. The respondents undoubtedly perceive a higher value when serviced by a human than with a robot. However, the implementation of cognitive robotics does increase the customers' self-reported Retention Rate.

There may be two explanations of the lower Perceived Value in the scenarios involving cognitive robots. The first is a communication problem (Sexton, 2009), where the discrepancy between Actual Value and Perceived Value is disproportionately large. Communicating the benefits of the technology to the customers could ensure Bayesian learning, thereby increasing the Perceived Value of the technology. Another explanation may be that Actual Value is in fact higher with human employees than with robots, reducing the probability that the lower Perceived Value is due to a communication problem.

The effort to innovate, and create new customer experiences may be something that customers consider as positive and valuable, resulting in increased loyalty for innovative banks. The shift in customer preferences mentioned earlier ultimately leads to increased expectations of customer experiences. Though the service does not appeal to customers, the attempt to be an innovation leader and a first mover may be viewed as positive (Kaplan & Norton, 2001). This could be the explanation of the increased Retention Rate with the implementation of cognitive robots.

The increased loyalty as a result of the implementation of cognitive robotics suggests that what Bagozzi and Lee (1999b) refers to as *Active Initial Resistance,* is not an issue for the future implementation of robotics in banks. Had this been the case, we would have seen a decrease in the Retention Rate as customers actively would have protested by boycotting the bank. This type of resistance is pre-programmed, and occurs nearly automatically before extensive processing of information regarding the new technology can occur (Bagozzi & Lee, 1999b). This paper gives indications of an increased Retention Rate with the implementation of robotics, which has positive implications for banks intending to implement the technology. This will be elaborated in chapter 5.2.

5.1.5 Academic Contribution

The research in this thesis contributes to the existing literature by using a model consisting of psychological barriers to predict adoption intentions of robotics technology. There are two contributions of particular interest, the first being the universality of Enjoyment as a predictor of technology adoption. Previous research has not emphasized the importance of Enjoyment in utilitarian based services, whereas in this thesis the construct is found to be strongly significant across all settings.

The second contribution to be noted from this study is the difference between the adoption barriers across various levels of robot interaction. Technology-based adoption literature has yet to highlight the need for tailored models according to the level of interaction with the technology. This study shows clear evidence of the need for distinct models, and additionally suggests the factors that will predict adoption intentions at various levels of technology interaction.

5.2 Managerial Implications

The findings from this research are of great importance to banks who are considering the implementation of cognitive robots in direct customer interactions in a variety of services. One of the purposes was to uncover whether a boundary exists for the type of service in which cognitive robotics can be successfully implemented. The research does however, not reveal any differences in customers' readiness to adopt cognitive robotics across different levels of interaction with the robot. This could indicate that cognitive robotics has the same potential for successful implementation regardless of the interaction level.

Bank customers are found to be moderately ready to adopt cognitive robotics in banking services, and the research uncovered major differences in potential customer barriers to adopt the technology across various levels of robot interaction. What this implies is that banks need to take different factors into consideration when implementing cognitive robots in services with various degrees of customer interactions, for it to be successful.

For services of high-complexity interaction levels, Trust, Enjoyment and Social Influence are the three most significant variables to take into consideration during the implementation. The level of Trust in the cognitive robot is the most important driver of adoption intentions. In the sample studied in this thesis the mean value of Trust in the cognitive robot among the customers is 3.23 on a 5-point scale. This leaves room for improvements of Trust, which consequently would increase the intention to adopt the technology. Banks intending to implement cognitive robots in services that require a high level of interaction with the customer should therefore focus on establishing Trust along three dimensions: Competence, Benevolence and Integrity. Emphasis should be placed on assurance and transparency in the service to establish Trust (Dimitriadis & Kyrezis, 2011).

The second most important driver of adoption intentions is Enjoyment. The customers who participated in this research have a mean value of only 2.73 for Enjoyment, implying that major improvements could be done concerning the level of Enjoyment. One of the main findings in this study is the importance of Enjoyment for adoption intentions. As bank customers are increasingly expecting more from their banks and as the competition in the industry is changing, it is crucial for banks to satisfy these demands and focus on more than just the utility aspect of a service. One possible way to enhance Enjoyment is by increasing the level of Self-Efficacy with robotics technology. This could be done by enlightening the customers on how to interact with cognitive robots. Childers et al. (2001) suggest that Enjoyment is driven by design characteristics, such as convenience and navigation, and could be enhanced by improving graphics and visual stimuli.

