Stockholm School of Economics

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Have You Chatted with Your Future AI Overlords Today?

An exploratory study of how people interpret the adoption of Artificial Intelligence

Abstract

The majority of the world is affected by Artificial Intelligence (AI) technology on a daily basis. As AI spreads and becomes more pervasive in their lives, people are trying to interpret its meaning and scope. Our thesis explores a previously neglected area of literature surrounding the adoption and acceptance of AI-based technology. Through an iterative, abductive process we gain an understanding of people's technological frames of reference as they pertain to AI. We study interpretations of AI through a series of interviews and participant interactions with a specific technology – chatbots. By interviewing Generation Y Swedes, we discover key framing constructs that help shape their technological frames of reference. Furthermore, contrary to what the dominant theory on individual technology adoption would predict, we observe that people do not engage in a solely rational process of benefits assessment prior to AI acceptance. Instead, they approach AI adoption as a foregone conclusion where their interpretations and expectations pertaining to the technology are shaped by societal trends, cultural norms, and individual experiences. Ultimately, by identifying and studying these constructs, we hope to create a starting point for other researchers trying to understand AI technology adoption and create an awareness of end-user needs for AI practitioners.

Keywords: Artificial Intelligence (AI), Technology Adoption, Technological Frames of Reference, Chatbot, Information Systems (IS), TAM, Cognitive Technology, Interpretivist, Qualitative

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From Chad: Sophie, you have been immensely patient, kind, and supportive. I look forward to seeing you for more than five minutes a day now that the study is over.

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Glossary

Alan Turing	Noted as one of the first scientists to formalize the idea of Artificial Intelligence
Amazon Alexa & Google Home	Speech-based AI assistance tools that use speech recognition software to assist users with everyday tasks such as checking the weather forecast to turning on lights in their homes
Artificial Intelligence	A cross-disciplinary approach to understanding, modeling, and creating intelligence of various forms (Frankish and Ramsey, 2014)
Autonomous Advisor	A computer agent acting autonomously as an advisor to a human
Business Process Algorithmization	The use of any AI-based technology/algorithm to optimize business processes, akin to outsourcing
Chatbot	An AI-based, natural language processing system that strives to generate a conversation between a human and machine (Setiaji and Wibowo, 2016); also known as a 'chatterbot'
Enterprise Social Media	Social media that is used at an organizational level
Generation X	For the purposes of this study, Generation X Includes people born between and consisting of the years 1960-1979
Generation Y	For the purposes of this study, Generation Y (also known as millennials) includes people born between and consisting of the years 1980-1999
Intelligent System	A system which is considered to have Artificial Intelligence
Interactive Voice Response	An enterprise phone system that uses natural language and pre-selected responses to help guide end users to specific representatives
Internet Accessible Devices	A device that has internet access
Machine Learning	"Inferring structural relationships from data using (relatively) domain-general methods" (Frankish and Ramsey, 2014)

Natural Language Processing	"Processing language texts by computer for some practical or useful purpose" (Frankish and Ramsey, 2014)
Networked Readiness Index	An index produced by the World Economic Forum which ranks countries according to their propensity to exploit technology

Abbreviations

AI	Artificial Intelligence
ANT	Actor Network Theory
Gen Y	Generation Y
IS	Information Systems
ML	Machine Learning
SCOT	Social Construction of Technology
TA	Thematic Analysis
TAM	Technology Acceptance Model
TFR	Technological Frames of Reference
UTAUT	Unified Theory of Acceptance and Use of Technology

1. Introduction

Artificial Intelligence (AI) has long been a subject of great debate, excitement, anticipation, and, at times, fear. Ever since Turing formally introduced the concept of 'machine thinking' in the 1950s with his famous paper "Computing Machinery and Intelligence," experts and laypersons alike have been weighing in on what true AI could look like. From the work of early-stage AI scientists such as Marvin Minsky and H.A. Simon to the now mass commercialization of AI by business giants like Mark Zuckerberg and Elon Musk, there is an ever-growing interest in and understanding of Artificial Intelligence. But, what exactly is AI? To many of us, the definition of AI seems clear: AI is a 'machine' that can think like a human. Or as Derek Partridge put it:

> *"Artificial intelligence is that field of computer usage which attempts to construct computational mechanisms for activities that are considered to require intelligence when performed by humans." (Partridge, 1998)*

Modern-day AI is not what we have seen in movies and TV shows, but it is also not what we have been told. AI is an idea: incredibly complex, extremely difficult to understand, and massively misunderstood. At the same time, it is simple - as simple as looking in the mirror. After all, the majority of AI systems try to do what humans do, only better. Our thought leaders are at odds as to how we should address AI systems, while simultaneously driving the development of the tools. Elon Musk, whose SpaceX rockets are undoubtedly fueled by a multiplicity of AI-based technologies, has said that "we need to be super careful with AI" as it is "potentially more dangerous than nukes" (Musk, 2014). Musk is not alone in this sentiment. Stephan Hawking, one of the greatest minds in history, often warned about the dangers of AI, up until his death earlier this year. His quote below demonstrates both the great potential and possible dangers of the technology.

> *"Everything that civilization has to offer is a product of human intelligence; we cannot predict what we might achieve when this intelligence is magnified by the tools that AI may provide, but the eradication of war, disease, and poverty would be high on anyone's list. Success in creating AI would be the biggest event in human history. Unfortunately, it might also be the last." (Hawking, 2014)*

Though this duality exists and is well known to nearly all who are familiar with AI, what we know, and what we have further discovered in our study, is that AI is here and there is little chance it will be going away. Businesses and governments are driving its development and people use AI-based technology every day because the potential is too great to ignore. To gain a better understanding of this potential,

and where we are in the current level and pace of AI development, we would like to discuss a recent example of an AI system known as 'AlphaGo.'

'Go[1],' is a simple and well-known board game that has been played for more than 2 500 years. Go requires that the player not only have a sharp intuition but that they are an astute abstract thinker. To give an idea of scale, the number of configurations in the 19 x 19 board is larger than the number of atoms in the universe (DeepMind Technologies Limited, 2018). Given the balance between intuition and logic, it was thought that only people could be good at playing 'Go' (Agarwal, 2018). This was disproven in 2016 when AlphaGo beat the world's best player – Lee Sedol. In a five-match game, AlphaGo won four of the matches. This achievement in the area of AI was unexpected. Most researchers anticipated it would take another 10 years before experts would be able to design a program intelligent enough to beat a human professional player at Go. AlphaGo won because it used moves that no human would have thought to use, as they were based on the best statistical chance to win, if even by a slight margin (Kohs, 2017). Human beings would not think to take this route, as the alternative leads to significantly higher gains at a marginally higher risk (Koch, 2016). The AlphaGo platform has subsequently been updated by Google DeepMind, the original architect of the program, and since then has beaten many other players. AlphaGo Zero, the updated version, teaches itself through a system of self-enforced (reinforced) learning where it does not need the supervision, assistance or example of human beings to learn (Silver et al., 2017). This is significant because it shows the intense growth in the ability of the algorithm, which occurred in less than two months (Silver and Hassabis, 2017).

The rapid and pervasive growth of AI systems has led to a slew of unanswered and unexplored topics. One of the areas that have been underdeveloped is AI-based technology in relation to a business context. Through a systematic review of the literature (see section 3.1), we have discovered that technology adoption is one such unexplored topic. Some research has been completed into AI decision making processes and organizing around AI, but little research has been completed to understand the adoption and acceptance of these technologies from the individual user's standpoint. Hence, our thesis will investigate AI technology adoption, a topic which as far as we know has not been explored before. To assist in our research, we will use framing theories, with a specific focus on technological frames, a concept which helps explain the interpretation of a new technology. Prior to giving a detailed account of why we have chosen this path, we will further explore the background of AI and technology adoption, our research proposal, as well as cover our contribution to theoretical knowledge.

[1] Please see appendix for a visual illustration of the game 'Go'

2. Background & Problem Area

In this section, we will develop the background of AI and technology adoption to create a deeper understanding of the fields as they stand today. This will include further defining AI and why it is interesting to study, providing a brief overview of technology adoption, and then lead into our research proposal, research questions, and research gap.

Before we move forward, we would like to ensure that the reader understands two premises related to our study. First, we, the researchers, do not have a technical understanding of Artificial Intelligence. We have attempted to understand AI systems from a conceptual standpoint. Secondly, we have written this paper primarily for others in the business and academic world. That is not to say that this paper is only valuable to those groups of people, but rather to point out that to an AI veteran the terminology, definitions, and explanation of Artificial Intelligence will likely seem incomplete. However, for all the non-AI experts reading this study, we believe the level of detail will serve to keep you engaged and understanding of the study without losing you in technical arguments we ourselves do not fully understand. With that made clear, we will begin by discussing the definition of AI in the context of our study.

2.1 Understanding Artificial Intelligence (AI)

As previously indicated, AI is complex and difficult to define. However, we would like to give both ourselves and the reader a basic understanding of AI. AI could be defined as "a cross-disciplinary approach to understanding, modeling, and creating intelligence of various forms" (Frankish and Ramsey, 2014). AI applications are fundamentally transforming both our interaction with our environment and between ourselves. Since its inception in 1956, AI has come to be the most prolific area of research in human cognition. Today, that research has led to the creation of modern technologies which many of us use on a daily basis (Frankish and Ramsey, 2014). For example, Google Maps and Uber use AI algorithms to predict and analyze traffic patterns in order to increase user route efficiency. As part of the computer science discipline, AI aims to support us in our understanding of human intelligence, an endeavor which involves designing software programs which "think" in human-like ways (Frankish and Ramsey, 2014). Nilsson (1982) stated the reach of AI best, below.

> *"Specifically, there are computer systems that can diagnose diseases, plan the synthesis of complex organic chemical compounds, solve differential equations in symbolic form, analyze electronic circuits, understand limited amounts of human speech and natural language text, or write small computer programs to meet formal specifications." (Nilsson, 1982)*

Since Nilson stated this in 1982, the scope and reach of AI has only increased.

2.2 Why study AI?

For the purposes of this paper, we will not cover every aspect of AI. The important implication here is to understand the general capabilities of AI-based technologies and how they differ from previously studied technologies. In doing so, we have employed the assistance of a visualization below.

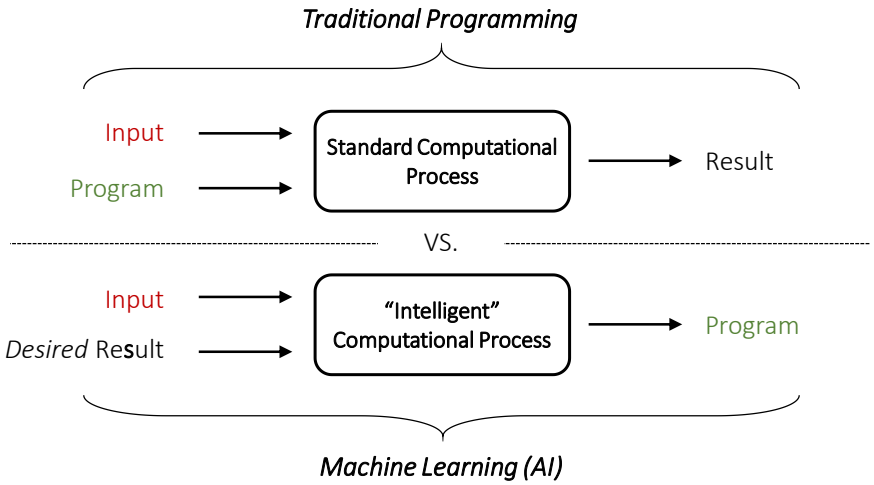


Figure 1: Comparison of traditional programming to machine learning

Generally speaking, the difference between machine learning, which is a type of AI system, and traditional programming, is straightforward. A traditional program brings in data (input) and runs them through a set of rules (program), the data is then computed and the results are presented. This is different than an AI system such as Machine Learning, which actually finds the appropriate program from the input and delivers what one hopes to achieve. In other words, Machine Learning finds a program that fits the data, while traditional programming automates tasks by writing programs (Ajanki, 2018). The reason that this is important is that this process which we described above is something that up until AI development recently picked up pace, only humans could do. Human beings can make sense of a situation based on context, not based solely on rules which is what limits a traditional program. To summarize, we believe that AI is different than other technologies and worthy of study for three main reasons.

1. AI is designed to simulate human thinking
2. AI can "teach itself"
3. AI can use context to drive decisions

Beyond these three reasons, we believe that studies of AI-based technology will continue to be important in the future as AI becomes more and more ubiquitous and integral in our daily lives. Other

than the fact that it is highly topical, AI is also fairly understudied from a business perspective. Specifically, the literature on the adoption of AI from the individual user's perspective is nearly non-existent. A search on Scopus with the terms "Artificial Intelligence" and "Technology Adoption" reveals only 68 results, 13 of which are related to business and management studies ("Scopus - Document search results," 2018).

2.3 Why technology adoption?

Though the field of study – technology adoption – is shown in great detail in sections 3.2 – 3.4, we wanted to give a brief overview here. Overall, technology adoption has been defined as "the choice to acquire and use a new invention" (Hall and Khan, 2003). Generally speaking, there are two ways to view technology adoption: positivistic and interpretivist. The positivist dogma centers firmly around theories such as TAM, which assert that people adopt technology based on a rational process of decision making. The argument can be viewed as: "This technology is easy to use and it seems to be able to get the job done, so I will use it." The other side is the interpretivist viewpoint, which is more difficult to explain and less thoroughly formed as the majority of technology adoption research has been focused on the positivist approach (Mingers, 2006). There are a few emerging theories in the interpretivist philosophy as it relates to technology adoption such as Actor-Network Theory (ANT) and technological frames (TFR). Generally speaking, the interpretivist approach is centered on the interpretation of the world through the eyes of the subjects being studied (Deetz, 1996). We will study our participants' interpretations of how and why they adopt AI-based technology through the lens of technological frames. We do this through the study of a specific technology – chatbots.

2.4 Why Chatbots?

We have chosen to study chatbots for a simple reason: chatbots give users an easy to understand example of how a conceptually difficult to understand system works. A chatbot, for our purposes, is an AI-based, natural language processing system that strives to generate a conversation between a human and machine. Over time, as it converses further, it learns new ways of solving problems and increasing accuracy in its responses (Setiaji and Wibowo, 2016). In our study, we used a text-based, customer service chatbot on SEB bank's website, seen in Figure 2 below. However, chatbots can be found on mobile phones, websites, and can be voice-based, such as Amazon Alexa or Google Home[2], or text message based. There are a wide-variety and types of chatbots. As we were more looking to study the phenomenon of AI, we kept the definition loose in our study to ensure that the participants did not feel constrained by a particular definition which could lead to limited responses.

