MY COWORKER THE AI: INVESTIGATING THE IMPACT OF ARTIFICIAL INTELLIGENCE ON ORGANIZATIONAL CULTURE ON THE EXAMPLE OF A CHATBOT CASE STUDY

Victoria Dorofeeva
Master's Thesis
Intercultural Communication
Department of Language and Communication
University of Jyväskylä
Autumn 2021

UNIVERSITY OF JYVÄSKYLÄ

Faculty Humanities and Social Sciences	Department Department of Language and Communication
Author Victoria Dorofeeva	
Title My coworker the AI: investigating the impact of artificial intelligence on organizational culture on the example of a chatbot case study	
Subject Intercultural and organizational communication	Level Master's degree
Month and year November 2021	Number of pages 58

Abstract

There is a surging trend among organizations to introduce artificial intelligence-based assistants to workplaces. Usually, such assistants' function is to perform a part of the employees' work. Most of the research on AI revolves around the topics of technologically induced unemployment, and labor market restructuration, but little light is shed on the ways the introduction of AI to workplace impacts employees' wellbeing, social dynamics at the workplace, and organizational culture of the company overall. To find out these impacts the case study of a Finnish enterprise was conducted. The case study helped to answer the research question and find out the way employees view the impact of AI on their organizational culture. The findings demonstrate that deployed internal Slack chatbots help create and reinforce the organizational culture of the enterprise. The chatbots' cultural value was found to be not only in liberating employees from menial repetitive tasks, but also in the improvement of manager-subordinate relationships, in serving a community building function, in flattening of the organizational hierarchy and in eliminating unproductive work-related communicative exchange. This study bridges and makes a contribution to the fields of AI and organizational studies.

Keywords: artificial intelligence, smart technologies, organizational culture, Schein, ANT, chatbots, case study

Depository University of Jyväskylä

Additional information

FIGURES

TABLE OF CONTENTS

1 INTRODUCTION

The rise of the technological advancements over several past decades has redefined the modern workplace and business operations. Currently, one of such game-changing and most promising technological innovations is artificial intelligence (AI). More and more companies adopt AI-driven solutions to enhance and promote the company's innovativeness and strategic savviness. While a skillful utilization of AI-based solutions yields benefits to the company and its customers, it is likewise vital to understand how the introduction and presence of this smart technology in the workplace impacts human-human and human-AI interactions, as well as employee's overall wellbeing and organizational culture.

The importance of this understanding is dictated by at least two factors (Schiff, Ayesh, Musikanski, Havens, 2020). Firstly, gradual societal development has summoned a ubiquitous focus on corporate social responsibility. Economic growth and profitability are no longer the pivotal Key Performance Indicators (KPIs) for the businesses, but employees' wellbeing is gaining more attention. Similarly, Cao, Vasek and Dusik (2018) conducted a survey on the employees' needs in the context of intelligent systems in the workplace and discovered that all workers' needs revolve around the central concept of wellbeing. Secondly, there are potential risks stemming from the growing power of digital companies and potential impacts of AI on every sector of society (Schiff, Ayesh, Musikanski, Havens, 2020*)*. That fact calls for the society to investigate and understand these impacts.

As it will be discussed further in this study, a lot of employee's failed expectations of AI emanate from their misunderstanding of the definition of AI-based technology and black-box phenomenon of AI, in other words, a lack of knowledge on how AI generally works and what tasks it pursues. It is important to mention, however, that there is no one agreed-upon definition of AI. In this study I will follow Kaplan and Haenlein (2019) who defined it as "a system's ability to correctly interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Kaplan and Haenlein, 2019, p. 17). Two salient characteristics of the system that stem from the aforementioned definition and distinguish this innovation from other current technological advancements are its autonomy and flexibility.