Social Influence is the third most significant factor to influence adoption intentions. Based on this it is important for banks to try to establish a positive word-of-mouth regarding cognitive robots, as customers are affected by what other people think about the technology. This could be achieved by a successful marketing campaign prior to the implementation of cognitive robots. Bagozzi and Lee (1999b) additionally suggest that marketing campaigns must change over time as customers pass through different stages in the adoption process.

When implementing cognitive robots in low-complexity interaction services, the three most important barriers to take into consideration are Habit, Enjoyment and Anxiety. Habit is found to be the number one driver of adoption intentions in these services. Banks therefore need to identify their customers' existing habits with the service prior to designing and implementing the service with a cognitive robot, in order for it to coincide with these habits. The customers in this study have a mean score on Habit of 3.27, which means that the service could be better designed to fit existing habits.

Enjoyment is the second most important factor to take into consideration. The proposed actions for high-complexity services also apply for low-complexity services in order to increase adoption intentions. The customers' mean value of Enjoyment is 2.77, leaving room for improvements.

The third factor to evaluate when implementing cognitive robots in low-complexity interaction services is Anxiety. Though the customers only have a mean value of 2.4 for Anxiety, a further decrease in this variable would lead to an increase in the intention to adopt robotics technology. As with Enjoyment, Self-Efficacy has an effect on Anxiety, and an increase in SE would therefore decrease the level of robotics anxiety. Yang and Forney (2013) suggest that testimonials from referents, such as positive word-of-mouth or consumer-generated reviews (e.g. blog posts), may reduce the anxiety experienced with the technology.

Rogers (2003) argues that in the early stages of implementation, mass media such as advertising is the best way to inform the customers and to create awareness around the new technology. Banks additionally need to build a desire for cognitive robotics by presenting it to customers as an opportunity, rather than a threat (Bagozzi & Lee, 1999b). Presenting the new service as a positive and attractive option, rather than a sacrifice, would ease the adoption for customers (Howard-Grenville & Hoffman, 2003).

Verplanken and Wood (2006) distinguish between two main interventions to implement new technologies successfully: Downstream and Upstream interventions. Downstream interventions refer to informational campaigns and self-help programs to enlighten customers on the new technology, while upstream interventions target social norms and habits. Further, they argue that when adoption intentions are not affected by established habits, it is sufficient with downstream interventions. The implication from this is that for banks intending to employ cognitive robots in high-complexity interaction services, success depends on educating and informing customers about the new technology and its benefits. This could additionally result in a positive word-of-mouth (Lanseng & Andreassen, 2007), increasing both SI and Trust and decreasing Anxiety. Educating customers by for example providing step-by-step guidance in texts or videos (Luo, Li, Zhang & Shim 2010) would enhance their perceived SE, thereby increasing the perceived Enjoyment and reducing Anxiety.

For services affected by established habits on the other hand, a combination of downstream and upstream interventions are needed (Verplanken & Wood, 2006). This means that in addition to communicating the benefits of robotics and educating the customers on the technology, banks should tailor the service to fit existing habits and try to establish new habits around cognitive robotics. This would apply for services of low-complexity interaction levels. In order to break down existing habits and establish new, Lewin's Change Management Model consisting of the three stages of Unfreeze, Change and Refreeze, could be a helpful tool (for a review, see Lewin, 1947).

The research indicates that initial active resistance is a non-issue for banks deciding to implement cognitive robotics. This means that customers will most likely not change their bank due to the implementation of robotics. On the contrary, the study found an increased loyalty due to the use of cognitive robots. Based on this the implementation of cognitive robotics in banking services is encouraged. Banks are however recommended to employ robotics gradually to ensure Bayesian learning. This recommendation is based on the indications that customers' intention to adopt the technology is affected by the current situation, with a lack of knowledge and experience with cognitive robots. A gradual implementation would enlighten customers on the Actual Value of cognitive robots, hence increasing the intention to adopt the technology. Additionally, a transition phase in which services are offered with both human employees and cognitive robots is recommended, as this will accustom the customer to the new technology and increase the likelihood of a successful implementation. It is also crucial for banks to take into account the aforementioned adoption barriers to be able to increase customers' Perceived Value of banking services.

5.3 Limitations

This study is among the first to be conducted on the adoption of cognitive robotics in direct customer interactions in banking services, and not surprisingly, a number of limitations exist in this research.