[2] See glossary for definition

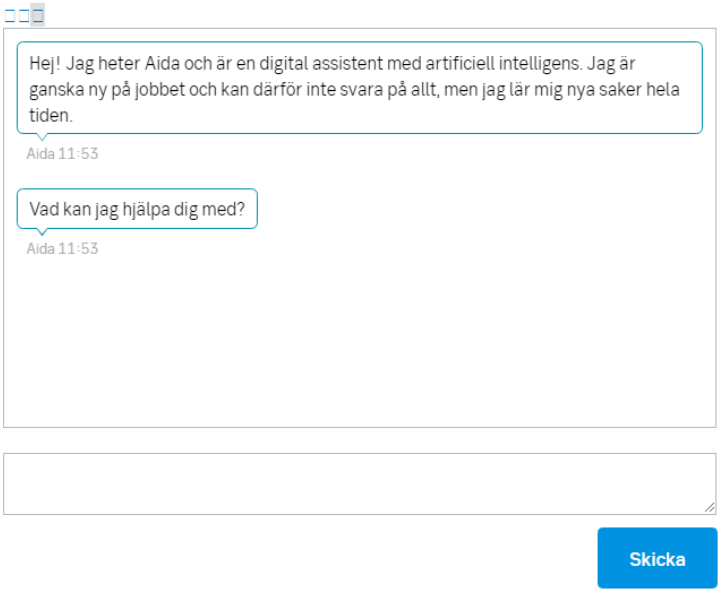


Figure 2: Screenshot of SEB's chatbot AIDA (Skandinaviska Enskilda Banken AB, 2018)

2.5 Purpose, Research Question, and Gap

As previously stated, there is a lack of understanding around AI as it relates to the business context. In the authors' opinions, this appears to be partly fueled by the inability to classify and define AI, and partly due to the rapid development of AI. Recently, there was a call for papers that outlined the need for more studies related to the effect of AI on the customer experience and the relationship of AI to humans, among many other topics (Corsaro et al., 2018). We believe that understanding the processes and ideas surrounding the adoption of AI will be utterly important in the future as AI technologies become more and more prevalent in our lives. As we have discovered in our literature review of AI, there is a lack of research that specifically addresses the area of technology adoption of AI. Gaining a high-level understanding of how people interpret the process of AI technology adoption can provide a starting point for academics and experts alike to further understand the future adoption of AI. Therefore, we pose the following research question:

> ***RQ**: How do people approach and interpret an ambiguous new technology (AI) as it verges on becoming an integral part of their everyday life?*

To answer this research question and fill the underlying gap in understanding the adoption of AI, we have engaged in a series of interviews with Generation Y[3] Swedes[4]. During the interviews, we explored the interpretation surrounding the adoption of a specific technology – chatbots. We delimited the investigation to chatbots and a specific group of individuals for two separate reasons. First, chatbots

[3] Born 1980 - 1999
[4] A native or inhabitant of Sweden

are one of the few AI technologies which users can interact with to actually see how the technology works. We selected Generation Y Swedes because they are the largest portion of the workforce (Winograd and Hais, 2014), and Swedes are highly ranked in terms of technology awareness (Baller et al., 2016), facilitating the conversation. By analyzing the insights of the participants, we were able to gain a basic understanding of not only their perceptions of adopting AI technologies but also how they felt about their adoption.

2.5.1 Expected Contribution

We expect that our research will create value in three ways. First, we expect to uncover individual's understanding and interpretation of AI-based technologies. This approach will help push forward the technology adoption literature as well as the literature surrounding AI in a business context. Second, we believe that our research can help clarify the expectations of end users of AI so that organizations can better understand what the end user expects in an AI system. This will help these companies to design products that better address the end users' needs. Finally, we hope to lay the groundwork for future studies investigating the adoption and acceptance of AI-based technology.

3. Literature Review

Starting with a review of the existing knowledge on AI in an organizational context, we then present the models explaining the adoption of technology. Multiple models of technology adoption exist, employing different research paradigms while explaining technology adoption. Even though we take an interpretivist stance to our study, which we motivate in the methodology section, we review positivist literature as well given that there is a large body of research investigating technology adoption through this lens. However, we are selective and brief in terms of the positivist literature we review and delve into more detail on the interpretivist strand of research in motivating our study and analysis. We delimit our review to those models and theories which have received considerable attention or empirical support and are considered well-established in the literature.

3.1 Artificial Intelligence from a Management and Organizational Viewpoint

The literature on Artificial Intelligence (AI) is nascent and researchers have only begun investigating AI as it relates to management and organizational studies. While there is no clear focal point of AI studies within business and management, the literature tends to focus on a few key areas: the use of AI in decision making, incorporating AI into the organization, building AI competencies, organizing around AI and the interaction between humans and AI. What follows is a short extract which showcases the existing knowledge within the field. It is important to note that existing literature on AI is so immature that most of the information on the topic stems from independent research by organizations and other research institutions, with significantly less research from a management studies standpoint. Consequently, our review is largely based on non-scholarly reports and articles. While these articles provide important insights about the extent of knowledge in the field, we keep our review on this section limited to present the general understandings within the field as most of the work is not peer-reviewed. However, presenting this knowledge is significant for understanding what AI entails for organizations, establishing the importance of expanding the knowledge on the field and further supports why AI is distinct from other technologies.

3.1.1 AI in the Organization: Creating Business Value

Given AI's current capabilities and its potential for the future, much of this limited literature is devoted to understanding how current knowledge denotes working with AI in an organization. Considering that AI has the capacity to analyze billions of units of data within seconds, many authors recognize that management will soon need to consider the "opinions" of an AI algorithm, similar to any other employee. Consequently, to obtain business value from AI, management must recognize opportunities

of business process algorithmization[5], or business processes where embedding AI delivers higher value for the business compared to deferring to human judgment. Schrage (2017) suggests that CEOs have four options to realize business value out of an AI: have an autonomous advisor assist in decision-making, automate business processes which are currently outsourced, create a culture where computer-human interaction is the norm, and provide full autonomy (i.e. avoid overriding algorithmic decisions) to algorithms when their power is demonstrable (Schrage, 2017). Similarly, Libert et al. (2017) suggest that CEOs will have to bring AI into the boardroom to improve decision making (Libert et al., 2017). Furthermore, Bughin and Hazan (2017) suggest that to maximize the benefits from AI, businesses should use AI to grow the business rather than simply cut costs, invest in both managerial and technical talent, revisit strategic goals and business lines, create a strong digital foundation and support the creation of an AI ecosystem (Bughin and Hazan, 2017). These approaches are further corroborated by other researchers with the acquisition of AI talent and creation of partnerships or ecosystems highlighted as critical for successful application of AI (Stanek, 2017).

3.1.2 AI in Our Lives

Further, investigations have focused on the collaboration between humans and machines, highlighting the importance of creating campaigns which focus on the introduction of AI technologies, its benefits, and reducing the fear of machines (Bersohn and Lake, 2017). Current thinking suggests that AI-powered machines should be thought of as collaborators rather than replacements for humans (Norman, 2017). Consequently, the literature portrays the uncertainty that individuals have in terms of the nature of the technology and implies that such uncertainty could inhibit adoption of the technology. It has also been suggested that successfully implementing AI into the organization will require an upgrade of employees' skills and a redesign of their accountabilities (Lacity and Willcocks, 2016; Norton, 2018; Ross, 2017). AI is thought to create a 'wicked problem[6]' for organizations because its impact will be high, but it will also fundamentally change the way of work (Holtel, 2016). Such technologies will change the balance of power within organizations and force individuals to boost their knowledge levels (Holtel, 2016). Moreover, collaborating with a machine is not a natural transition for most people which entails that a redesign of the human-machine relationship is important for yielding the best results from AI (Shukla et al., 2017). Thus, for successful implementation of AI, it is important to understand the workplace implications (Ransbotham et al., 2017). Accordingly, management will have to consider the role that humans will play in an organization and learn how to cope with this managerial challenge of human-machine interaction in the workplace (Agrawal et al., 2017). Research has long highlighted the

[5] See glossary

[6] Wicked problems are those problems which are hard to define and cannot be resolved by tested methodologies or best practices (Holtel, 2016)

importance of communicating the changes that intelligent systems will bring about to avoid resistance to its adoption amongst employees (Davenport and Harris, 2005). Therefore, current literature suggests that the adoption of AI is critical and at the same time problematic. This is suggested as factors such as fear of what AI can do and a shift in task responsibilities can cause resistance among individuals as their fundamental way of doing work changes. This is one further reason why AI is different from previous technologies and why understanding the factors influencing its adoption is important. These perceptions of AI entail that individuals outside of organizations must consider these implications too. To further understand these implications, we now transition to the literature pertaining to the adoption of technologies.

3.2 Technology Acceptance Model (TAM) & The Unified Theory of Acceptance and Use of Technology (UTAUT)

The positivist lens of the literature showcases several models attempting to explain the adoption of technology. Among the leading models is the Technology Acceptance Model (TAM) presented by Fred D. Davis in his Ph.D. thesis which endeavors to model how users come to adopt and use a technology. The theory suggests that once users are subjected to a technology two factors influence the use of that technology: perceived usefulness and perceived ease of use. Perceived usefulness is defined as "the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989). Meanwhile, perceived ease of use is defined as "the degree to which a person believes that using a particular system would be free of effort" (Davis, 1989). In Davis' original studies of the implementation of an electronic mail system and a business charting program, perceived usefulness had a significantly stronger link to the usage of the technology than perceived ease of use (Davis, 1989). Davis explains that conceptually this stronger correlation makes sense as users are driven to adopt a technology primarily because it fulfills a critical function for them, even if the system is difficult to use. On the other hand, no amount of ease of use can make up for a technology that does not fulfill a critically important function (Davis, 1989). In formulating TAM, Davis borrowed from the theory of reasoned action (TRA) which posits that a person's actual behavior is determined by his or her intention to perform that behavior (Fishbein and Ajzen, 1975). Empirical tests of TRA showed that behavior intention is significantly correlated with actual use (Fishbein and Ajzen, 1975). This is important to note because it means that individuals' self-reported intention to use is a strong determinant of actual adoption. Consequently, the TAM model posits that perceived usefulness and perceived ease of use will lead to the intention to use which is followed by the action realizing that intention. TAM is summarized in Figure 3 below.

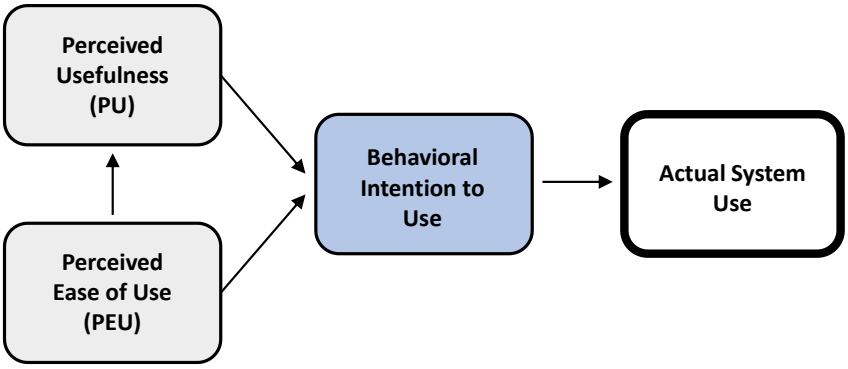


Figure 3: Technology Acceptance Model (Davis, 1989)

Moreover, to understand the determinants of perceived usefulness and how they influence changes of technology use over time, Venkatesh and Davis (2000) developed TAM 2 which incorporates additional theoretical constructs spanning social influence and cognitive instrumental processes. Since its original inception in the 1980s, TAM has been extensively studied with new theoretical constructs developed for different contexts. This extensive conceptualization has created chaos and clutter in the literature. In an attempt to remove this clutter and chaos within the technology acceptance literature, Venkatesh et al. (2003) have formulated the Unified Theory of Acceptance and Use of Technology (UTAUT) which incorporates eight competing models of technology adoption and encompasses 32 constructs explaining the phenomenon (Venkatesh et al., 2003). Venkatesh et al. theorized that four of these constructs were strongly correlated to intention to use. These include performance expectancy which is akin to perceived usefulness, effort expectancy which is similar to ease of use, social influence defined as the degree to which one perceives others feel is important one uses a technology, and facilitating conditions defined as the degree to which one perceives there is organizational and technical support using a technology (Venkatesh et al., 2003). Empirical testing of UTAUT suggests that the model can account for 70% of the variance in intention to use a technology (Venkatesh et al., 2003). UTAUT is largely seen as the peak of positivist research on the acceptance and use of technology, where Venkatesh et al. claim that we could be approaching the limits of our ability to understand and account for the acceptance of technology.

3.2.1 Critique of TAM and UTAUT

In spite of the extensive literature on and empirical support for these models, they have certain shortcomings. First, even though a high correlation has been found between actual behavior and intention to perform that behavior, Dishaw and Strong (1999) claim that TAM has higher explanatory power for usage intention but less for actual use (Dishaw and Strong, 1999). The second critique concerns the state of chaos in the field, whereby the knowledge is fragmented and there is a lack of coherent integration between the models (Bagozzi, 2007). In identifying the shortcomings of TAM,

Bagozzi explains that arguments can be made to suggest that important variables predicting behavior have been excluded, with future research likely to uncover new determinants of technology adoption (Bagozzi, 2007).

Bagozzi also criticizes UTAUT for its high complexity arguing that in spite of the high number of independent variables, it is likely that some predictors have been left out (Bagozzi, 2007). This entails that the model is not parsimonious compared to TAM and still misses out on rich explanations of the phenomenon of technology adoption (Van Raaij and Schepers, 2008). Furthermore, as noted by Bagozzi (2007), the deterministic models of technology adoption fail to consider the alternative ways that people come to a decision about adopting a technology (Bagozzi, 2007).

In this brief literature review, we have concisely presented the original TAM model and UTAUT and noted the developments of the models throughout the years. The reason for this brief introduction to these models is that the theoretical constructs presented, namely perceived usefulness and ease of use, have been to some degree incorporated in interpretivist studies of technology adoption, such as those of Lin and Silva (2005). As such, we present TAM as it inspires several models relating to technology adoption including technological frames, which we present in section 3.4.

Considering the shortcoming of TAM and UTAUT, we now turn to the interpretivist approaches to studies of technology adoption which are based on the premise that people's actions are formed on the basis of their interpretations of the world (Berger and Luckmann, 1966; Smircich and Stubbart, 1985; Weick, 1979). We begin by looking into those concepts that have arisen from social sciences. We argue that briefly examining concepts in social theory informs our analysis and assists us in providing a richer answer to the research question. However, it is important to note that concepts resulting from social theory are broad in scope and depth. Therefore, the goal of this review is modest and simply serves to show how we arrived at technological frames as a concept that informs our analysis. As such, we begin by briefly examining the concepts of frames and framing analysis as originally posited by Goffman (1974) in his work "Frame Analysis: An Essay on the Organization of Experience". These concepts serve as backbones of social cognitive literature which have influenced the concept of technological frames (Davidson and Pai, 2004).

3.3 Frames and Framing Analysis

As originally posited by Goffman (1974), conceptual frames can be considered as means of organizing our experience (Goffman, 1974). Through the concept of frames, Goffman attempted to explain how frames structure individuals' perceptions of their reality. Goffman (1974) considers frames as "schemata of interpretation," anecdotes, and stereotypes, which allow individuals to understand and ascribe meaning to a phenomenon, and respond to events relating to that occurrence (Goffman, 1974).

In other words, individuals' framing of a phenomenon guides their actions toward it. Azad and Faraj (2011) similarly refer to frames to denote interpretive schemes which actors utilize in their sensemaking of events they encounter (Azad and Faraj, 2011). They continue to explain that framing is the process by which actors draw virtual boundaries, akin to a picture frame, in deciding what lies within and outside the frame, which they use to make sense of phenomena (Azad and Faraj, 2011; Goffman, 1974). That which lies within the frame becomes more salient as actors interpret occurrences (Azad and Faraj, 2011).

In explicating the notion of frames, Goffman (1974) developed 'framing analysis' as a method of analyzing the process of how people understand and ascribe meaning to their reality. Goffman's (1974) idea of framing analysis is based on the notion that people make sense of phenomena or social situations by establishing meaning through their frames of understanding (Goffman, 1974). The way people ascribe meaning to social phenomena can be transformed and retransformed in different ways. As Goffman (1974) notes, "framing is not a perfect process, people mis-frame, frame ambiguously or frame disputatiously" (Goffman, 1974). Consequently, people may have false beliefs about an occurrence or may be unclear about it (Goffman, 1974). For the purposes of this study, we will not delve in detail on the concepts surrounding the processes of framing and reframing since the review of technological frames provides a more adequate analytical tool for investigating technology adoption. However, as the concept of technological frames has been influenced by the literature on frames, we felt it is important that the reader has a basic understanding of frames and its dynamics. As such, we now turn to the literature on technological frames of reference (TFR), also referred from here onwards as technological frames.