There are multiple applications of AI-based technologies in organizations across various industries, starting with image recognition technologies in video surveillance and health care, analyzing and predicting in finance, logistics, decision-making and forecasting, individual customization of services and recommendations, and ending with conversational assistants such as chatbots. In any case, the essence of AI's work is the automation of processes and augmentation of human performance, that are, notwithstanding, interconnected (Raisch and Krakowski, 2021).

Considering AI's purpose of humans' work optimization and the fact, that the name of the innovation itself promises a striking similarity with human performance, it may precipitate mixed feeling of the employees working closely with AI assistants. For instance, one of such widespread anxieties may be a perceived fear of future unemployment caused by employees' tasks being delegated to AI (McClure, 2018).

While many scholars and practitioners maintain that the feasibility of AI fully substituting all human jobs in the foreseeable future is close to zero (at the exception of menial repetitive jobs such as waste sorting or any other jobs that are confined to a small range of monotonous tasks), many employees still treat AI as a competitor rather than as an opportunity for own professional development. Since collaboration with an AI assistant usually provides a number of benefits to the employee as well as to the organization in general, the issue seems to be determined by people's negative perception or misinterpretation of AI. The problem, therefore, is to seek ways to organize comfortable and effective coexistence of human workers and AI agents in the workplace. Multiple enterprises have done a great job hosting workshops and trainings for their personnel to educate them about AI as a phenomenon and teach them how to collaborate with it effectively. Notwithstanding, more often than not these trainings are focused on providing knowledge, and therefore aimed at employee's rational thinking, but not their emotional component. Consequently, irrespective of the knowledge that employees acquired during trainings they may still experience prejudice against working alongside AI. One possible way to approach this issue is to employ the concept of organizational culture and make sure an AI-based solution is integrated as a part of this culture. However, there is a lack of studies discovering the impact of smart technologies on organizational culture and employees' wellbeing. Most of the studies seem to revolve around the topics of AI's impact on global labor market, its restructuration, and new skills in a digital workplace. On the contrary, little is investigated about the way artificial intelligence changes social dynamics in the workplace, as well as what it means for people to have an AI-powered "co-worker". That constitutes a research gap that this study addresses. The study conductor assumes that the insights form organizational studies can help find answers to these questions. This fact justifies the relevance and novelty of the study.

Therefore, the research purpose of this study is to bridge the fields of organizational studies (organizational culture and organizational communication) and artificial intelligence to investigate employees' wellbeing in the form of perception and attitude to working alongside AI, and the impact of AI introduction on organizational culture and human-to-human relationships in the workplace. This approach helps to discover the phenomenon of AI-co-worker with the focus on human experiences.

To fulfil this purpose, the literature review will firstly investigate the consequences of introducing AI to a workplace. Secondly, organizational culture will be discussed as an entry point to understanding the role of AI at work. Thirdly, human perception of AI and the place of human and non-human actors in organizational culture network will be explained. Finally, the way employees perceive the impact of their AI-coworkers on the organizational culture will be investigated on the example of a case study of the middle-management Slack chatbots in a Finnish digital enterprise. This study contributes to organizational studies by introducing the topic of integration of organizational culture and AI.

2 LITERATURE REVIEW

2.1 Consequences of introducing AI to a workplace

The era of AI and intelligent systems is often referred to as Industry 4.0, which, in turn, relates to the fourth industrial revolution (Kagermann et al., 2013). According to Oosthuizen (2019), "the concept of Industry 4.0 describes the increasing digitisation of the entire value chain and the resulting interconnection of people, objects and systems through real-time data exchange" (p. 19-20).

Even though separate research fields of artificial intelligence (AI) and organizational studies are burgeoning and receive sufficient attention, the research field integrating AI and organizational (or corporate) culture is currently in its infancy. Very few studies have focused on investigating the interplay between these two phenomena. Most of the research that has studied the introduction of AI to the workplace either simply acknowledges the importance of approaching AI development and utilization from the humanities perspective without putting forward any specific suggestions or issues or revolves around the topic of technologically induced unemployment. However, research suggests that the introduction of any type of new technology into a workplace inevitably changes work practices as well as social interaction dynamics at the workplace (e.g., Actor Network Theory by Latour (1988)). Yet, little is known about how AI introduction affects an organization as a system, and especially how it impacts social dynamics, relations, and communication within it. By synthesizing available literature and conducting a case study this research attempts to shed light on this topic.