Setting

This study has addressed two different settings in which cognitive robotics may be implemented, and as such, one should be cautious generalizing the results. The study only involved one bank, and this was a relatively small, pure online bank, making self-selection bias a possible limitation. The relatively low response rate of 7.8 percent may also be the result of self-selection regarding the distribution method, as the questionnaire was distributed by e-mail. Additionally, as a result of the skewed customer base of the bank, the sample was relatively skewed regarding age and gender. This lead to an underrepresentation of young customers and women, limiting the generalizability for these segments.

Cognitive robotics is a relatively new technology, and has yet to be introduced to a large scale by banks in the country where the survey was conducted. This lead to concerns that, even though the technology was explained by best effort, and as simple as possible in the questionnaire, respondents would not completely understand and grasp the full potential of the technology. Though the realism checks proved the plausibility of the scenarios, there may be some uncertainty as these mainly focused on the scenario as a whole, and not solely on the technology.

Method

The survey conducted in this study is a one-time cross-sectional study. Previous research has suggested that a limitation of this type of study is that it cannot infer the causality of the research results (Agarwal & Karahanna, 2000). A limitation of the PLS method is that it may underestimate the structural path connecting the constructs with the dependent variable, and overestimate the connection between the constructs and the measurement questions (Chin et al., 2003). For complex models, there are no known ways of testing this.

Some of the factors were formed as single-item constructs, to shorten the length of the questionnaire, to make it less monotone and burdensome for the respondent, and to reduce Common-Method Bias. However, internal consistency reliability and predictive reliability of these constructs could not be measured, limiting the reliability and validity of the results (Hoeppner, Kelly, Urbanoski & Slaymaker, 2011; Diamantopoulos, Sarstedt, Fuchs, Wilczynski & Kaiser, 2012). Due to a lack of resources, a test re-test could not be conducted, limiting the external reliability. Additionally, criterion-related validity could not be measured, as actual behavior patterns were not available.

The use of a scenario-based survey has some drawbacks. As pointed out by McCollough, Berry and Yadav (2000), the use of scenarios increase the likelihood that respondents form an interpretation of the purpose behind the study, and correspondingly change their responses to fit that interpretation. Respondents may also be unable to reproduce their behavior and thoughts as they would in a real situation.

Model

A limitation of the model is the use of Intention as a predictor of actual behavior. Self-reported intention may be a good predictor of actual use, but it relies on the assumption that the respondents are sufficiently self-aware and reliable. Several scholars argue that actual behavior is primarily driven by intentions (Limayem et al., 2007). However, a study on adoption should ideally use observations of actual behavior to obtain accurate results. As the technology is still not in use, this was not possible in our study. Some researchers have also highlighted that the link between intention and actual adoption may be unclear (Bagozzi, 2007). Several mechanisms, such as self-regulation, may intervene in the period between an intention is manifested, and adoption behavior occurs (Bagozzi & Lee, 1999a).

Some of the factors in the research model may be difficult to test in reality, and especially in a self-reported form. Habit is defined in our study as automaticity in behavior, and is strongly related to subconscious actions. The result of this could be that respondents are unaware of their performed behavior, leading to erroneous answers on this construct and a mismatch in the correlation with Intention.

The Resistance to Change construct originally consists of 17 questions (Oreg, 2003). In order to shorten the length of the questionnaire, one question from each of the four factors were selected to serve as a proxy for the RTC scale. One of the items did however not pass the validity test. This could be a limitation for the accuracy of RTC as a moderator in the model.

6 Conclusion and Future Research

6.1 Conclusion

This study found Anxiety, Enjoyment, Habit and Trust to be the four main drivers of customers' intentions toward adopting cognitive robotics in a retail bank setting. Further, Enjoyment was found to be the most consistent predictor of adoption intentions, regardless of the setting. When applying the model in various levels of interactions with the cognitive robot, the barriers to adopt differed greatly. In low-complexity interaction services Enjoyment, Anxiety and Habit were found to display strong significant effects on adoption intentions, while in services of higher interaction complexity Enjoyment, Social Influence and Trust were important drivers. Additionally, Self-Efficacy was found to exert significant effects on adoption intentions through Anxiety and Enjoyment across all settings.

Bank customers were found to be moderately ready to adopt cognitive robotics in banking services. The readiness to adopt could be increased by focusing on potential barriers during the implementation of robotics in banking services. The research did however not reveal an increase in customers' Perceived Value by the implementation of robotics. This may be a result of bank customers' unfamiliarity with the technology and its benefits.