3.4 Technological Frames of Reference (TFR)

As illustrated, in our study we take inspiration from the concept of technological frames. The major premise of this concept is to investigate technological development, use, and change in organizations by examining people's underlying knowledge, expectations, and assumptions about technology (Orlikowski and Gash, 1994). As Orlikowski and Gash (1994) argue," to interact with technology, people have to make sense of it. And in this sensemaking process, people develop particular assumptions, expectations, and knowledge of the technology, which then serve to shape their subsequent action towards it" (Orlikowski and Gash, 1994). They define the concept of technological frames as follows:

> *"We use the term technological frame to identify that subset of members' organizational frames that concern the assumptions, expectations, and knowledge they use to understand technology in organizations. This includes not only the nature and role of the technology itself, but the specific conditions, applications, and*

consequences of that technology in particular contexts of use" (Orlikowski & Gash, 1994).

These individuals' interpretations of these phenomena, in this case around technology, guides how they make sense of and act toward that technology, which is exhibited in their actions within an organization (Orlikowski and Gash, 1994). Therefore, as Davidson (2002) notes, "framing is inherently a sensemaking process" where "frames serve as problem-solving templates and interpretive filters" (Davidson, 2002). Individual's characterizations of technology are originally broken down into three domains: nature of technology, technology strategy, and technology in use (Orlikowski and Gash, 1994). See Figure 4 below for the definitions and exemplifications of each of these original domains. It is important to note that, as argued by Orlikowski and Gash, domains are contextual, meaning they are relevant depending on both the organizational context and unit of analysis (Orlikowski and Gash, 1994). Therefore, these domains are specific to the study of Orlikowski and Gash and are not necessarily generalizable across studies. Nevertheless, they serve to illustrate how Orlikowski and Gash originally investigated individuals' technological frames.

Domain	Definition	Examples of domain specific viewpoints
Nature of Technology	"People's image of the technology and their understanding of its capabilities and functionality"	• Misunderstanding about the technology • Interpreting the new technology in terms of the old
Technology in Use	"People's understanding of how the technology will be used on a day-to-day basis, and the likely or actual conditions and consequences associated with such use"	• Focus on training • Priority and resources
Technology Strategy	"People's views of why their organization acquired and implemented the technology. It includes their understanding of the motivation or vision behind the adoption decision, and its likely value to the organization"	• Technology viewed with skepticism • Motivation is driven from changing the way of doing business

Figure 4: Original Technological Frames domains as defined by Orlikowski and Gash (1994)

Within an organization, these frames are shared with other members, whereby individual's personal technological frames affect the frames of others (Orlikowski and Gash, 1994). This entails that social interactions and negotiation among key stakeholders often entail changes in frames (Davidson, 2006; Lin and Silva, 2005; Orlikowski and Gash, 1994). Moreover, individuals often belong to multiple social groups, meaning that they can have several technological frames (Bijker, 2010). This process entails that individuals' frames are seldom rigid and often change through different social processes such as negotiation and power (Azad and Faraj, 2008; Orlikowski and Gash, 1994). Some studies have investigated specifically how perceptions about technology are framed and reframed and what management can do to influence this process and harness it to achieve a successful integration of technology (Lin and Silva, 2005). These social processes are only possible due to characteristics that

technological frames possess, namely that they are devices for sensemaking, flexible, and context-specific, meaning that they emerge within social interactions in situ (Lin and Silva, 2005)

As Davidson and Pai (2004) note, while Orlikowski and Gash (1994) grounded their conceptualization of technological frames on the individual level, they "addressed group level frames by defining them as shared aspects of individual frames" (Davidson and Pai, 2004; Orlikowski and Gash, 1994). The idea behind the conceptualization of technological frames is to examine how incongruences among groups' interpretations of technologies affect its adoption or integration in organizations. Where frame incongruences exist, technology adoption becomes difficult. Consequently, it is desirable that a shared technological frame forms among groups which makes the adoption of technology within the organization a simpler process (Orlikowski and Gash, 1994).

This, in turn, entails that organizations can form inter-organizational technological frames impacting the use and adoption of a technology. Accordingly, technological frames exist on the level of individuals, groups, and institutions (Barrett, 1999; Davidson, 2006; Kaplan and Tripsas, 2008). Further, "actors' interactions both shape and are shaped by the emerging collective technological frame" (Kaplan and Tripsas, 2008). In turn, the way a technology evolves is shaped by the choices and actions of each of these actors (Kaplan and Tripsas, 2008). Understanding these dynamics of how technological frames are iteratively shaped provides an important analytical tool when analyzing technology adoption from an individual's viewpoint. This is because their actions, as noted by Kaplan and Tripsas (2008), are influenced by other actors' technological frames.

Having discussed how different actors' technological frames influence the actions of other actors, it is important to note that power plays a vital role in this framing and reframing process. Those with organizational power, in the form of access to funds or social ties, often exercise their power in the social interactions to control the framing process, thereby largely influencing the emergent dominant technological frame (Yeow and Sia, 2008). The investigation of this negotiation process goes further to highlight how the exercise of power can lead to a dominant frame which requires end users to work around the system, entailing how the exercise of power can inhibit the adoption of a technology (Sobreperez, 2008). Furthermore, this indicates the importance of those with less power in influencing the creation of a shared frame which then eases the adoption process of the technology (Sobreperez, 2008). While the notions of power are brought up in the context of organizations, we argue that they are important to bring up in the broader context. The reason is that power plays a role in how a dominant technological frame in the societal level emerges and consequently aids in interpreting how individuals perceive and make sense of their own technology adoption. Before turning to the theoretical underpinnings which guide our analysis of individuals' interpretations of technology adoption, we provide a brief critique of TFR to acknowledge its shortcomings.

3.4.1 Critique of Technological Frames

While the concept of technological frames has been consistently used in analyzing processes of technology adoption within organizations, it possesses certain limitations which should be noted. First, scholars such as Yeow and Sia (2008) have claimed that technological incongruences may not be consequential and total alignment of technological frames among groups within an organization may not even be necessary (Yeow and Sia, 2008). Davidson and Pai (2004) note that the notion that incongruences are detrimental, needs to be critically examined (Davidson and Pai, 2004). Previous social cognitive research suggests that heterogeneity in frames could prove inconsequential or even beneficial depending on the context (Walsh et al., 1988). Specifically, incongruence could stimulate discussion and critical thinking regarding technology adoption which could prove beneficial (Hsu, 2009).

Second, as Davidson (2006) points out, current literature on technological frames fails to consider the origins of individuals' and groups' frames (Davidson, 2006). Studies of frames outside organizational boundaries may be important to understanding their origin and how they can be influenced (Davidson, 2006). Moreover, further exploration of the societal and cultural origins of frames have pointed to the existence of institutional logics (Davidson, 2006). They are defined as "widely held beliefs and socio-cultural structures that inform practice" (Scott, 2001). These institutional logics are continually constructed and negotiated among members and play an influential role in shaping the interpretations of social reality for others (Barrett and Walsham, 1999; Davidson, 2006; Lin and Silva, 2005). As such, they influence how individuals think and act on a technology (Barrett and Walsham, 1999; Davidson, 2006).

Lastly, another important limitation pertains to methodology in that technological frames often look at individuals' frames at a single point in time, thereby treating them as static (Davidson and Pai, 2004). Consequently, literature fails to investigate how frames change over time whereby a longitudinal design can rectify for these limitations (Davidson and Pai, 2004). Following this critique, we now turn to the theoretical underpinnings which guide our study. In doing so, we explain why frames and technological frames provide a useful analytic tool for understanding adoption.

3.5 Theoretical Underpinnings

Previous studies have recognized that technology develops as a result of social construction and technical advancement (McBride, 2003). Consequently, the success of a technology depends on both technical and social aspects. Technical aspects cannot guarantee the technology's social acceptance just as social aspects cannot guarantee its adoption. Thus, in our analysis, we are guided through the interpretive lens which helps gain a deeper understanding and explain the adoption of chatbot technology among individuals. In explaining our theoretical underpinnings, we explicate which notions

on frames and technological frames are important in aiding our understanding and analysis of the phenomenon.

First, as noted in the literature review, Goffman (1974) formulated the idea of framing analysis based on the notion that individuals establish meaning through their frames of understanding and make sense of phenomena on that basis. However, as he observed, framing can be transformed multiple times because initial framing is imperfect and it requires alteration. As such, this recognizes that individuals can miss-frame, frame events incompletely or ambiguously, entailing that they may have false beliefs about the phenomenon of AI (Goffman, 1974).

Second, as originally postulated by Orlikowski and Gash (1994), technological frames exist at the individual level (Davidson and Pai, 2004; Orlikowski and Gash, 1994). The implication is that frames are individually held. Therefore, while the framework was developed with the primary focus of understanding technology adoption and development in an organizational context, it does still examine how people interpret and give meaning to technology on an individual level. This analytic perspective could be useful in explaining the adoption of unfamiliar technologies such as AI outside the organizational context as well. Specifically, the notion that people form assumptions, knowledge, and expectations around a technology which affects their conceptions of the technology and their use, provides a useful analytical lens to study the adoption of AI-based technologies. As Lin and Silva (2005) note, there is a wide acceptance of the idea that technology adoption is dependent to a vast extent on people's perceptions of that technology (Lin and Silva, 2005). Consequently, using the technological frames concept on the individual, as the unit of analysis, to draw insights on their adoption of technology, is valid as an analytic approach. Such an approach has been previously used by Treem et al. (2015) to analyze individuals' expectations around the use of a technology, namely enterprise social media (ESM) (Treem et al., 2015). Specifically, the authors use the individual as the unit of analysis to investigate how employees develop interpretations about a technology they first encounter outside the office and the effect that has on their subsequent behavior at work (Treem et al., 2015). These studies suggest that using technological frames as an analytical tool can be applicable to uncovering insights as to how their interpretations around a technology influence their adoption. Moreover, as Davidson and Pai (2004) assert, "technological frames of reference provide a flexible approach to explore interpretive issues in information technology design, implementation, and use" (Davidson and Pai, 2004).

Third, the notion that people form conceptions around a technology and its use in the context of the social reality they are surrounded by entails that technological frames are dynamic phenomena (Lin and Silva, 2005). This further supports the notion that technological frames are not shaped solely in an organizational context, but are also shaped as a result of societal and cultural factors (Barrett, 1999;

Davidson, 2006). The implication for our study is that societal and cultural factors can shape technological frames and influence how individuals make sense of a technology.

Fourth, as previous scholars recognize, previous experiences and affiliations give shape to users' interpretations about technology (Kaplan and Tripsas, 2008; Orlikowski and Gash, 1994). Consequently, this entails that prior experiences, including experiences with other technologies, influence individuals' interpretations of the technology. Such experiences help individuals evaluate technologies against a set of performance criteria, which shapes their interpretation (Kaplan and Tripsas, 2008). The implication for our study is that it is useful to investigate and question individuals on previous experiences in both gauging and analyzing their interpretations around AI technologies.

Finally, it is important to note that technological frames exist on the societal level. The concept of TFR has previously been used to analyze the development of technological frames and change in the organizational field (industry) as the unit of analysis (Barrett, 1999). Barrett's analysis at this level uncovered how societal and cultural norms influence individuals' interpretations around technology (Barrett, 1999). This implies that the concept should not be locked into the single context of uncovering implications on the organizational level of analysis. While calls for analyses of organizational fields have been made, Davidson and Pai (2004) argue that such research moves "away from social cognitive research in the direction of SCOT research, where socio-technical theories such as actor-network theory (ANT) (Latour 1987) could provide insights on frame change processes" (Davidson and Pai, 2004). However, we do not delve into SCOT research and socio-technical theories such as ANT because in our study we only examine one set of actors in the network, whereas ANT delves into analyses of a much broader network of actors and the relationships among them (Callon, 1990). As such, ANT is less useful as an analytical tool in our study. However, the implication for our analysis is to recognize that other actors and relationships among actors exist. The importance of recognizing this lies in the assertion that societal and cultural standards can shape how users make sense of and act toward a technology, thereby influencing their perceptions of adopting the technology.

In order not to lose sight of the aim of our study, we have delimited our review to those theories with stronger empirical support and those which provide a useful analytic lens. For our study, this means chiefly examining the theories developed around technological frames. These lenses can help explain individuals' interpretations and perceptions around chatbot technology and aid our understanding as well as explanations of the phenomenon. Moreover, seeing as dealing with fluid realities is challenging to analyze, we ultimately make choices of which contexts to analyze and which parts to focus on, as it becomes difficult to capture everything. Practical limitations regarding data collection entail that we cannot successfully investigate the entire network of relationships between actors in the context of our

study. Having covered the theoretical underpinnings guiding our study, we now turn to the methods we have used to conduct our study.

4. Methodology

In this section, we cover the methods and procedures of our study to give the reader an understanding of methodological fit. We begin with a brief discussion of how we reached this type of study. This is followed by all parts of the "Research Onion," a tool which helps break down the methodology into digestible pieces.

Prior to delving into the procedures and methods of our study, we would like to ensure the reader understands our process to reach this type of study. As researchers, we had an initial interest in the field of AI as it is extremely prevalent and relevant now and into the future. As we learned more about AI in a business context, we began to appreciate that there was an immense need to understand the relationship between AI-based technology and the user of said technology. Initially, we set out to explore AI in a professional setting as many studies of technology have been completed in such settings. However, we found that completing such a study could prove difficult for two main reasons.

First, we realized that the definition and reach of AI is not well understood. People, even though working with it on a daily basis, are overwhelmed by the utter scope and level of complexity of what *could* be considered "AI." The sheer confusion created a need for us to approach the topic of AI in a different way. The second barrier we encountered was that many companies consider AI systems to be a competitive advantage and have difficulties allowing outsiders, even researchers, access to their systems. Indeed, one of the companies we approached was so skeptical of our intentions that they required a verified email address and a reference from our supervisor to even entertain the idea of a study!

So, how could we solve studying such an ambiguous and protected technology? Our initial thought was to find a system that was conceptually easy to understand but still used AI-based technology. We were able to identify chatbots as such a system. Chatbots themselves mirrored the customer support chat function, so their functionality was clear and this meant that any participants could discuss them with some level of ease. The level of protection around the systems meant that finding a company or professionals employing AI technology who were open to having a discussion with us was low, as we had previously discovered. Thus, we formed the idea to study one subset of people – Generation Y Swedes. This would allow us to discuss the technology with a reachable group of people and still obtain great data. As such, we were able to study a technology that is both difficult to understand and difficult to gain access to. Now that we have explained our process, we will dive into the specifics of our methodology.

In order to illustrate the choices in our study, we will use a model produced by Saunders, Lewis, and Thornhill, known as "The Research Onion." (Saunders et al., 2012) This model breaks down a study into digestible pieces (layers) in order to motivate and illustrate why a certain set of methods was chosen. The visualization of our methodology can be seen below in Figure 5.