With the growing number of businesses adopting AI-based solutions due to multiple benefits that they entail, there is an ongoing debate concerning possible repercussions of introducing AI to workplaces. One of such bones of contention is the discussion of the possibility of the smart technologies to lead to future mass unemployment.

2.1.1 Fear of AI substituting human workers

Observably, most of the academic works tend to discuss the impacts of AI introduction to workplaces exclusively in terms of future technologically induced unemployment and convey overall negative attitude to human-AI collaboration. Irrespective of the level of accuracy of these claims, such approach to evaluation of AI-caused impacts appears to be lopsided, and needs to be enriched with diverse perspectives, the effects of AI introduction to workplaces on human-human interaction and organizational culture being several of the many. Nevertheless, since technologically induced unemployment constitutes a considerable part of literature on the topic of the research interest, it is essential to discuss several prominent works from this aspect.

There are several popular sources used to argument for the negative impact of AI on the future of humans' employment. One of them is the report of The World Economic Forum (2016). According to this report "developments in areas like Robotics and Artificial Intelligence will transform the nature of our economies and eliminate many current occupations" (Walsh, 2018, p. 1). Another widespread reference is the Oxford University scholars Frey and Osborne's extensive work on the susceptibility of jobs to computerization (2013). The authors maintain that "47 percent of total US employment is at risk" (p. 1). Finally, many sources mention the words of the prominent technology experts such as Stephen Hawking and Bill Gates, who pointed out the threat of mass unemployment (Brougham and Haar, 2018; Kravchenko, 2019).

There may be a big issue with referencing and citation of these sources. Firstly, one characteristic they have in common is the power of authority of the source. All of them are perceived by many as respected and competent sources, and, presumably, scholars and journalists will favour to support their own arguments with sources that are perceived in the aforementioned way, so that the power of authority will persuade scholars' and journalists' audiences to believe them (Cialdini, 1987). This is a valid approach; however, the citation and referencing should be careful and critical. For example, Kravchenko (2019) in their study do not approach technological unemployment critically, but only iterate "jobs will be taken". Secondly, the citations in question often appear to be extracted from either introductory or conclusion parts of the articles, leaving the nuances and contexts explained in the main body in the shadows. Noticeably, such general negative claims as future mass unemployment may instil fear in the audience, and there is a jeopardy that they will extrapolate this fear to their own employment cases. There is also a possibility that the researchers deliberately choose urgent and alarming tone for their studies to ensure funding opportunities. Cath, Wachter, Mittelstadt, Taddeo and Floridi (2018) illustrate it on the example of the UK report concerning national AI regulations.