6.2 Future Research

Method

A re-test based on a real pilot with cognitive robots used in different banking services, rather than a written scenario, is recommended. As other researchers have pointed out (e.g. Benbasat & Barki, 2007; Shaikh & Karjaluoto, 2015), we recommend conducting a longitudinal, multi-stage model to better capture the influence of the adoption barriers on the intention to adopt, as well as actual robotics adoption at different stages of implementation. Most studies, including this thesis, are typically cross-sectional in nature and measure perceptions at a single point in time, making it difficult to elicit extensive generalizations from the results (Shaikh & Karjaluoto, 2015). Benbasat and Barki (2007) point out that longitudinal studies are likely to be more revealing than cross-sectional studies.

Model

Future research is suggested on the construct of Playfulness as a moderator of adoption intentions, as the results from this paper contradict theory and previous literature. Due to the limited reliability and validity of Image in this study, future research is suggested on this construct. We also recommend future research to implement actual adoption behavior to the proposed model in order to examine the relationship between intention and actual usage.

Once cognitive robots have been employed by banks, future research could incorporate the Endowment Effect (Kahneman, Knetsch & Thaler, 1990) as a psychological factor in the proposed model. In addition, the Prospect Theory (Kahneman & Tversky, 1979) and the Status Quo Bias (e.g. Samuelson & Zeckhauser, 1988; Polites & Karahanna, 2012) can be incorporated by giving the same respondent two scenarios, one with the cognitive robot and one with a human employee. The proposed model could also be extended with Facilitating Conditions, as this is found to have a significant impact on both intention and actual adoption behavior by several studies (e.g. Yang & Forney, 2013; Venkatesh et al., 2012; Venkatesh et al., 2011).

Demographics, such as age, gender and the level of education completed, are other variables that can be incorporated to the model as moderators (e.g. Martins et al., 2014; Venkatesh et al., 2012; Brown & Venkatesh, 2005). This could allow for a comparison of the adoption behavior and barriers between different segments of the population. Previous Experience is another factor that could be incorporated as a moderating variable once the technology has been implemented by banks (e.g. Martins et al., 2014; Venkatesh et al., 2012). Several studies have found a link between Previous Experience and variables such as Habit. With increased experience with a technology, Habit will have a smaller impact on the intention to adopt (e.g. Venkatesh et al., 2012; Limayem et al., 2007).

Level of Robot Interaction

Regarding the effect of the level of interaction on the intention to adopt robotics technology, this study only examined two different services. To allow for conclusions that are more generalizable, future research should study a number of services with various levels of interaction with cognitive robots.

Added Value to Customers

Measuring CVA due to the implementation of robotics was beyond the scope of this thesis. However, it would be interesting for future research to conduct an extensive CVA analysis. Such an analysis would have to make appropriate judgments on what to include and classify as variable costs. A proper CVA analysis would also monetize the Perceived Value of the service, as this would act as the ceiling on the price that customers would be willing to pay for the service (Sexton, 2009).

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8 Appendix

Appendix 1: Questionnaire

Adoption Barriers:

All items were administered using a five-point Likert scale where 1=Disagree, 2=Somewhat disagree, 3= Neither agree nor disagree, 4= Somewhat agree, 5= Agree

Image

Brand Image:

IB: I have a positive image of my bank.

Image-Congruence (Self-Image):

IC: This service suits my identity.

Self-Efficacy

SE1: I possess the knowledge and ability required to use this service.

SE2: It would be easy for me to use this service. (Adapted from Venkatesh et al., 2012)

Habit

H1: This service fits my habits.

H2: This service fits my values and traditions.

Social Influence

SI1: People who are important to me think that I should use this service. (Adapted from Venkatesh et al., 2012)

SI2: People who influence my behavior think that I should use this service. (Adapted from Venkatesh et al., 2012)

SI3: This service would give me higher social status.

Trust

Competence:

T1: I would trust the information *Amelia/Kari* gave me.

Integrity:

T2: I would trust *Amelia/Kari* to keep her promises.

Benevolence:

T3: I would trust *Amelia/Kari* to act in my best interest.

Enjoyment

E1: It would be fun to talk to *Amelia/Kari*. (Adapted from Venkatesh et al., 2012)

E2: This service would give me joy. (Adapted from Venkatesh et al., 2012)

E3: This service seems exciting. (Adapted from Childers et al., 2001)

E4: This service would make me feel cool.

Anxiety

ANX1: If I were to talk to *Amelia/Kari* I would become stressed.

ANX2: If I were to talk to *Amelia/Kari* I would feel uncomfortable.

ANX3: It seems intimidating to talk to *Amelia/Kari.* (Adapted from Venkatesh et al., 2003)

Value

V1: This service seems to be of high quality.