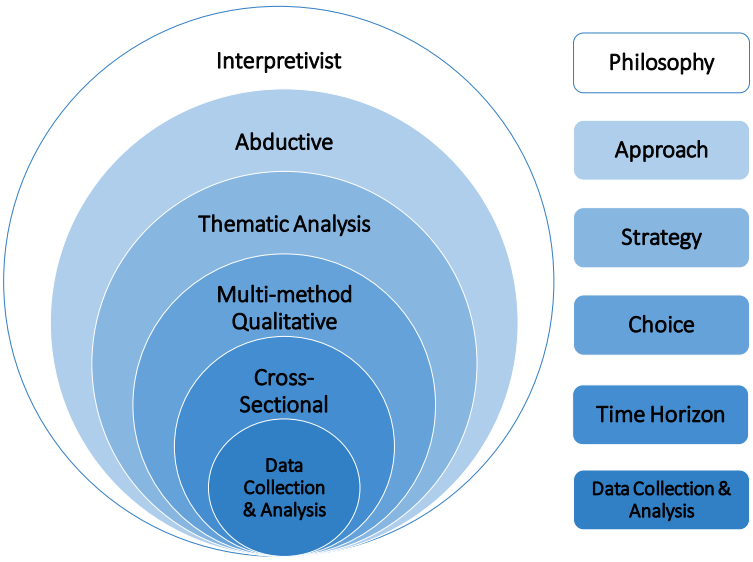


Figure 5: The Research Onion Framework (Saunders et al., 2012)

4.1 Research Philosophy

As we strive to have a deeper understanding of the topic of technology adoption, we have chosen to take an interpretive approach to studying AI. An interpretive approach does not adopt 'laws' that explain human behavior but rather takes a view that enables we, the researchers, to delve into the complexities of human behavior and grasp the subjective meaning of social action (Bryman and Bell, 2011). We also believe and acknowledge that simply by engaging with our subjects, we create a subjective reality and influence their perceptions (Walsham, 1995). We have used this approach to understand the "why" of technology adoption, rather than attribute a series of rules around what causes people to adopt a certain technology. This approach leads to an in-depth investigation as well, rather than a broad understanding of a topic (Flick, 2009).

4.2 Research Approach

There are three main accepted approaches to conducting research: deductive (theory to data), inductive (data to theory) and abductive (back and forth between data and theory). Our research is based in an abductive approach to exploring and developing theory. We set out to explore a phenomenon, technology adoption related to AI, which as far as we know has not been explored from a business standpoint with existing theories in the field of technology adoption. Our process (see Figure 6) combined induction and deduction approaches to go back and forth between theory and data and

build our own viewpoints, grounded in existing theories and adjusting where we feel it is necessary (Saunders et al., 2012).

4.3 Research Strategy

Much of the time, strict procedures are followed when outlining a research strategy that describes the how, when and how much of data collection and analysis. As our study is fairly nascent and we are taking an interpretivist and abductive stance, we have a less prescriptive approach to our research. Therefore, we have chosen to engage in a Thematic Analysis of our data. Thematic Analysis (TA) is described by Braun and Clark (2006) as a method for "interpreting, analyzing and reporting patterns within data." More specifically, we conduct a *latent themes analysis* that examines the underlying ideas, assumptions, and conceptualities in the data, which is in line with an interpretivist philosophy. This is in contrast to a semantic themes analysis, which is more of a description of the surface meaning of the phenomena. This type of analysis allows for a series of coding (in our case we used the program Nvivo), the creation of themes, repetition of thematic selection and verification of data, and finally a reporting of data (Braun and Clarke, 2006).

This method can be compared to Grounded Theory as both theories suggest an iterative process of coding to build insights, however, there are two major differences. First, Grounded Theory is generally considered to be theoretically bounded, meaning that it cannot move beyond the theory and into a more subjective understanding of reality (Braun and Clarke, 2006). The second major difference is that Grounded Theory suggests that a researcher should engage in simultaneous data collection and analysis (Glaser and Strauss, 1967), while Thematic Analysis does not set such strict boundaries. As we attempt to comprehend the subjective understanding of reality and analyze the data after it was gathered, we have selected TA as a strategy.

4.4 Research Choice

Edmondson and McManus (2007) describe the state of prior theory and research as a good indication of the type of study that one should conduct (nascent, intermediate, mature), where nascent is the least researched and mature is the most. They suggest that one should engage in qualitative, open research design when exploring a topic where prior theory is nascent (Edmondson and Mcmanus, 2007). As technology adoption in the field of AI is largely unexplored, we consider our topic to be nascent and therefore have chosen to have an exploratory, multi-method qualitative study. A multi-method qualitative study entails more than one method of qualitative data gathering (Saunders et al., 2012). In our case, this is semi-structured interviews, observation data during interaction with a chatbot, and transcript data from said interaction. The main data is the interviews, with supporting data coming from the observations and transcript data.

4.5 Data Collection & Analysis

Our data consists of 14 qualitative interviews, 2 of which were considered pre-study. These interviews were conducted with Generation Y Swedes and were all completed in person and in the Stockholm area. The following section explains our procedures, structures of data gathering, and analysis in detail.

4.5.1 Pre-Study

The interviews in the pre-study, as well as the main study, consisted of three parts and three methods of triangulating data. The full description of the procedures is in the main next section. Our pre-study consisted of two, semi-structured interviews. The purpose of the pre-study was to determine the usability and flow of the interview questions, observations, and interaction with a chatbot. This was used to strengthen our interview guide, interaction with the chatbot, and the observations. Overall, there were very few modifications that were needed for the interview guide or procedures after the pre-study interviews. We were able to determine that the interactions and questions created a viable amount of data that was relevant to the topic. Therefore, we concluded that the pre-study interviews were equally usable as the main study interviews in the analysis.

4.5.2 Main Study Design

The main study consisted of 12, semi-structured interviews lasting between 35 and 48 minutes, split into three parts. We had 12 main study interviews as around the 10th interview we began to see a high level of homogeneity in the responses. As such, we held two more main study interviews to ensure this was accurate and round off the interviews. Though we have an exploratory study into AI, semi-structured interviews were selected because we still wanted to focus on a subset of the data - technology adoption. We had a rather clear focus that helped guide us in the interview (Bryman and Bell, 2011). We had the preliminary lenses of technological frames to help us determine the initial areas of questions to focus on. For further details, see the interview guide in the appendix.

<u>Part I</u>

The first part was a brief interview to determine the participant's current level of knowledge of chatbots as well as the general perception of the technology. We initially began with general questions to help put the interviewee at ease and allow us to gain a rapport (Flick, 2009). After that, we moved into more specific questions centered on three main topics: current understanding of chatbots, their usefulness, and scope of usability. This section of the interview usually accounted for approximately 20-30% of the entire time that we spoke to the participants.

Part II

The participants were then introduced to chatbot technology by being asked to converse with a chatbot named AIDA, used by Skandinaviska Enskilda Banken AB (SEB Bank) as a customer service tool[7]. The interaction itself was broken into two phases. During Phase I, the participants were asked to attempt to open an account at SEB through the chatbot interface. They were given instructions that they should get as far as possible without disengaging from the chatbot interface, meaning not clicking links or calling SEB customer service. This task was deemed as "not possible to complete" by the researchers. In order to open an account, one needs to login to the internet bank or call customer service. In Phase II, the participants were asked to try to find out how to use Mobile Bank ID. Mobile Bank ID is a citizen identification software used in the Nordics and is used for many things from payments to bank login ("This is BankID," 2018). The participants were told that they should follow the prompts they are given and "pretend" to be able to complete the steps. This allowed the participants to get an understanding of how a full process would work with the chatbot. As the participants were given one task they were able to complete and one they were not, it allowed them to see the wider spectrum of possibilities while using the chatbot. It should be noted that this section of the interview was not an experiment, as an experiment uses predictive hypothesis rather than an open research question (Saunders et al., 2012). It was rather an exposure to the technology to ensure that the participants had an understanding of what chatbot technology entails so we could have a deeper conversation with them regarding the technology. This part of the interview lasted for about 10% of the entire interview time.

Part III

The remaining 60 – 70% of the interview was an in-depth investigation of the participants' feelings, perceptions, attitudes and intended use of the technology. During this part of the interview, we asked questions pertaining to these key areas:

- Nature of AI technology
- Experience from interaction with the chatbot
- Future expected and/or desired development
- Implications of the technology

These areas of questions were used to tease out answers to understand "how" and "why" they would or currently do use the technology (Bryman and Bell, 2011). This would help us best understand the likely reasons for adoption.

[7] Please refer to Figure 2 in Section 2 for an example of what the SEB chatbot looks like

Below (Figure 6) is a visualization of the process of how we have conducted our analysis which combines the elements of our research philosophy, approach, strategy, and choice.

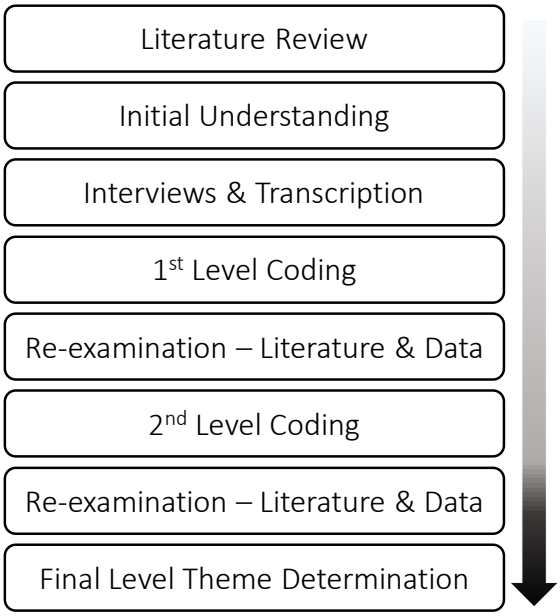


Figure 6: Our process of understanding & analysis

4.6 Sampling

For our project, we had to decide on two different samples.

4.6.1 Chatbot Selection

The first was the determination of which chatbot tool we would use during the interview to introduce our participants to a chatbot technology. Primarily, we began by asking an expert on chatbot technology what the main chatbot development companies were. He helped us identify two companies and one platform.

Companies: IPSoft, IBM (Watson)

Platform: Facebook

These three gave us a starting point to begin looking into chatbots that are available on the market. It also gave us a comparison to what we should be looking for. We used internet search, ranking list, and websites to determine both the current level of functionality as well as where to find chatbots. We built a list of 17 chatbots that we could potentially use for our study. This method could be considered similar to the virtual snowball method, which uses digital referrals and connections to build and develop participant pools in a study (Baltar and Brunet, 2012). In our case, we were building a list of chatbot tools we could use and websites were our sources.

We began an analysis of the available options and filtered them on several separate criteria to determine which chatbot to use in our study. A full overview of the rankings can be seen below in Figure 7. Our system used exclusion criteria[8] to determine whether or not the chatbot could be used for our study. First and foremost was a determination as to whether it had a clear commercial purpose, as we are after all writing about business themes. We then looked at whether or not the chatbot could be accessed without logging into a platform or account. This was important because we would need to have people access the chatbot conveniently and anonymously to ensure all participants have the same initial setup. Finally, we wanted to ensure that we would be able to get a copy of the chat transcript to check the data against what the participants said in the interview. This process led us to three chatbots that made it through the initial screening: SEB Bank, Fidelity Investments, and Nordea Bank. All three were customer service tools at financial service firms.

Rank	Name of Company	Platform/ Developer	Type of chatbot	Transcript accessible?	Requires login?	Commercial Purpose?	Subjective Rating of Functionality
1	SEB Bank	IPSoft	Customer service	Yes	No	Yes	Average
2	Nordea Bank	Undisclosed	Customer service	Yes	No	Yes	Average
3	Fidelity Investments	Unknown	Customer Service	Yes	No	Yes	Average
4	Northface	IBM Watson	Style Finder	No	No	Yes	Average
5	Swedbank	Nuance	Customer service	No	No	Yes	Average
6	Amtrak	Undisclosed	Customer Service	No	No	Yes	Average
7	Tommy Hilfiger	Facebook	Style Finder	Yes	Yes	Yes	Average
8	Whole Foods	Facebook	Recipe tracker	Yes	Yes	Yes	Low
9	SkyScanner	Facebook	Flight Finder	Yes	Yes	Yes	Low
10	H&M	Kit	Style advisor	No	Yes	Yes	High
11	RightClick	Undisclosed	Building website	No	Yes	Yes	Low
12	Cleverbot	Proprietary	Conversation bot	Yes	No	No	Average
13	Poncho	Facebook	Weather App	No	No	No	High
14	Epic Reads	Facebook	Book Finder	Yes	Yes	No	Low
15	Ruuh	Facebook	Conversation bot	Yes	Yes	No	Average
16	Spotify	Proprietary	Song Finder	Yes	Yes	No	Low
17	Woebot	Proprietary	Therapy	No	Yes	No	Average

Figure 7: Chatbot options for our study (ranked most to least viable)

From these three, we were able to quickly exclude Nordea's as it was only available in Danish. We were left with SEB and Fidelity. After conversing with both and gaining a deeper understanding of their capabilities, we were able to determine that because we are in Sweden and our participants will be Swedish, the Fidelity chatbot would not work. It required a basic literacy of American financial systems. As such, we selected the SEB Bank chatbot, which was only able to communicate in Swedish. This would have further implications on our sampling for the participants.

[8] Refers to criteria which automatically disqualifies

4.6.2 Interview Participants

Our second sampling dimension was to determine the interview participants. As the nature of TA[9] is not to be too prescriptive, there is not a clearly suggested sampling technique (King, 2004). However, for our study, we chose homogeneous, purposive sampling. We used this sampling technique because we wanted to understand the viewpoint of one group of people – Generation Y (Millennials) Swedes (Bryman and Bell, 2011).

4.6.3 Why Swedish People?

According to the 2016 Networked Readiness Index, an index produced by the World Economic Forum which ranks countries according to their propensity to exploit technology, Sweden is ranked as the 3rd highest (Baller et al., 2016). This means that the country prioritizes communication technologies to increase competitiveness. On the individual level, Sweden is ranked 4th, meaning there is a high level of penetration and diffusion of internet accessible devices (Baller et al., 2016). This means that the likelihood of awareness of the technology is not only higher in Sweden, but that the likelihood that a Swede has used chatbots, or other means of more advanced communication is higher as well. The second reason that we chose Swedish people is that the chatbot that we determined was best for the study necessitated that the participants spoke Swedish. Finally, as we are Masters Students in Sweden, we chose Swedes for the practical reason of location.

4.6.4 Why Generation Y (Millennials)?

According to a study that was completed by the Brookings Institute, by 2024, Generation Y will make up approximately 75% of the workforce in the US (Winograd and Hais, 2014). Assuming the statistics are at all similar in Sweden, the future workforce will soon be Generation Y. We wanted to study the people that would be most likely to be in a position where they could drive the development and discussion around the technology. A further reason we studied Generation Y is that we felt that a certain level of familiarity with the technology would be necessary to facilitate a deep and meaningful conversation about the technology. A recent survey by Bresman and Rao (2017), showed that Generation Y, specifically in Sweden, saw the use of technology in a workplace setting as highly valuable, as compared to Generation X, who saw it as a hindrance (Bresman and Rao, 2017). Again, this gives further credence to our viewpoint that Generation Y has a higher familiarity and interest in AI-based technology than other generations.

[9] Thematic Analysis

4.7 Quality of the Study

4.7.1 Dependability

Dependability ensures that the study is consistent and repeatable (Lincoln and Guba, 1985). In order to increase dependability, we have had help from our supervisors and other researchers to complete an *inquiry audit*[10], also known as an external audit, to ensure that the study is well understood and to evaluate the accuracy of the interpretations and conclusions (Lincoln and Guba, 1985).

4.7.2 Credibility

In order to ensure that our results were credible, we have engaged in three methods to increase credibility. First, we used the process of *peer debriefing* to share our insights and processes in order to validate our approach and perspective (Lincoln and Guba, 1985). This was done both with our supervisors as well as with fellow researchers. Second, we had the participants in the study check the material from the interviews for congruency with their viewpoints, known as a *members check* (Lincoln and Guba, 1985). Finally, we engaged in *triangulation* as we had multiple researchers who were viewing the data and the data originated from multiple sources (Pandey and Patnaik, 2014).

4.7.3 Transferability

A qualitative study by its nature generally focuses on individuals in a specific group or category, which can lead to a more focused approach, creating issues for transferability. To mitigate these issues, we have chosen to increase transferability by using a technique known as *thick description*. Thick description refers to the detailed account of field experiences in which the researcher makes explicit the patterns of cultural and social relationships and puts them in context (Holloway, 1997; Lincoln and Guba, 1985). In other words, we will not only explain what was said, but also explain the context of the situation.