Research has indicated that workers of the companies, that have implemented or are planning on implementing AI-based technologies for the purpose of automating certain tasks and thus enhancing enterprises productivity, may experience negative feelings towards AI since they are worried about AI substituting them fully in their jobs and leaving them unemployed. One frequently cited study exploring employees' negative attitudes to AI in their workplace was conducted by Brougham and Haar (2018). They assert that employees' awareness of smart technology, artificial intelligence, robotics, and algorithms (STARA) is positively connected with their low commitment to work, depression and increased job turnover. "STARA awareness is a measure that encapsulates the extent to which employees feel their career could be replaced by these modes of technology" (Oosthuizen, 2019, p. 17). Unfortunately, the authors do not explain the quality of employee's awareness, that is, what exactly they are aware of, what kind of discourses are present in their communities, what sources they use to raise their awareness (even though they acknowledge consumed media landscape limitation). The example that the authors offer to demonstrate the connection between STARA awareness and its negative outcomes is a person witnessing their employer exploring ways to replace employees with robots on the conveyor belt. They put forward, that such observations will make the employee feel undervalued and replaceable with technologies, thus undermining their organizational commitment. However, in this example Brougham and Haar (2018) do not entertain such aspects as organizational culture of that company, specifically the way managers treat their subordinates. For instance, the employer may be looking into opportunities to automate work at the conveyor belt, but little is known about whether they are planning to offer new opportunities or retraining options to employees, and how they address automation issues in general. These details need to be considered, otherwise Brougham and Haar's statement may be superficial. On the other hand, the researchers emphasise career planning as a tool to neutralize negative outcomes of STARA awareness (p. 252). They suggest that career prospects cannot be limited by STARA, on the contrary, STARA allows people to self-develop. Ultimately, they conclude their study saying that "the overall findings show that employees in general do not perceive STARA to be a threat, despite what well respected businesspeople, scientists, and academics are predicting" (p. 254). To conclude, it seems that many articles citing Brougham and Haar's (2018) research misinterpret their findings or present them in a contextless way.

Even though Brougham and Haar's (2018) research has various limitations, this study manifests the existence of such phenomenon as employees' bias towards AI in the workplace. Similarly, Heikel, Leppänen, Lindén, and Bäck (2019) mention that "the arrival of new technology has often caused anxiety and uncertainty" (p. 48). It is natural for people to be suspicious and careful about new things they come across, technology arguably being the most widespread example of unfamiliar novelty that requires time and learning to get acquainted with. Technology adoption life cycle model (Rogers, 1962) reflects this phenomenon well by suggesting that only a small part of the population (about 16%), represented by the innovators and the early-adopters groups, will start using a particular technology as soon as it enters the market. According to the model, the majority of the population will adopt the product or technology later, their personal networks and the high level of the new product adoption within these networks being a major influencer. Consequently, it can be stated that the more frequently people encounter a new product or a technology within their network, the more likely they will adopt it. However, Kravchenko (2019) states that "the more people come across intelligent machines in their daily work activities, the more realistic the threat of human obsolescence in the workplace is" (p. 42). This claim appears to be compromised because it is not supported by any scientific evidence or arguments, and it seems to contradict technology adoption life cycle model. Moreover, the mere presence of smart technologies in the workplace may not signify the obsolescence of human work. It is rather necessary to study how people feel about having AI-co-workers in a combination with organizational practices of a given workplace.

There seem to be various factors that can affect people's attitudes towards AI, quality and the depth of the knowledge people have being one of them. Walsh (2018) has conducted a qualitative study to find out the difference between AI-experts' and non-experts' predictions of future AI-induced unemployment. Findings demonstrate that the experts in AI and Robotics are more cautious in such predictions than non-experts, even though the former did not deny the risk of automation for a large group of occupations. This can be explicated by the fact that AI and Robotics experts are more aware of how smart technologies work and that they understand that AI cannot leave most of the population jobless. Thus, the amount and quality of knowledge the general public possesses forms a vast gap between experts' and public's expectations of AI and its capabilities. Moreover, when people get to collaborate with AI assistants, AI's perceived affordances (Nagy and Neff, 2015) may be in conflict with AI's real functionality and lead to disappointment of the users. Hence, Walsh (2018) suggests investing more effort in public's expectation management concerning the rate of progress in the field of Robotics and AI. That can also help to avoid future AI winters.

McClure (2018) conduced another study to discover the reasons for biased attitudes towards AI. They focused on the fears of technologically induced unemployment and drew a conclusion that the majority of respondents who reported having such a fear seem to constitute a sizable population of technophobes or "those who fear robots, AI, and technology they do not understand" (p. 139), and many of them "exhibit higher than average anxiety-related mental health issues" (p. 152). The study indicates that gender, education, and race impact the level of technophobia: "statistically, females, non-White minorities and those with the least amount of education are more likely to fear these developing technologies" (p. 152). McClure mentions that the fear of technological unemployment has not been studied enough, the focus of many academic works being mostly on the technological unemployment. However, technophobia is not a new phenomenon. For example, the History has witnessed Luddite rebellion in England in the early 1800s. Finally, it is important to be aware that McClure's study was conducted in the US and the population sample was broadly representative of the general US population. It is vital to remember that socio-economic and cultural differences of the countries may have an impact on research outcomes of the topic in question.