V2: *Amelia/Kari* would provide me with quick and efficient advisory services.

V3: This service would provide me flexibility.

V4: *Amelia/Kari* would give me favorable terms and conditions.

Individual Characteristics:

All items were administered using a five-point Likert scale where 1=Disagree, 2=Somewhat disagree, 3= Neither agree nor disagree, 4= Somewhat agree, 5= Agree

Resistance to Change

RTC1: I generally consider changes to be a negative thing. (Oreg, 2003)

RTC2: When I am informed of a change of plans, I tense up a bit. (Oreg, 2003)

RTC3: Often, I feel a bit uncomfortable even about changes that may potentially improve my life. (Oreg, 2003)

RTC4: Once I have come to a conclusion, I am not likely to change my mind. (Oreg, 2003)

Need for Social Interaction

NSI1: Human contact is important to me when contacting my bank.

NSI2: I would rather talk to a human, even when it would be more efficient to communicate with a machine/ technological solution.

Playfulness

P: Trying new technological solutions is fun.

Intention to Adopt Robotics Technology

To what extent do you wish to use this service?

- I do not want to use this service (=1)
- I am skeptical, and do not think I want to try this service. (=2)
- I am undecided. (=3)
- I am skeptical, but I think I want to try this service. (=4)
- I would like to use this service. (=5)

Realism Checks

All items were administered using a five-point Likert scale where 1=Disagree, 2=Somewhat disagree, 3= Neither agree nor disagree, 4= Somewhat agree, 5= Agree

1. The situation described in the scenario was realistic/understandable. (Dabholkar, 1996)
2. I had no difficulties imaging myself in the situation (described in the scenario). (Dabholkar, 1996)

Perceived Value:

All items were administered using an eleven-point Likert scale.

PV1: How negative/positive are you towards this service?

PV2: To what extent do you perceive this service to be useful/valuable?

PV3: To what extent will this service provide you with a great customer experience?

PV4: To what extent will this service simplify your customer relationship with the bank?

Retention rate (RR):

All items were administered using an eleven-point Likert scale.

Robot scenario: How likely is it that you would remain a customer in you bank if this service was provided in addition to traditional advisory services?

Human scenario: How likely is it that you would remain a customer in your bank if this was the only option provided for this type of advisory services?

Demographics:

Age

- 18-30
- 31-50
- 51-65

Gender

- Male
- Female

Education

- Elementary school
- High School
- University (1-3 years)
- University (4-5 years)
- Ph.D./ University (more than 5 years)

Appendix 2: Scenarios

Scenario 1a: Robot advisor - Pension plans

Imagine the following scenario: You want to start saving for your retirement, or make changes to your existing pension plan. You want advice regarding what to choose, how much you need to save, and how this fits with your personal finances.

You contact your bank by logging on to your online bank, and then start a conversation with Amelia, who you can see and hear. You discuss your personal requirements and needs with Amelia, who provides advice regarding what pension plan that suits you, and she calculates how much you need to save.

Scenario 1b: Human advisor - Pension plans

Imagine the following scenario: You want to start saving for your retirement, or make changes to your existing pension plan. You want advice regarding what to choose, how much you need to save, and how this fits with your personal finances.

You contact your bank by phone, and Kari answers. You discuss your personal requirements and needs with Kari, who provides advice regarding what pension plan that suits you, and she calculates how much you need to save.

Scenario 2a: Robot advisor - Refinancing

Imagine the following scenario: You have mortgages in another bank and you want to move these to Bank X in order to receive interest rates that are more favorable. You want to know more about what terms and conditions you can get and how to proceed in order to refinance the loan.

You call Bank X and speak with Amelia, who can answer all your questions regarding the refinancing.

Scenario 2b: Human advisor - Refinancing

Imagine the following scenario: You have mortgages in another bank and you want to move this to Bank X in order to receive interest rates that are more favorable. You want to know more about what terms and conditions you can get and how to proceed in order to refinance the loan.

You call Bank X and speak with Kari, who can answer all your questions regarding the refinancing.

Description of Amelia provided to the respondents:

Amelia is an intelligent robot that can understand, learn, and show emotions like a human being. Amelia knows everything about your customer relationship with the bank, and she can give you advice based on analysis.

By contacting Amelia, you will avoid having to wait, and the advisory service will be quick and efficient.

Description of Kari provided to the respondents:

Kari is a financial advisor in your bank. She can advise you based on what you tell her, and based on her own competence and experience.