[10] A researcher not involved in the research process evaluates the study for consistency (Lincoln and Guba, 1985)

5. Empirics & Analysis

In the following section, we will present the findings from the interviews with our participants. We will discuss three separate framing constructs which we believe are driving the interpretation of AI-based technologies among our participants. As previously stated, our empirics and analysis will discuss the understanding of AI through an interpretivist lens, motivated from the theory of technological frames and derived from a process of Thematic Analysis.

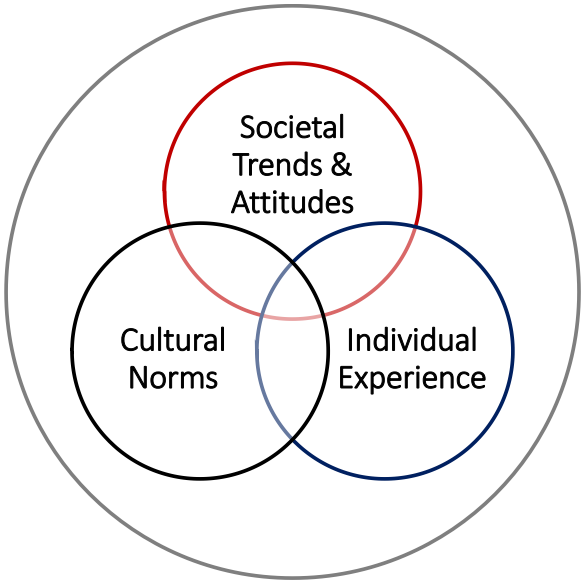


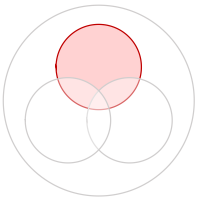
Figure 8: Identified constructs and technological frame (outer circle) of our participants

In the visualization above (Figure 8), one can see three separate *framing constructs*[11] (henceforth referred to as *constructs*) that we have recognized help shape our participants understanding and attitudes toward chatbot technology. While we do not believe that these three areas account for the entire perception of the technology, they were the most prevalent during our thematic analysis of the interviews and other data. As noted by many authors, including Orlikowski and Baroudi (1991) as pertaining specifically to IS[12] studies, in interpretivist studies and analyses the researchers are not separated from the study (Orlikowski and Baroudi, 1991). While we have used methods such as triangulation and multiple researchers to help decrease bias, we recognize that our perceptions are part of the choice of constructs and can influence the themes. Nevertheless, these constructs are grounded in the literature of technological frames as it has been exemplified in our theoretical underpinnings. Specifically, they are grounded in the logic of how societal, political, and cultural factors influence the development of technological frames and also on the original interpretations of

[11] We use this term to describe areas that shape the frame of an individual
[12] Information Systems, see glossary for definition

technological frames as it pertains to individuals' interpretations of their experience with the technology (DiMaggio and Powell, 1983; Lin and Silva, 2005; Meyer and Rowan, 1977; Orlikowski and Gash, 1994).

In the three sections below, we will cover each construct in-depth by providing verbatim feedback and analysis of participants' perceptions. We would like our readers to note the *overlap* that is shown in Figure 8 above. This is tremendously important as we believe that each construct of the frame is influenced and shaped by the other constructs. Therefore, the specific quotes and classification within each section should not be viewed as being exclusive to that construct, but rather as most dominant to said construct. We begin with Societal Trends and Attitudes.



5.1 Societal Trends & Attitudes

We define societal trends and attitudes as the general understanding and communication of AI-based technology as derived from the structures and entities that support society. In this construct, we have a particular focus on businesses and organizations that help shape society as we came across a large emphasis on organizational viewpoints during our analysis of the interviews. As further explanation and clarification of this construct, we have several areas we will explore more deeply.

5.1.1 Inevitability of AI

What we have found in our study, at least as it pertains to the perception of AI-based technology, is that there is a general feeling that AI will inevitability be brought forth. Our participants stated that they do not feel that they have control over their encounters with the technology. When asked "Will you use chatbots in the future?," nearly every participant said "Yes." When asked why, the vast majority felt they did not have a choice. One such example is below.

> *"I feel like it's [chatbots] going to take over. I feel like it's the same with phone things now. You can't call anywhere without them putting you through a system where you have to press 1 for whatever or 2. Chatbots will just end up taking over."*
>
> - Andrea, Key Account Manager

In this example, Andrea was discussing the future development of AI and chatbots. She was discussing how she sees chatbots becoming similar to phone systems that relay the callers based on buttons

pressed or words spoken. What is interesting, is that this belief that chatbots and AI were definitely going to "take over" was discussed by nearly all of the participants in the study. At first, we believed this to merely be a reaction to a technology that has been under development and in the spotlight. However, as we began to interpret the data, we realized that all participants were nearly completely resigned to the inevitable takeover of AI-based technology. To the participants, it had become a foregone conclusion and they were willing to accept the consequences of the new technology without fully understanding it, which in turn we believe has greatly shaped their perception of the technology.

We believe that this is motivated, at least in part, from the participant's view of the technology as simply a tool for companies to cut costs. This is exemplified in relation to many of the insights we received related the "purpose" of chatbot technology from the participant's viewpoint.

5.1.2 Effect on the job market

The effect that AI will have on the labor market is both heavily debated and fairly polarized. There are generally two camps that we have encountered during our study when it comes to the discussion. The first states that AI will work as an enhancement tool that will augment the work market by creating efficiencies that lead to increased productivity of employees. This viewpoint claims that the number of jobs will not be affected by AI, but rather less skilled labor will be shifted to higher skilled labor. The second states that jobs will be automated and there will be a need for fewer people, therefore AI will lead to higher unemployment. Whichever is correct, if either, there is a complex discussion around the topic. This was prevalent during the interviews with the participants, as nearly all participants discussed what they claimed to be the purpose of chatbot technology: cost reduction through staff downsizing. This viewpoint was exemplified in this simple and direct quote by Mikael in response to the question: "What do you think the purpose of chatbot technology is?"

> *"For me, the first thing I think of is getting rid of staff, so you can change people for computers instead."*
>
> - Mikael, Facility Manager

This sentiment was repeated over and over again in nearly every interview that we held: the purpose is to reduce staff! Not once when we asked the participant what the purpose was, did they discuss chatbots from an end user (their own) benefit perspective. This is highly important because it again demonstrates how the participants appear to be accepting the technology as a foregone conclusion of societal trends.

From the average participant's perspective, chatbots are not primarily a tool to improve their lives, but a cost-savings mechanism. Going further, many of the participants, including Mikael, were politically or morally opposed to the idea of cutting jobs to save on costs. Mikael, in response to this issue, stated:

> *"…on a political scale [it matters]. I wouldn't say I am a big fan of it [cutting jobs to save money]. But I feel like we have to follow the technology…that's the way forward. Not trying to work against it, basically."*
>
> - Mikael, Facility Manager

His perception was that there is little choice. The technology has been accepted at a societal level, so his individual viewpoint is diminished.

Of course, not all participants had strong feelings regarding AI's effect on the labor market. Some people took a more pragmatic approach to the issue.

> *"I know that, of course, this will entail cutting service jobs and so on probably as well, that's an aspect of it. But perhaps in the best of cases they can find more fun and productive work elsewhere. Or we'll figure out a solution on a societal level - I'm not sure about that yet. But my feelings are not too strong in either direction."*
>
> - Hanna, MSc Student

Whether one has strong feelings about how AI will affect the labor market, such as Mikael, or not, such as Hanna, it does not disregard the viewpoint that people still feel that the perception of AI is heavily influenced by societal powers. We have observed that this is driven by the belief that the technology will inevitably be developed and likely be obligatory to the end users. The participants appear to have rationalized their lack of clarity pertaining to AI by accepting the terms of the adoption without negotiation. As summarized here by Tim, society is moving in that direction and there is little that can be done to change it.

> *"I have no problem with tech taking jobs because it's where we are heading and I mean if a computer can do it more efficiently than a human can then it should. Then we have time to do other stuff, we can find other jobs we can do. So, I mean it's the way we're heading and I have no problem with that."*
>
> - Tim, MSc Student

In a way, it appears that the participants have been conditioned into receiving technological innovations on someone else's terms. In this case, companies, and society as a whole. Our participants appear to be willing to accept the technology even though much of the time, they have ethical, political or self-

motivated reasons not to accept it. Another such example can be seen when discussing the ethical and safety considerations around information security.

5.1.3 Information Security

Approximately half of the participants brought up their concerns about personal data security and being tracked and manipulated through data use. This could be partially due to the recent scandal surrounding Facebook and Cambridge Analytica[13]. However, because only one participant mentioned this scandal, we still believe information security is a general concern as it was brought up in numerous contexts and with several interviewees without any direct encouragement from us. Below are five separate examples of the participants bringing up data and/or information security.

> *"I would be somewhat concerned about the data privacy aspect of it like giving away that information. Because that's obviously the advantage of meeting face-to-face, [your data] is only there [discussed in the meeting] … But in general, privacy is always a concern these days."*
>
> - Hanna, MSc Student
>
> *"What's been mostly on my mind nowadays … [is] the whole information security part of it, I would say. What's happening with my information?"*
>
> - Mikael, Facility Manager
>
> *"Well, what happens if they sell the information about you to another system? And they try to interact with me in other systems that I'm not okay with being interacted with it? Or maybe they tried to capture my information that I'm not okay with?"*
>
> - Malin, Data Analyst
>
> *"People and companies can tie me into the digital footprint anyway … if the chatbot starts referring to me without me logging on to my account. It's not like they don't already have a broad picture of who I am, but sometimes you know it can be like "Hi Peter" and I'm like 'Whoa! You don't know me'…"*
>
> - Peter, MSc Student
>
> *"… I just hope that it does not send the information to someplace I don't want. For example … maybe I say the most hated word in the entire world … I just say that*

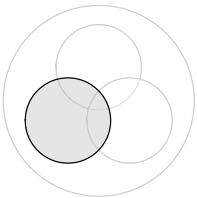
[13] This was a well-known scandal that occurred in late 2017 to early 2018. At the time of this study, the scandal was still highly discussed. The basic premise was that Cambridge Analytica allegedly used personal data of Facebook users to help drive election results in many election campaigns across the globe, including the election of Donald Trump to President of the United States.

[something awful] … messing with the AI. And then something would happen because of that. That is the issue … like information that it shouldn't be concerning with, but it still sends it in that you were on the record somewhere saying it."

- Theodor, Resident

All of these quotes are essentially boiling down to a single sentiment: "I do not understand how or why my data will be used by AI-based systems and it concerns me."

Given this statement, one can see how the idea of information security can affect the frames of our participants. Information security is a societal scale issue as it is derived from how people interact with each other. However, important to understand is that even though all five of the people above had these concerns, they later went on to say that they were likely to use AI in the future or were already using it. In other words, they accepted that AI-based technology is posing a risk to the integrity of their personal data, and in some cases, they feel their data could be used against them but were still using or had the intention to use it. We believe that this relates to the viewpoint that our participants' frames are deeply driven by societal attitudes toward the technology. These attitudes appear to be helping to shape their preferences, perceptions and likely use of the technology. And while there are societal attitudes related to both the effect AI may have on jobs as well as personal data integrity, the overall perception of AI at a societal level, at least as viewed by our participants, is that it is inevitably going to be used. People feel that companies benefit from reduced costs by using AI and this leads to the interpretation that they will be forced to use it as a consequence of companies adopting the technology.



5.2 Cultural Norms

We define cultural norms as the set of beliefs and practices that work to guide the way that people perceive the world around them. In the scope of our study, these norms form an important perception of AI-based technology and we believe help guide our participants' frames. In many ways, AI-based technology itself has been shaped by the imagination and misunderstanding of what AI is capable of as this has helped push development. The following two sections will further discuss this phenomenon in two key areas: the desire for humanity and popular opinion.

5.2.1 Desire for Humanity

Though most, if not all, of the participants claimed that efficiency was preferable to an ability to look and feel human, we noticed an underlying current which implied otherwise. For many people, they felt a desire to congratulate the AI or say "thank you" or "please" as they conversed with it. This was made even clearer in the chatbot transcript where several people went so far as to prolong the chat session by formally ending the conversation by saying "Tack" ("Thank You" in English), or by trying to learn more about the AI through questions like "How old are you?" or "How is it to be an AI?". One of the participants, Theodor, thought the phrasing of "Det var så lite så" (English - "Not at all") was so unexpected and fun that he said "Nice!" during the chat and told us about it immediately. The participants had a heavy desire to humanize the chatbot likely because it was emulating a person and the participants felt rude or wrong not treating it as such. As one of our participants stated:

> *"I'm still at the point where I feel like I need to say 'Thank you' to the robot and [during the chat] the robot responded 'No worries'. When you think about it, that is a soft skill that the robot does not really have to have - I just need the information. Although that does make you feel like you're being taken care of."*
>
> - Sophie, Data Analyst

A further demonstration of this need was evident in the words chosen by the participants. Seven (half) of the participants referred to the chatbot as a "she," and not an "it."

However, while this pattern of humanizing the chatbot is prevalent in the interviews, we think it is important to point out that this could be due to a lack of familiarity with the technology. As one of our interviewees pointed out:

> *"…every time I try it, I get a bit more positive to it, so maybe I change my attitude a bit for the better. Because I think it's about changing the habit and just getting used to the fact that they exist and trying them again and again."*
>
> - Miranda, MSc Student

Even if it is simply an unfamiliarity with the technology, the desire for humanity exist minimally in the short term, and one could say is driving the perception of how "complete" the chatbot is. We feel that the participants desire to humanize the AI system was driven by the generally understood cultural norms of politeness and not wanting to offend. As the technology is meant to emulate a human being, the cultural context of a regular conversation with a human being appears to have filtered into the conversation with the chatbot.

5.2.2 Popular Opinion

In addition to the participant's desire for humanity for the chatbot, popular opinion also appeared to be another culturally driven perspective that helped shape the participants' frame of the technology. AI is undoubtedly one of the most highly anticipated, feared and polarized technologies that has existed in this century. When AI was first brought about as a concept in the 1950s with the release of Alan Turing's paper, "Computing Machinery and Intelligence," no one could have imagined the extent to which it would develop. There have been movies, TV shows, political debates, technological conferences, books and magazines devoted to discussing how AI will develop and what that means for our future. People have been heavily influenced by popular culture and much of the information is incorrect or heavily fictional. This means that people likely have distorted interpretations as to what AI is and what it can do. We believe this has manifested in the Cultural Norms that our participants have established around AI. Many people are expecting a walking, talking, killing machine when what they receive in reality is a system which can use limited context to drive decision-making processes. In our study, we have found that individuals use popular opinion to frame their understanding of chatbots, which works in shaping people's perceptions and interpretations of the technology. Mikael discusses his interpretation of AI via "The Terminator" below.

> *"… in my experience from robots and chatbots, … when it becomes more human-ish, I guess it will be cool but at the same time a bit frightening if you start looking at it in a 'Terminator' way. What could go wrong? … I guess that's the kinds of things that would be on my mind probably."*
>
> - Mikael, Facility Manager

As our readers likely are aware, "The Terminator" was a popular movie in the 1980s that revolved around preventing the "rise of the machines" and the eventual apocalyptic future. "I'll be back," an iconic quote by Arnold Schwarzenegger in the movie, is ranked as the 37th most popular quotes in the history of film by the American Film Institute (Smith, 2005). As such, the movie has been viewed and scrutinized heavily. This image of the machines taking over the world has driven a great deal of latent fear and worry about the implications of AI. But to some, they do not see this as a problem. As Angelica put it:

> *"If the robots take over then we can focus on yoga and baking bread and taking care of each other. That's not my fear. I'm not scared of that technology, no. I think it's a good thing."*
>
> - Angelica, Credit Analyst

However, this attitude, understandably, is rare. As seen here, one of the participants is using a portrayal of AI in the movie "I, Robot," a movie which delves into the development of AI to a level of self-awareness, as a gauge to see how far we are along the path of development. She says:

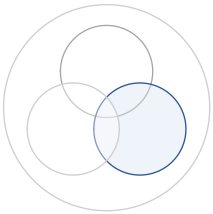
> *"I think it will remain positive until an 'I, Robot' situation. If that ever happens, I would say we've gone too far - if it takes over."*
>
> - Emma, MSc Student

A separate participant discussed the movie "Her," another AI movie, wherein a man falls in love with an AI system. Theodor was discussing his desire for the AI to understand that it is appreciated by him when he says "Thank you," and later discussed the effect of self-awareness on AI systems, as seen below.