It turns out that the motivation to adopt new technologies can be caused not only by excitement about the new possibilities. Song (2003) claims that a considerable amount of people is prone to adopt these new technologies out of the "fear of being left behind". On the one hand, this may be an indication that a significant amount of people does not see personal and societal opportunities in technological adoption or does not understand them. On the other hand, Song (2003) conveys that depending on the stage of technological adoption in the society overall, the initial excitement may for many people turn into a necessity. That is in line with the technology adoption life cycle model (Rogers, 1962), according to which technophobes can also adopt new technologies in case they become a necessity.

Finally, Saner and Wallach (2015) raise a question of whether there are conditions, when human labor automation by AI is likely and feasible. The authors maintain that technological unemployment can be possible in case people are rendered standardised and predictable (machine-like). They see it as an outcome of global trends that lead to high standardization of education, workplaces, and cultural norms in the organizations (similar speech codes, performance measurements, surveillance, and monitoring). Saner and Wallach call this situation functional equivalence and warn against the possibility of standardization of human labor due to globalization. The unique value of their research lies in the fact that they suggest a new methodological perspective by considering both technological and socio-economic trends and contexts.

To conclude, this subchapter attempted to introduce a different perspective on the ubiquity of the fearful bias towards AI that is communicated to the general public by various respected sources but does not follow the purpose to degrade studies mentioned in it. Further hypotheses on the reasons of such biased attitudes are presented in Chapter 2.1.4.

2.1.2 Global impact of AI on the labor market

Regarding the impact of AI introduction on labor market, scholars are divided by different standpoints. For example, Huang, Rust, and Maksimovic (2019) put forward, that while machines are better than people at analytical and thinking tasks, humans should instead focus on empathetic and interpersonal tasks, of which AI is not currently capable, to ensure their future employability. Though this is a valuable insight shedding light on the current AI capabilities, such dichotomy seems to be compromised in practice. Firstly, humans need to have access to analytical and thinking tasks to exercise their brains, and secondly, it would be dangerous to outsource such tasks to AI without any regulations, as AI's output may sometimes be unpredictable.

Another dichotomy that can be observed among the researchers' points of view is a division into low or menial labor and high-skilled labor. Researchers who support this dichotomy emphasize disproportional effects of AI introduction on population, stating that not all jobs can be automated. As an example, Su (2018) argues that low and medium-skilled labor will suffer from AI advancements the most (p. 38). However, such outlook seems to be limited and unrealistic, because firstly, jobs are rarely divided strictly into only menial and only high-skilled labor. Usually, they involve a certain amount of both. Secondly, current AI assistants are often able to perform well only specific tasks, and thus cannot fully substitute a human's job. It is worth adding that there is a prominent debate in the current field of AI whether an artificial general intelligence (AGI) (Hodson, 2019) or the so-called "strong AI" can be created. The term strong AI is reserved for the AI with general cognitive abilities and consciousness (and thus the ability to potentially do a human job), that can perform any task a human can, and week AI means a task- or problem-specific artificial intelligence. The existence of the former is currently completely hypothetical, while the latter is the AI the world currently has.

Wisskirchen, Biacabe, Bormann, Muntz, Niehaus, Soler, and von Brauchitsch (2017) propose a different approach: in the context of AI-human collaboration there should be, and, they maintain, will be in the future, a focus on routine versus non-routine work, rather than physical versus cognitive work (p. 48). This approach allows to understand better which menial and routine tasks can be delegated to and automated by AI. Moreover, the understanding of such division by the general public could help propagate a perception of AI as a helper or assistant rather than a competitor and would be beneficial in managing public's expectations of AI.

On the other hand, Wisskirchen et al. (2017) do point out that in specific industries routine jobs are under threat of displacement. It is not worth denying that employees, whose jobs include a prevalent amount of specific menial tasks might be much more sensitive to the problem of AI automation than others. Similarly, McClure (2018) points out that a "skills bias" has resulted from technological improvements that advantage the highly educated" (p. 140). This "threat" to employment can be interpreted in a positive light, because to upgrade to a less automatable job a person would need to get better education and more advanced competences and skills. That, however, elicits a problem of the quality and accessibility of education worldwide, which is not the immediate object of this research area, but emphasises the importance to study technological development in synthesis with socio-economic development (Saner and Wallach, 2015).

Summing up, scholars maintain that the prevailing majority of human workers will not be substituted by AI, rather the structure and content of their work are likely to become more sophisticated in the future. Moreover, one of the impacts of AI on the global labor market is the increased urgency and necessity to develop the quality and accessibility of education worldwide, as well as employee-oriented governmental and corporate practices.

2.1.3 Human-AI collaboration

Opposed to the concept of work automation many scholars sustain the concept of human performance augmentation, emphasizing that employers should choose employees' performance augmentation where possible, instead of simply replacing workers with AI, in order to secure workers' employment and harvest benefits of human-AI collaboration (Walsh, 2018; Jarrahi, 2018; Raisch and Krakowski, 2021). Performance augmentation in this case means that humans' capabilities are extended with the help of smart technologies. Jarrahi (2018) provides the following example: "AI can extend humans' cognition when addressing complexity through a superior analytical approach, whereas humans can offer a more holistic, intuitive approach in organizational decision making" (p. 577). Thus, AI enhances human performance and yields benefits for both the employees and the organization.

While there is research on the benefits of human-AI collaboration in context of specific job activities, it is also vital to understand and predict its impact on the society in general and on organizational environment. One of the extended and multidimensional studies on the effects of AI introduction on society and work life is reflected in the report "Artificial Intelligence and Robotics and Their Impact on the Workplace" by the IBA Global Employment Institute (GEI) (Wisskirchen, et al., 2017). This report tackles and attempts to foresee trends not only in the impact of AI on labor market, but also in the organization of work, organizational structure, types of employment, health, data protection and other matters. The context of smart technologies' impact on the organization of work is the most relevant for this study. The authors explain that "intelligent systems actively contribute to a better inclusion in the establishment" (p. 55). Specifically, the achievements in AI and robotics allow people with disabilities and older people to integrate into the process of work, by performing or assisting with tasks these people have hardships with and be a part of the organization. This is in line with the fact that communication technologies offer employees novel ways of participating in the projects, by intertwining technologies with their work (Siitonen and Aira, 2019). Moreover, the same benefits can be applied to people without special needs: "the time saved, especially for dangerous work, can be used by human beings for other work or for leisure" (p. 117). Consequently, Wisskirchen et al. (2017) maintain that if human collaboration with AI and smart technologies leads to the rise of productivity, employees will not be fired, since the rise of productivity implies a growth in orders and profit. Importantly, they admit that the relevance of investigating peculiarities of a particular sector, country and region will yield more precise statements. Moreover, Wisskirchen, et al. (2017) discuss the impacts of smart technologies introduction on organizational culture. They reckon that "the cross-linking of single employees by new technologies allows easier communication and enables a better exchange of information" (p. 49). It seems that human-AI collaboration in the workplace lead to the flattening of the organisational structure and hierarchy, both withing the organization and in relation to customers. This impact will be studied further in the next chapters.