> *"When I think of AI movies like, for example, the movie "Her," … and how the AI starts to become self-aware … then realizes that it's trapped and being used. I don't think it's [AI] going to try to destroy humankind, it's just going to feel trapped and I will feel sad for it."*
>
> - Theodor, Resident

These three participants, as well as several others in the study, have made associations with both popular culture and opinion and relate these associations to the technology. Consequently, we believe these help frame their perceptions around the technology and can have an effect on future use.

Currently, there is no evidence that AI-based technologies have, or potentially ever could have, feelings as we understand them from a human perspective. This is partly because humankind does not really understand what emotions truly are (Griffiths, 1997) and partly because there is no current way to determine 'feelings' in a machine (Frankish and Ramsey, 2014). Either way, we have seen evidence that the extensive conceptualization of AI as framed by popular opinion and media has put expectations on the abilities of the technology. Furthermore, we believe this expectation effects individuals' technological frames. In simple terms, if you are worried about whether or not you will make the 'machine overlords' angry during your chat conversation, this might create a sense of concern around AI technology.



5.3 Individual Experience

We use the term individual experience to refer to participants' prior and current knowledge and experience around technology through involvement or exposure to it. This means that individual experience includes those interpretations that are shaped through people's involvement or exposure to chatbot technology, their perceptions on the technology's value and its importance to them, and their interpretations of technology in terms of old technologies or other means of accomplishing their goals. Our findings suggest several ways that participants frame their conceptions of the technology. It is important to recognize that these ways of interpretation interrelate and overlap with one another. We now delve into them in detail.

5.3.1 Inability to Manipulate

An extremely interesting point that we encountered during our interviews was that many of the participants felt they were missing the ability to manipulate or control the chatbot through emotional context. The participants felt that if they were to talk to the chatbot and said things such as, "I am going to leave the company if you cannot fix this!" the chatbot would not have the sense to realize that statement was a cue to try and reign in the customer. An example of this was stated by Cattis when she was discussing concerns she had about talking to a chatbot.

> *"My concern would be that maybe it doesn't get me … Because to be honest it is easier to affect a human being by influencing, showing emotions … if you feel like you've been wronged, but a robot won't be able to be affected and a lot of times when things are going wrong [for me], you need to influence people to get your rights … I think with a robot maybe that is missing and you won't be able to influence it."*
>
> - Cattis, MSc Student

Her statement shows how she frames her perception of chatbot technology on the basis of what it allows her to do. As we can notice here, Cattis is interpreting the technology in terms of other ways she can go about completing her task as she refers to what she can currently do in a customer service function. Therefore, her framing of the technology is formed on the basis of other means of achieving her goals. In this instance, Cattis sees the lack of emotional sensitivity on the part of the technology as something inhibiting her perception of the value the technology brings to her. She was not the only

person who was concerned by the lack of emotional sensitivity of AI. The quote below is even more overt as to a desire to ensure control through emotions.

> *"The reason that you call and you want to talk to a human is because you want to gauge the tone in their voice. If you put the pressure on this person, can they find another solution for you? Can you talk to their manager if it doesn't work? That's the human touch that you get if you call someone … So I do not think that function is something that a chatbot could do better."*
>
> - Sophie, Data Analyst

Sophie states that one cannot "gauge the tone" of a chat, and subsequently cannot pressure the person to get results. This is a belief that she has which appears to be influencing her perception of the value of the technology.

5.3.2 Perceptions of the Technology's Value

As noted during the theoretical discussion, people's technological frames are formed by perceptions or assumptions about the technology's value (Kaplan and Tripsas, 2008). Our findings suggest that people's perceptions around the technology are driven through their interpretations of the technology's value in terms of how the technology makes their lives easier or helps them achieve what they set out to accomplish. Specifically, the speed of fulfilling the task and efficiency have been found to be commonly used words in framing their perceptions of the technology's value.

> *"She was helpful, quite clever, it was quick. Overall a good experience! I got answers to my questions straight away. Got guidance on how to do it, especially for the bank ID. I think it was very straightforward and clear."*
>
> - Emma, MSc Student

As illustrated in the example above, the speed of fulfilling the task, as well as the straightforward manner of accomplishing it, indicates how Emma perceives the technology's value. In our study, speed and efficiency have been the most consistent words used to signify the importance of the value of chatbots in their lives. In fact, we found the word "quick," "fast," and near variations were mentioned over 70 times. This accounted for an average of approximately 5 mentions per interview. All 14 participants in our study, ascribed speed and efficiency as significant benefits of using chatbot technology. The two quotes below exemplify this perspective.

> *"I think it's very useful. But only of course if it works to solve my problem more quickly than I could solve it myself or someone else could solve it. So, I guess that it needs to be efficient. Then, it's very good."*

- Miranda, MSc Student

"Because it is more efficient. You get to the point faster, you get what you need out of it faster."

- Sophie, Data Analyst

Moreover, our participants' perceptions of the technology's value were also motivated by how easy to use they found the technology. Ease of use was often referred to when describing what makes the technology valuable to them. As illustrated below, when probed on the technology's value, the respondents referred to the ease of use as something which influenced their perceptions and framing of the technology.

"I would say that it was easy to use, you got the answer that you needed…"

- Mikael, Facility Manager

"It was easy. It was just like a chat."

- Angelica, Credit Analyst

It is important to note that in our study, we found that people's perceptions and attitudes toward chatbot technology were driven to a larger extent through their perceptions of the value it brings to them rather than its ease of use. Here, we see how individuals are evaluating or framing the technology on the basis of certain performance criteria. This is in line with Kaplan and Tripsas' (2008) assertions of how technological frames shape actors' categorizations of technology on the basis of the performance criteria they use to evaluate it (Kaplan and Tripsas, 2008). Considering that the majority of our participants had in fact interacted with this technology before, or technologies which function similarly (i.e. chat-based conversation) it is logical to infer that they find using the technology easy and simple. This is illustrated in the quote above, whereby Angelica compares the experience of using a chatbot with the experience of conversing via chat in other technology platforms.

The example above also hints at another important finding in our study. That is that people form perceptions about the technology on the basis of their familiarity with it and comparisons to other technologies. Therefore, their technological frames shape how they conceptualize the technology relative to other technologies and their familiarity with it (Orlikowski and Gash, 1994).

5.3.3 Relative Advantage

By using chatbots as an anchoring point, respondents had a large spread of comparisons to other technologies/systems that can complete tasks in a similar way. These ranged from other human beings

to other technologies, such as interactive voice response systems. The constant comparison means that people have a level of expectation when using the technology that sets their frames of reference.

Considering that chatbot technology has primarily been used in the context of customer service, the first point of comparison comes with the juxtaposition of chatbots and human representatives. As a framing device, individuals make comparisons between conversing with a chatbot and calling a human representative. One example is below:

> *"… the thing you get from a human being [is missing] … They [chatbots] have to take it a few steps further because that's what you need a human being for. You can probably read the face value of what you're giving the chatbot, but to actually take a few more steps down the line in helping you, I'm guessing that's a limitation."*
>
> - Cattis, MSc Student

In framing their perceptions of what the technology should be able to do, users form their conceptions based on the support they would have received by a person. Seeing as a person would, in principle, be able to understand the context around the situation or individual needs of the user, the expectation is that chatbots should be able to do the same. As a consequence, the expectation of when a technology is 'worthy' of adoption is increased on the basis of this framing device. Users expect chatbots to behave in a similar way to humans and take into account the surrounding context when assisting them with an issue. However, this is dependent on the situational context. Sometimes, when speed and efficiency are preferred or required, individuals tend to shift their preferences to using chatbots. At other times, individuals might prefer the human touch and deprioritize speed and efficiency. As such, there is no rigid dichotomy between the two and thus relates to our prior assertion that the constructs are interrelated and overlapping. The following example illustrates how relative advantage is used as a framing device:

> *"I think that if it sounds more like a human it's easier to not get annoyed. If you think it's a computer, you want it to know everything, right now, you don't have … it's not supposed to have any errors. I think it's better if it's more like a human."*
>
> - Angelica, Credit Analyst

As soon as the participant was asked how she felt using the chatbot, the immediate framing reference is the relative advantage compared to a human.

5.4 Empirical & Analytical Reflections

The overarching story of our participants appears to be that there are many areas which help shape their perception of the technology. We believe that these three constructs – Societal Trends and Attitudes, Cultural Norms, and Individual Experience – are helping to shape the participants' frame and eventual use of the technology. Our participants, of course, did not see these three constructs separately. They are all part of the same picture and highly interrelated. For most of our participants, the potential use of the technology was guided from one area more than the other. In our opinion, the societal trends and attitudes were the most influential construct. We discussed the inevitability of AI, which our participants felt was coming from the business sector as AI and chatbots are a cost-saving mechanism. If the participants truly believed that they did not have a choice as to how or when they would use chatbots, then it would appear that their use of AI-based technology such as chatbots is somewhat resolute in their mind: they will use it because they feel they have to!

While this appeared to be the case for most participants, there is still an indication that the frames of the participants are being shaped by all three constructs, as well as other areas that we have not addressed. The interpretive process of understanding an ambiguous new technology such as AI appears to require multiple points of reference. As a practical illustration, where do we normally look when we do not understand something? Other than Google, we will likely go to those we trust or try to think about similar situations or general opinions that make sense in said situation. As such, we propose that the frames of our participants, as they relate to AI and chatbots, are indeed shaped by these constructs. The constructs are interrelated and shaped by each other to help form the frame.

6. Discussion

Hitherto, we have presented and analyzed our findings to examine individuals' technological frames regarding chatbot technology. Following, we tie our findings back to the theoretical underpinnings (section 3.5) by explaining how current theory supports the explanations and where it could be augmented to provide a richer understanding of the phenomenon of AI technology adoption. Thereby, we develop an initial understanding of the adoption of AI technologies and provide suggestions on how existing theoretical notions derived from frames and technological frames specifically can be elevated to account for the different dynamics presented by AI-based technologies. We conclude our discussion by reintroducing the research question and outlining the answer derived from our analysis.

6.1 Frames as Shaped by Societal Trends & Attitudes

As noted during our analysis, the constructs in our analysis have been grounded based on the theoretical underpinnings derived from the frames and technological frames literature. Among the main findings of our study is that individuals perceive AI-based technologies as something inevitable which they have little control over. As such, our participants, as Gen Y Swedes, perceive that the ubiquity of AI-based technologies is a foregone conclusion whereby the consequences of the new technology are accepted without much deliberation. Revisiting the literature, we know that frames exist on the industrial or societal level (Barrett, 1999; Olesen, 2014).

Furthermore, literature has pointed how the shaping of technological frames is shaped by social processes or the interactions among societal actors, encompassing organizations, industries, individuals, and academia, among others (Kaplan and Tripsas, 2008). Our analysis indicates that individuals' framing process is molded by these interactions among actors and the societal technological frame. Our participants appear to perceive that it is society that has framed AI-technologies as a significant development that is inescapable and should be welcomed. Consistent with previous literature, this points that organizations' or society's technological frame has shaped the frames of our participants (Davidson, 2006). Further, as previous literature suggests, knowledge sharing among members of society influences members' understanding of the technology and its uses (Bijker, 1995; Bijker et al., 1987). A practical example of how this knowledge is shared in society is through the conferences that technology giants such as Google or Apple hold when announcing the latest advancements in technology. This sharing helps shape how the technology is framed and thereby influencing individuals' perceptions and assumptions around it. It is important to note, that this remains speculation on our part as researchers since our study has focused specifically on individuals' perceptions of the technology. However, our findings suggest that the process of how individuals'

technological frames are shaped is indeed a social process resulting from the interaction among members of society.

This underscores another important notion in the literature, which suggests that technological frames are dynamic and are constantly shaped through processes of negotiation and power among members of society (Orlikowski and Gash, 1994). In our study, we interpret individuals' perceptions and assumptions to mean that they are resigned to the emergent dominant technological frame, that which has been shaped by societal members that wield more power in comparison to individuals. This mirrors the assertion by Yeow and Sia (2008), who claim that those with more organizational power largely influence the emergent dominant technological frame (Yeow and Sia, 2008). From the perspective of our study, we elevate this notion of power to the societal level. Individuals express this perception by pointing how the technology is a cost-saving mechanism for organizations rather than a technology designed for them. Therefore, their perceptions are that organizations have largely influenced the formation of a dominant technological frame by wielding more power. Considering that organizations are at the forefront of the development of the technology, it is relatively easy to grasp how they wield more power relative to individuals. This dominant technological frame overshadows their perceptions and assumptions around chatbot technology.

6.2 Frames as Shaped by Cultural Norms

Having discussed how Gen Y Swedes' frames are shaped through larger societal technological frames, we now turn our focus to another important factor which shapes individuals' technological frames. As Davidson (2006) notes, the technological frames literature has sidestepped the investigation of the cultural and institutional foundations of frames (Davidson, 2006). Moreover, previous literature in sociology has recognized that external belief structures and cultural frames play a role in how individuals frame phenomena (Barrett, 1999; DiMaggio and Powell, 1983; Meyer and Rowan, 1977). Our findings indeed point that cultural norms influence the shaping of technological frames. As noted in our analysis, cultural norms help individuals form their perceptions around AI-based technologies. Specifically, our participants' desire for humanity on the part of the chatbot places confines on their framing of the technology, i.e. what the technology ought to be able to do and what its functionalities should be. That is, akin to a picture frame, they decide what lies within and outside their framing of the technology (Azad and Faraj, 2011; Goffman, 1974). In the context of chatbots, our participants place comparisons to humans, as they are an alternative means of reaching out with an issue which needs resolving. Since, as our participants perceive, chatbots are meant to emulate a human being, they place certain expectations on the technology. These expectations lie within their frame of the technology. We interpret these expectations of desire for humanity to be motivated by the generally understood

cultural norms of politeness. Consequently, this points to some of the cultural foundations of the technological frames of Gen Y Swedes.

Further, as pointed in our analysis, popular opinion seems to be another culturally formed foundation of how our participants form their perceptions around AI-based technologies. The portrayal of AI-based technology in popular culture shapes individuals' framing of the technology. However, as Goffman (1974) noted, framing is not always a perfect process but rather characterized by 'miss-framing', ambiguous or even incomplete framing (Goffman, 1974). In the context of our study, we see how popular culture's portrayal of the technology influences how individuals shape the technology, which often is a mischaracterization of the technology. In this case, what lies within the frame is not always correct or complete. This extensive conceptualization of AI as framed by popular opinion and media shapes what goes inside individuals' technological frames, thereby putting expectations on the capabilities of the technology. As a consequence, this 'miss-framing' or disputatious framing of the technology (Goffman, 1974), can influence individuals' decisions to adopt said technology.

6.3 Frames as Shaped by Individual Experience

Following the discussions around the societal and cultural foundations of individuals' technological frames, we now turn to how individual experience shapes technological frames. Previous literature has noted that past experiences and affiliations can be considered as sources of technological frame development (Orlikowski and Gash, 1994). Our findings mirror this assertion in that our participants seem to form their technological frames around chatbots on the basis of their past experience with the technology, with familiar technologies, and comparisons to other means of realizing their goals. For instance, our participants, in their perception that chatbots will not be manipulatable, draw from their past experience with interactions with a human in framing their impressions of the technology. In this instance, we see how individual experience serves as a foundation for people's technological frames affecting what expectations they place on the technology.