Based on the previously demonstrated research findings, it turns out that AI-assistants and robots perform tasks outsourced to them by humans that the later are unwilling or unable to perform. Though Liberati and Nagataki (2019) accentuate that this "does not mean that tasks on which human intelligence focuses have substantially reduced. Rather, they have been transformed so that more advanced work has been placed upon us" (p. 334). Borenstein (2011) is convinced, that this trend "is likely to grow considerably over time" (p. 88). However, in contrast with Wisskirchen, et al.'s (2017) standpoint on the unlikelihood of employee dismissal due to increased productivity and profits stemming from collaboration with AI, Borenstein (2011) admits the importance of profit margins improvement with the help of automating, downsizing, and outsourcing for the businesses, which "do not necessarily equate with investing in and retaining employees" (p. 88). Remarkably, the author draws attention to the fact that their study focused on the American cultural context, pointing out the peculiarities of American business and cultural environment: "American corporations might not invest in the long-term future of their employees if it is not deemed to be profitable enough" (p. 90). Therefore, Borenstein (2011) reinforces the necessity to moderate automation effects via governmental regulations and corporate policies (p. 90).

Regarding the predictions of the digital workplace of the future, Saner and Wallach (2015) claim that it is uncertain whether techno-optimists' or the neo-Luddites' approaches are more valid for predictions of our future collaboration with AI agents, but they underscore the importance of investigating both the technological and the cultural aspects of this issue, rather than focusing on one of them exclusively (p. 78).

All in all, there is enough scientific evidence on the benefits of human-AI collaboration in the workplace. Many scholars who investigated this topic agree that the introduction of AI into workplace will change the organization and the structure of people’s jobs but rather for the better for the employees themselves. However, the question of regulations in relation to people’s employability under the effect of AI-automation remains open and may have a more urgent status in specific socio-cultural environments.

2.1.4 Socio-cultural effects on the perception of AI

Based on both personal observations and existing scientific literature, it appears that the overall attitude of the employees to their AI-based “co-workers” is highly influenced by the socio-economic, cultural, and political realities of their country. According to Schein and Schein (2016), “broader assumptions about human nature often derive from the larger culture in which the organization is embedded or from occupational units that cut across organizations” (p. 25). For example, the majority of Russian media articles speculating about the future of AI in Russia convey mostly negative and despaired tone, and AI is referred to as the primary reason for many people's unemployment in the future. There is an opportunity, that these beliefs and perceptions are reinforced by the peculiarities of social reality in Russia. In Russia the cost optimization and high margins seem to be the ultimate goals for the business and the government alike, and in case the workers’ wellbeing and quality of life are in the way of that goal, decisions are made in favour of the former, and such attitudes are pervasive in the system. Hence, Russian workers’ suspicion of smart technologies seems understandable and reasonable. Similar example regarding American national culture was introduced in the previous chapter based on Borenstein’s (2011) study.

In contrast, in Finland and a number of other EU countries workers’ wellbeing appears to be of a paramount importance. Even though the long-term cost optimization is important for Finnish society as well, the worth of an individual’s life plays a huge role in public and individual perception of future cohabitation with advanced technological systems. This may be a determinant of more positive discussions about performance augmentation by AI, and a perception of smart technologies enabling people to devote more time to creative tasks and develop professionally faster. Thus, discourses about AI as a co-worker make more sense in such social reality. Ostensibly, for the countries with particular socio-economic, cultural and political realities in which the worth of an individual’s wellbeing is currently compromised the issue of governmental regulations and corporate policies in the context of work automation is more urgent and relevant.

Moreover, when discussing and designing comfortable human-AI collaboration at the workplace, it is important to add the dimension of cultural preferences and culturally induced perceptions of technologies. For example, Mavridis, Katsaiti, Naef, Falasi, Nuaimi, Araifi, and Kitbi (2012) investigated opinions and attitudes towards humanoid robots in the Middle East and discovered that their population sample exhibited preferences in the application areas for AI that differed from research on American or Asian population samples. Additionally, religion, age and gender were reported to be impactful on the peoples' attitudes towards AI-based robots.