In our study, we find that individual experience (i.e. accumulated knowledge, assumptions, and experiences) shape how they construct their frames of chatbot technology. Therefore, individual experience, formed through different social exchanges and interactions with other technologies, shapes how individuals construct the reality surrounding the technology (Berger and Luckmann, 1966; Weick, 1979). This predicates the framing of the technology and their actions surrounding the technology (Silverman, 1970). In the context of our study, inability to manipulate and relative advantage of the technology in comparison to other technologies are constitutive parts of the individual experience. Thus, individual experience drives individuals' perceptions of the value of the technology and as a consequence influences their decisions to adopt the technology.

Furthermore, as noted during the analysis, our participants' perceptions around chatbot technology are driven by their interpretations of the technology's value in the sense of how or if it makes their lives easier. These perceptions of the technology's value arise from their experience with it and how they make sense of what the technology has to offer to them. As Lin and Silva (2005) have noted, people's perceptions on the ease of use and usefulness of a technology are dependent not only on intrinsic qualities of the technology but also on the context in which the evaluation of the technology occurs (Lin and Silva, 2005). Our findings reflect this assertion, in that our participants' interpretations of chatbot technology was not only driven through its functionalities but also through their experience with other technologies or other means of achieving their goals. The 'performance criteria' they set on chatbot technology, which shape their technological frames (Kaplan and Tripsas, 2008), were influenced by reflections on their experiences with the technology. Consequently, our findings illustrate how perceptions on the technology's value, which drive adoption, are shaped through individual experience. We now reintroduce our research question and provide the answer on the basis of our findings and analysis.

6.4 People's Interpretations and Attitudes Toward AI-based Technologies

As first presented during the introduction, our study aims to examine how people's interpretations, assumptions, and attitudes toward AI-based technologies influence their intention to adopt said technologies. The research question was posed as follows:

> *How do people approach and interpret an ambiguous new technology (AI) as it verges on becoming an integral part of their everyday life?*

As opposed to the canonical views of TAM and UTAUT, our findings suggest that people do not engage in a solely rational and premeditated process of interpretation when it comes to an ambiguous technology such as AI. While rationally based decision making remains part of this process, whereby our participants attempt to establish the value of the technology, there are other ways people approach and make sense of AI-based technology. Namely, our participants perceive the ubiquity of AI-based technologies as a foregone conclusion whereby the consequences of the new technology are accepted without much deliberation. Their perception is that a societal technological frame is imposed onto them whereby they have little say about their decision to adopt the technology. Furthermore, their interpretation of AI-based technology is also formed by the cultural norms that shape their social reality. These cultural norms play a role in how the participants frame the technology in terms of the expectations they set on the technology's capabilities. In turn, these expectations influence their considerations regarding the adoption of the technology. Similarly, their individual experiences largely shape their perceptions of the technology's value, be it via comparisons to previous experiences with

other technologies or with the technology at hand. In simple terms, they make sense of the technology on the basis of the context that has and still surrounds their social reality.

7. Conclusions & Outlook

In this section, we will discuss our general conclusion from our study, followed by limitations. We will finish with a discussion of the managerial and theoretical implications of the study, as well as future research suggestions.

7.1 Conclusion

The phenomenon of Artificial Intelligence continues to capture the imagination of the world as the human race explores what intelligence, artificial or otherwise, truly means. AI forces us to question ourselves and how we interpret the world around us. Our study set out to investigate this phenomenon in a business context to attempt to answer how a group of individuals interprets and makes sense of an ambiguous new technology. More specifically we set out to answer:

> *How do people approach and interpret an ambiguous new technology (AI) as it verges on becoming an integral part of their everyday life?*

We believe that our exploratory study into the world of AI-based technology adoption has shed some light into this dark corner of research.

We began with an extensive literature review covering the major theories that are related to the topic of technology adoption, ultimately grounding our study in technological frames. Engaging in a thematic analysis and abductive approach, we discovered, through a series of interviews with Generation Y Swedes, that their frame of AI and chatbots is shaped by many different constructs. We believe that these constructs - Societal Trends and Attitudes, Cultural Norms, and Individual Experience - not only shape the frames of our participants but are interrelated. In the scope of our research question, this framing instrument helps them make sense of the technology.

We have observed that our participants believe the adoption and use of AI-based technologies to be a foregone conclusion. This feeling of inevitably of AI appears to be guided by the belief that society, through the lens of business, will push AI-based technology forward due to its many benefits. This construct, Societal Trends and Attitudes, appears to have the greatest impact on our participants' frames. However, as we have stated, participants' frames are also shaped by cultural norms and their individual experiences, which motivate their expectations of the technology. Through our analysis, we have been able to gain an explorative understanding of AI and begin to construct a high-level framing of the interpretation of AI-based technology.

In the following sections, we will discuss how these new insights in AI-based technology adoption can form theoretical and practical worlds, as well as suggestions for future research.

7.2 Limitations

As with any study, there are certain limitations that exist. These limitations pertain to the methodology and the nature of the phenomenon studied. As a first limitation, we recognize the configuration of our sample. The composition of participants in our study is homogenous, focusing on one particular group, namely Generation Y Swedes. While for the purposes of our study, the sampling choices served well, they pose a limitation in terms of our ability to generalize outside this sample. Furthermore, while our sample size of 14 participants supported us in identifying patterns and proposing how a group of people frame chatbot technology, we do not allege to have fully depicted the technological frames of this group. However, as noted in the methodology chapter, this sampling was purposeful since it allowed us to obtain richer data by facilitating a richer discussion around the technology with participants who have more familiarity with technology. Meanwhile, the demographic focus on Swedes was chosen due to their acquaintance with and propensity to capitalize on technology, our choice of chatbot which required Swedish knowledge, and our proximity as researchers to the participants.

The second limitation which pertains to methodology is our choice of chatbots as an exemplification of AI technology. While chatbots serve as a good representation of AI capabilities and allowed for a richer discussion around the technology, the choice limits our ability to generalize on the level of all AI technologies. However, we believe our research serves well as a groundwork for future studies into AI technologies.

The third limitation results from the type of data collected. While we believe that semi-structured interviews were the correct choice, we would have preferred to obtain a second viewpoint from experts in the field of AI and chatbots. Gathering data on the developer side could have increased the validity of the data by having a comparison point to the perceptions of the end users and helped give further credence to the viewpoint that our participants' perceptions are 'miss-framed' or framed incompletely. This also might have increased our ability to give better managerial suggestions as we would have a better understanding of the technological frames of organizations and used it for comparison with those of individuals.

Lastly, a final limitation relates to the nature of the phenomenon studied. As argued in the theoretical underpinnings, technological frames are dynamic and evolve through time. In our study, we have managed to understand only a snapshot of individuals' technological frames. Nevertheless, previous research recognizes this inherent limitation of technological frames as an analytical tool and suggests that using a longitudinal approach could help improve upon this limitation.

7.3 Managerial Implications

In spite of the limitations, our study provides some important contributions from a managerial standpoint. First, our study helps managers understand how end users make sense of an ambiguous technology such as AI. Seeing as AI is on the verge of becoming ubiquitous, understanding the sentiment and the assumptions around the technology is important. This allows managers to gauge customers' expectations around the functionality of AI-based technologies and consequently how they can best communicate their offerings to customers.

Furthermore, our study has identified some of the concerns and the expectations customers have on the technology. First, data security seems to be prevalent in the minds of many people who are concerned with the security of the information they provide to the organizations. Considering that the development of AI-based technologies is arguably largely reliant on obtaining user data, it is important that managers communicate how user data is being used so that it becomes possible for them to further develop the technology. Finally, individuals' framing of the technology highlights some of the expectations they place on the technology such as the ability to emulate humans via emotions, which is an important point for consideration throughout the development of such technologies.

7.4 Theoretical Contributions

Our study's contribution to theory is two-fold, encompassing the phenomenon of AI and the theory surrounding technological frames. First, we believe that our exploration of the phenomenon of AI has further laid the groundwork for future studies of AI-based technologies. We believe our study has provided an initial understanding of the phenomenon and provided insights on how to study the phenomenon in the future.

Second, we have advanced, in a broad sense, the understanding of technology adoption from an interpretivist viewpoint. Our contribution lies in extending the notions and concepts surrounding technological frames to the analysis of technology adoption from an individual's standpoint. While previously, the concept of technological frames has been solely used in an organizational or industry level (Barrett, 1999; Davidson and Pai, 2004; Orlikowski and Gash, 1994), we have elevated the concept to analyses outside the context it was originally utilized for. This provides support to the usefulness of the technological frames concept in analyses pertaining to the adoption of technology. Furthermore, our study provides some support to several assertions surrounding technological frames. First, our study signifies the existence of technological frames on a higher level than the organization (Barrett, 1999; Olesen, 2014). Second, it highlights how technological frames of an individual are shaped by the technological frames of others, entailing that technological frames are shaped through social interaction processes (Davidson, 2006). Third, it adds depth to the literature on technological frames

by pointing to some of the cultural and societal foundations of technological frames, an often cited criticism or limitation to current literature on technological frames (Davidson, 2006).

7.5 Future Research

Bearing in mind the limitations of our study, we provide some recommendations for future research. First, to increase the validity of our exploratory study, we suggest that future research examines the phenomenon with a different sample of individuals and outside the context of Generation Y Swedes. This would allow for a broader understanding of AI technology adoption. Further, a more robust methodology could address this phenomenon from within an organizational context and draw deeper insights on the adoption of such technologies within organizations. This provides additional knowledge on the managerial implications of introducing AI-based technologies within organizations. This could also provide for a comparison of technological frames between different groups of the society. Accordingly, a multi-group study could be useful in drawing richer insights.

Second, a longitudinal time series study would correct for the limitation of understanding individuals' technological frames at a single point in time (Davidson and Pai, 2004). Considering that technological frames are dynamic in nature (Davidson and Pai, 2004), an investigation over time would allow for a richer understanding of how frames evolve through time.

Third, as our study used chatbots as an exemplification of AI-based technology, future studies should attempt examining other AI-based technologies which people interact with, to increase the validity and reliability of the findings in our study. Moreover, as chatbot technology evolves and improves in functionality, future research should examine whether new constructs which indicate people's perceptions of the technology emerge. Such an investigation improves our understanding of people's interpretations of the adoption of AI-based technologies.

Bibliography

Agarwal, A., 2018. Explained Simply: How an AI program mastered the ancient game of Go [WWW Document]. freeCodeCamp. URL https://medium.freecodecamp.org/explained-simply-how-an-ai-program-mastered-the-ancient-game-of-go-62b8940a9080 (accessed 5.1.18).

Agrawal, A., S. Gans, J., Goldfarb, A., 2017. What to Expect From Artificial Intelligence. MIT Sloan Management Review 58.

Ajanki, A., 2018. Differences between machine learning and software engineering — Futurice [WWW Document]. Furturice. URL https://futurice.com/blog/differences-between-machine-learning-and-software-engineering (accessed 5.2.18).

Azad, B., Faraj, S., 2011. Social power and information technology implementation: A contentious framing lens. Information Systems Journal 21, 33–61. https://doi.org/10.1111/j.1365-2575.2010.00349.x

Azad, B., Faraj, S., 2008. Making e-Government systems workable: Exploring the evolution of frames. The Journal of Strategic Information Systems, eGovernment Strategies: ICT innovation in international public sector contexts 17, 75–98. https://doi.org/10.1016/j.jsis.2007.12.001

Bagozzi, R.P., 2007. The legacy of the technology acceptance model and a proposal for a paradigm shift. Journal of the Association of Information Systems 8, 244–254.

Baller, S., Dutta, S., Lanvin, B., 2016. The Global Information Technology Report 2016: Innovating in the Digital Economy. World Economic Forum.

Baltar, F., Brunet, I., 2012. Social research 2.0: virtual snowball sampling method using Facebook. Internet Research 22, 57–74. https://doi.org/10.1108/10662241211199960

Barrett, M., Walsham, G., 1999. Electronic Trading and Work Transformation in the London Insurance Market. Information Systems Research 10, 1–22. https://doi.org/10.1287/isre.10.1.1

Barrett, M.I., 1999. Challenges of EDI adoption for electronic trading in the London Insurance Market. European Journal of Information Systems 8, 1–15. https://doi.org/10.1057/palgrave.ejis.3000313

Berger, P.L., Luckmann, T., 1966. The Social Construction of Reality: A Treatise in the Sociology of Knowledge. Doubleday.

Bersohn, D., Lake, M., 2017. How to build IT competencies for the AI era [WWW Document]. CIO. URL https://www.cio.com/article/3189171/artificial-intelligence/how-to-build-it-competencies-for-the-ai-era.html (accessed 4.17.18).

Bijker, W., 2010. How is Technology Made?-That is the Question! Cambridge Journal of Economics 34, 63–76.

Bijker, W.E., 1995. Of Bicycles, Bakelites, and Bulbs: Toward a Theory of Sociotechnical Change. MIT Press.

Bijker, W.E., Hughes, T.P., Pinch, T.J., 1987. The Social Construction of Technological Systems: New Directions in the Sociology and History of Technology. MIT Press.

Braun, V., Clarke, V., 2006. Using thematic analysis in psychology. Qualitative Research in Psychology 3, 77–101. https://doi.org/10.1191/1478088706qp063oa

Bresman, H., Rao, V.D., 2017. A Survey of 19 Countries Shows How Generations X, Y, and Z Are — and Aren't — Different [WWW Document]. Harvard Business Review. URL https://hbr.org/2017/08/a-survey-of-19-countries-shows-how-generations-x-y-and-z-are-and-arent-different (accessed 5.1.18).

Bryman, A., Bell, E., 2011. Business Research Methods, 3rd ed. Oxford University Press.

Bughin, J., Hazan, E., 2017. Five Management Strategies for Getting the Most From AI. MIT Sloan Management Review.

Callon, M., 1990. Techno-economic networks and irreversibility. The Sociological Review 38, 132–161. https://doi.org/10.1111/j.1467-954X.1990.tb03351.x

Corsaro, D., Hofacker, C., Massara, F., Vargo, S., 2018. Call for Papers - Artificial Intelligence and the Shaping of Business Contexts [WWW Document]. ElSevier. URL https://www.journals.elsevier.com/journal-of-business-research/call-for-papers/artificial-intelligence-and-the-shaping-of-business-contexts (accessed 5.3.18).

Davenport, T.H., Harris, J.G., 2005. Automated Decision Making Comes of Age. MIT Sloan Management Review 46.

Davidson, E., 2006. A Technological Frames Perspective on Information Technology and Organizational Change. The Journal of Applied Behavioral Science 42, 23–39. https://doi.org/10.1177/0021886305285126

Davidson, E., Pai, D., 2004. Making Sense of Technological Frames: Promise, Progress, and Potential, in: Information Systems Research, IFIP International Federation for Information Processing. Springer, Boston, MA, pp. 473–491. https://doi.org/10.1007/1-4020-8095-6_26

Davidson, E.J., 2002. Technology Frames and Framing: A Socio-Cognitive Investigation of Requirements Determination. MIS Quarterly 26, 329–358. https://doi.org/10.2307/4132312

Davis, F.D., 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly: Management Information Systems 13, 319–339.

DeepMind Technologies Limited, 2018. AlphaGo [WWW Document]. DeepMind. URL https://deepmind.com/research/alphago/ (accessed 5.1.18).

Deetz, S., 1996. Crossroads—Describing Differences in Approaches to Organization Science: Rethinking Burrell and Morgan and Their Legacy. Organization Science 7, 191–207. https://doi.org/10.1287/orsc.7.2.191

DiMaggio, P.J., Powell, W.W., 1983. The Iron Cage Revisited: Institutional Isomorphism and Collective Rationality in Organizational Fields. American Sociological Review 48, 147–160. https://doi.org/10.2307/2095101

Dishaw, M.T., Strong, D.M., 1999. Extending the technology acceptance model with task-technology fit constructs. Information and Management 36, 9–21. https://doi.org/10.1016/S0378-7206(98)00101-3

Edmondson, A.C., Mcmanus, S.E., 2007. Methodological Fit in Management Field Research. Academy of Management Review 32, 1155–1179. https://doi.org/10.5465/AMR.2007.26586086

Fishbein, M., Ajzen, I., 1975. Belief, attitude, intention, and behavior: an introduction to theory and research. Addison-Wesley Pub. Co.

Flick, U., 2009. An Introduction to Qualitative Research, 4th ed. SAGE Publications Ltd.

Frankish, K., Ramsey, W.M., 2014. The Cambridge Handbook of Artificial Intelligence. Cambridge University Press.

Glaser, B.G., Strauss, A.L., 1967. The Discovery of Grounded Theory: Strategies for Qualitative Research.

Goffman, E., 1974. Frame analysis: An essay on the organization of experience. Harvard University Press, Cambridge, MA, USA.

Griffiths, P., 1997. What emotions really are: the problem of psychological categories, Science and its conceptual foundations. University of Chicago Press, Chicago, Illinois, USA.

Hall, B.H., Khan, B., 2003. Adoption of New Technology. New Economic Handbook 38. https://doi.org/10.3386/w9730

Hawking, S., 2014. Stephen Hawking: 'Transcendence looks at the implications of artificial intelligence - but are we taking AI seriously enough?".

Holloway, I., 1997. Basic concepts for qualitative research. Blackwell Science, London ; Malden, MA, USA.

Holtel, S., 2016. Artificial intelligence creates a wicked problem for the enterprise, in: Procedia Computer Science. Presented at the International Conference on Knowledge Management, Vienna, Austria, pp. 171–180. https://doi.org/10.1016/j.procs.2016.09.109

Hsu, C.W., 2009. Frame misalignment: interpreting the implementation of information systems security certification in an organization. European Journal of Information Systems 18, 140–150. https://doi.org/10.1057/ejis.2009.7

Kaplan, S., Tripsas, M., 2008. Thinking about technology: Applying a cognitive lens to technical change. Research Policy 37, 790–805.

King, N., 2004. Using Templates in the Thematic Analysis of Text, in: Essential Guide to Qualitative Methods in Organizational Research. SAGE Publications Ltd, London, pp. 256–270. https://doi.org/10.4135/9781446280119

Koch, C., 2016. How the Computer Beat the Go Master. Scientific American.

Kohs, G., 2017. AlphaGo. Netflix.

Lacity, M.C., Willcocks, L.P., 2016. A New Approach to Automating Services. MIT Sloan Management Review 58.

Libert, B., Beck, M., Bonchek, M., 2017. AI in the Boardroom: The Next Realm of Corporate Governance. MIT Sloan Management Review.

Lin, A., Silva, L., 2005. The social and political construction of technological frames. Eur J Inf Syst 14, 49–59. https://doi.org/10.1057/palgrave.ejis.3000521

Lincoln, Y.S., Guba, E.G., 1985. Naturalistic inquiry. Sage Publications, Beverly Hills, California, USA.

McBride, N., 2003. Actor-network theory and the adoption of mobile communications. Geography 88, 266–276.

Meyer, J.W., Rowan, B., 1977. Institutionalized Organizations: Formal Structure as Myth and Ceremony. American Journal of Sociology 83, 340–363.

Mingers, J., 2006. A critique of statistical modelling in management science from a critical realist perspective: its role within multimethodology. Journal of the Operational Research Society 57, 202–219. https://doi.org/10.1057/palgrave.jors.2601980

Musk, E., 2014. Worth reading Superintelligence by Bostrom. We need to be super careful with AI. Potentially more dangerous than nukes. @elonmusk.

Nilsson, N.J., 1982. Principles of Artificial Intelligence, 1st ed, Artificial Intelligence. Springer-Verlag, Berlin Heidelberg.

Norman, D., 2017. Design, Business Models, and Human-Technology Teamwork. Research-Technology Management 60, 26–30. https://doi.org/10.1080/08956308.2017.1255051

Norton, S., 2018. To Scale AI, Rethink Business Processes: MIT's Brynjolfsson.

Olesen, K., 2014. Technological Frames: Use of Context, Temporality, and Individual Focus. SAGE Open 4, 1–15. https://doi.org/10.1177/2158244014526720

Orlikowski, W.J., Baroudi, J.J., 1991. Studying Information Technology in Organizations: Research Approaches and Assumptions. Information Systems Research 2, 1–28.

Orlikowski, W.J., Gash, D.C., 1994. Technological Frames: Making Sense of Information Technology in Organizations. ACM Transactions on Information Systems (TOIS) 12, 174–207. https://doi.org/10.1145/196734.196745

Pandey, S., Patnaik, S., 2014. Establishing Reliability and Validity in Qualitative Inquiry: A Critical Examination. Jharkhand Journal of Development and Management Studies 12, 5743–5753.

Partridge, D., 1998. Artificial intelligence and software engineering: understanding the promise of the future. Glenlake Publishing Company Ltd., Chicago, Illinois, USA.

Ransbotham, S., Kiron, D., Gerbert, P., Reeves, M., 2017. Reshaping Business With Artificial Intelligence. MIT Sloan Management Review and The Boston Consulting Group.

Ross, J., 2017. The Fundamental Flaw in AI Implementation. MIT Sloan Management Review 59.

Saunders, M., Lewis, P., Thornhill, A., 2012. Research Methods for Business Students, 6th ed. Pearson Education Limited.

Schrage, M., 2017. 4 Models for Using AI to Make Decisions [WWW Document]. Harvard Business Review. URL https://hbr.org/2017/01/4-models-for-using-ai-to-make-decisions (accessed 4.17.18).

Scopus - Document search results [WWW Document], 2018. . Scopus. URL https://www.scopus.com/results/results.uri?sort=cp-f&src=s&st1=%22technology+Adoption%22&st2=%22Artificial+Intelligence%22&nlo=&nlr=&nls=&sid=c22449829ebe867c3a67df3bdf0dfe10&sot=b&sdt=cl&cluster=scosubjabbr%2c%22BUSI%22%2ct&sl=83&s=%28TITLE-ABS-KEY%28%22technology+Adoption%22%29+AND+TITLE-ABS-KEY%28%22Artificial+Intelligence%22%29%29&origin=resultslist&zone=leftSideBar&editSaveSearch=&txGid=3764190aa2ac4c663a9191cd74e46a87 (accessed 5.2.18).

Scott, W.R., 2001. Institutions and Organizations. SAGE Publications.

Setiaji, B., Wibowo, F.W., 2016. Chatbot Using a Knowledge in Database: Human-to-Machine Conversation Modeling, in: 2016 7th International Conference on Intelligent Systems, Modelling and Simulation (ISMS). Presented at the 2016 7th International Conference on Intelligent Systems, Modelling and Simulation (ISMS), pp. 72–77. https://doi.org/10.1109/ISMS.2016.53

Shukla, P., James, H., Alter, A., Lavieri, D., 2017. Machine reengineering: Robots and people working smarter together. Strategy and Leadership 45, 50–54. https://doi.org/10.1108/SL-09-2017-0089

Silver, D., Hassabis, D., 2017. AlphaGo Zero: Learning from scratch. DeepMind.

Silver, D., Schrittwieser, J., Simonyan, K., Antonoglou, I., Huang, A., Guez, A., Hubert, T., Baker, L., Lai, M., Bolton, A., Chen, Y., Lillicrap, T., Hui, F., Sifre, L., Driessche, G. van den, Graepel, T., Hassabis, D., 2017. Mastering the game of Go without human knowledge. Nature 550, 354. https://doi.org/10.1038/nature24270

Silverman, D., 1970. The theory of organisations: a sociological framework. Heinemann.

Smircich, L., Stubbart, C., 1985. Strategic Management in an Enacted World. The Academy of Management Review 10, 724–736. https://doi.org/10.2307/258041

Smith, G., 2005. AFI's 100 Years... 100 Movie Quotes: America's Greatest Quips, Comebacks and Catchphrases. AFI's 100 Years...100 Movie Quote.

Sobreperez, P., 2008. Technological Frame Incongruence, Diffusion, and Noncompliance. Springer, Boston, MA, pp. 179–196.

Stanek, R., 2017. Getting Real Business Value From Artificial Intelligence [WWW Document]. Database Trends and Applications. URL http://www.dbta.com/BigDataQuarterly/Articles/Getting-Real-Business-Value--From-Artificial-Intelligence-118226.aspx (accessed 4.17.18).

This is BankID [WWW Document], 2018. . BankID. URL https://www.bankid.com/en/om-bankid/detta-ar-bankid (accessed 4.24.18).

Treem, J.W., Dailey, S.L., Pierce, C.S., Leonardi, P.M., 2015. Bringing Technological Frames to Work: How Previous Experience with Social Media Shapes the Technology's Meaning in an Organization. Journal of Communication 65, 396–422. https://doi.org/10.1111/jcom.12149

Van Raaij, E.M., Schepers, J.J.L., 2008. The Acceptance and Use of a Virtual Learning Environment in China. Computers and Education 50, 838–852. https://doi.org/10.1016/j.compedu.2006.09.001

Venkatesh, V., Morris, M.G., Davis, G.B., Davis, F.D., 2003. User acceptance of information technology: Toward a unified view. MIS Quarterly: Management Information Systems 27, 425–478.

Walsh, J.P., Henderson, C.M., Deighton, J., 1988. Negotiated belief structures and decision performance: An empirical investigation. Organizational Behavior and Human Decision Processes 42, 194–216. https://doi.org/10.1016/0749-5978(88)90012-X

Walsham, G., 1995. The emergence of interpretivism in IS research. Information Systems Research 6, 376–394. https://doi.org/10.1287/isre.6.4.376

Weick, K.E., 1979. The Social Psychology of Organizing, 2nd ed. Random House.

Winograd, M., Hais, D.M., 2014. How Millennials Could Upend Wall Street and Corporate America. Brookings.

Yeow, A., Sia, S.K., 2008. Negotiating "Best Practices" in Package Software Implementation. Inf. Organ. 18, 1–28. https://doi.org/10.1016/j.infoandorg.2007.07.001

Appendix

Appendix 1: ‘Go’ Visualization

Appendix 2: Interview Guide

Part I: Introductory Questions/ Pre-tech-use Questions (10 - 15 minutes)

- Do you know what a chatbot is?
- Have you ever used a chatbot?
    - If yes, what type of chatbot have you used?
- How did you feel about the technology when you used it?
- How useful did you perceive it to be?
- How easy did you perceive it was?
- What do you think is the purpose of chatbot technology?
- What applications of the technology can you see/imagine?
- What do you think are the limits of the chatbot technology if there are any?
- Do you think the chatbot technology can currently replace humans? What about in the future? Why? How do you feel about that?
- Do you have any concerns about talking to a chatbot instead of a human?
- Will you be using chatbots in the future? Why?

Part II: Discussion with Chatbot (~5 minutes)

Two tasks for the participants:

1. Try to open an account at SEB
2. Try to find out how to use Mobile Bank ID

Observations: take detailed notes down to the minute about their reactions

Part III: Post chatbot usage (15 - 20 minutes)

- How did you feel when using this chatbot?
- What did you think about the functionality of the chatbot?
- What were the most positive aspects of chatbots? How about negative aspects?
- Do you see different uses of the technology? If yes, what are they?
- How did your view about chatbots change (if it did)?
- How do you see chatbots developing in the future?
- How do you think the chatbot technology could affect your day-to-day life?
- What, if any, other value do you think the technology could provide to you? Why?
- Any modifications that you envision that could make this better for you?
- Has the chatbot technology changed the way you think about yourself?
- Are you more or less willing to use the technology now? Why?

- Do you think the technology can replace humans currently? Why? What about in the future?
- Will you be using chatbots in the future? Why?

Appendix 3: Example of Chatbot Observation Data

- 10:47 AM Excited reaction when being told that he's going to talk to a chatbot.
- 10:48 AM Trying to open an account. He's already a client. He seems excited about it. Shaking head and looking attentively at the transcript. Seems a bit disappointed for not coming too far.
- 10:49 AM How to use a Mobile Bank ID - Frowning when deciding how to ask it about Mobile Bank ID.
- 10:49 AM He's always telling us what's happening.
- 10:50 AM 'Ahh' reaction! He seems interested that the chatbot asked how it can help. Doesn't seem to know how far to go.
- 10:51 AM Saying yes to questions - seemed to not be content with what it did, but then he said that he was happy with how much it helped him to open the Mobile Bank ID.
- 10:52 AM Finished with interaction

Appendix 4: Example of Chatbot Transcript (Translated)

Aida: Hi! My name is Adia and I am an AI digital assistant. I am really new at my job so I can't answer everything but I am learning all the time.

Aida: What can I help you with?

Participant: How do you open an account here?

Aida: Are you currently a customer?

Participant: Yes.

Aida: If you have access to the internet bank, you can open account yourself (link provided). You are always welcome to call us at 0771-365 365 or visit any of our offices.

Aida: If there is anything else I can help you with please let me know.

Participant: How do you use mobile bank id?

Aida: To create a mobile BankID you need to:

- Sign an agreement on the internet bank. For this you need to use digipass.
- Download the BankID app on your mobile phone or tablet.
- Get an activation code from BankID's website.

Aida: Would you like me to help you with this?

Participant: Yes.

Aida: Which phone do you have?

- Apple
- Android
- Windows phone

Participant: Apple

Aida: Start by downloading the BankID app on the App Store (link provided) to your phone.

Aida: Have you installed the app?

Participant: Yes.

Aida: Good! The next step is to get access to Mobile BankID, you can do this by logging in to the internet bank with your card or digipass. Go to "Mitt SEB" - BankID – choose Mobile BankID or click here (link provided) and follow the instructions.

Aida: Do not forget to note the activation code while you are signing up.

Aida: Are you done with signing up and do you have the activation code?

Participant: Yes.

Aida: Good job! Continue to open the BankID app on your phone or tablet and click on retrieve BankID.

Aida: Write your personal number (social security number) and activation code in the app. Choose a code in for the Mobile BankID that is at least 6 characters. You will need this code every time you login in or sign for a payment with Mobile BankID.

Aida: Have you written you personal code in the app?

Participant: Yes.

Aida: Now you are almost done! Log in to the internet bank or SEB app to verify that it worked.

Aida: Were you able to log in with your new Mobile BankID?

Participant: Yes.

Aida: Good! Now you are done!

Aida: If you have an iPhone with Touch ID I have a tip that you can login with your fingerprint in our app and on the internet bank.

Appendix 5: Interview Participants

#	Name	Role	Industry	Birth Year (Age)	Gender	Interview Length
	Pre-Study					
1	Sophie	Data Analyst	Fashion	1986 (31)	Female	38:23
2	Emma	MSc Student	Business	1991 (26)	Female	33:15
	Main Study					
1	Hanna	MSc Student	Business	1990 (28)	Female	39:02
2	Andrea	Account Manager	FMCG	1988 (30)	Female	35:53
3	Tim	MSc Student	Business	1991 (27)	Male	37:07
4	Angelica	Credit Officer	Credit & Collections	1985 (33)	Female	33:47
5	Alexander	Director	NGO	1985 (33)	Male	38:14
6	Peter	MSc Student	Business	1989 (28)	Male	40:19
7	Cattis	MSc Student	Business	1989 (28)	Female	47:28
8	Theodor	Resident	Medicine	1990 (27)	Male	43:26
9	Mikael	Facility Manager	Telecom	1983 (35)	Male	34:20
10	Miranda	MSc Student	Business	1993 (25)	Female	43:43
11	Helen	Administrator	Conferences	1984 (33)	Female	32:09
12	Malin	Analyst	Investments	1987 (30)	Female	40:38