To sum up this chapter, it needs to be accentuated that AI is not a monolithic term (Kaplan and Haenlein, 2019), but there are multiple various application cases and specific technological affordances (Nagy and Neff, 2015) to each AI-powered solution. Therefore, understanding of the context and caution is strongly advised when discussing topics of AI-induced unemployment. It matters which specific tasks AI can perform in the context of human work automation (or augmentation) and what are the nuances of a person's work.

Technological unemployment is a type of structural unemployment, and many scholars maintain that AI introduction will lead to the restructuration of labor, instead of mass unemployment (Wisskirchen, et al., 2017). While jobs and specific work tasks will be restructured and reshaped due to smart technologies, this may also indirectly increase the significance of academic research in AI and organizational studies. Generally, people's relations to and expectations from cohabitation with AI in the workplace can be placed on the spectrum from "AI as a threat" to "AI as an opportunity". It is possible that people on the "AI as a threat" side of the spectrum may also be unwilling to develop themselves, and would prefer to stick to simple routine jobs, since self-development requires effort and motivation. In that case smart technologies are simply rejected as something that disturbs the comfort zone.

Ultimately, while there is scientific evidence on the existence of negative attitude of the employees towards AI-based technologies, there seems to be few suggestions on how to help people see opportunities rather than threats in AI and avoid inexplicable repulsion towards it. Some scholars underscore the importance of special trainings for employees to prepare them for new jobs that are unlikely to be automated by AI (Kaplan and Haenlein, 2019, p.12). On the other hand, it is possible, that this approach may only aggravate people's fears of AI-based technologies. Other organizations host workshops to explain how AI works and how it can be useful. However, approaches like these are aimed at rational thinking and do not seem to take into account people's feelings. This forms a research gap, which this study aims to address by exploring the concept of organizational culture as a vantage point to investigate the impact of AI-based innovations on the employees and their social environment in the workplace.

2.2 Organizational culture as an entry point to understanding the role of AI at work

2.2.1 Understanding organization and culture

There have been multiple attempts to understand and define such social phenomena as organization and culture, and it is no surprise that the field of humanities is abundant with various definitions, approaches, and models on this topic. To explain the concept of organization in this study, the following simple and functional definition will be referred to: "organization is a social unit of people, systematically structured and managed to meet a need or to pursue collective goals on a continuing basis" (in Wrench and Punyanunt-Carter, 2012). The most important nuance in this definition is the existence of collective goals, that are pursued on a continuing basis. This seems to be the descriptive characteristic of the organization as a unit of people. However, in order to pursue collective goals, there needs to be a shared, or at least prevailing, understanding of how to achieve the organizational purpose, that would guide daily work within the organization as well as in relation to external stakeholders. That would be an organizational culture (OC). Explained in plain language, culture is "the way we do things around here" (Deal and Kennedy, 1982). Thus, organizational culture is "the way we do things in the organization". In general, the function of culture appears to be in helping people arrange their lives, introduce meaning and structure to it. It can also be viewed as a tool for combating anxiety that may stem from the inability to comprehend or foresee events transpiring in the future and/or outside of the group(s) an individual belongs to. Alvesson (2012) and Schein (1986) also reckon that a culture reduces uncertainty. Remarkably, culture is always collective and is shared via different modes of communication (e.g., language, verbal and written modes, nonverbal behaviour, cultural artifacts, etc.). The aforementioned fact makes organizational culture a form of community building. Brain (2004) understands community as activities that people do together and he sees shared understandings and expectations as prerequisites for a strong community. Thus, practices aimed at the creation and enhancement of a community are vital for the sound functioning of an organization.

While culture as a social phenomenon may appear to be hard to define and comprehend, it is important to remember that culture, and specifically organizational culture, are not monolithic terms, and seem to be ambiguous (Alvesson, 2012). This fact elicits an assumption that there may be multiple parts (or smaller cultures) of a culture of a particular organization. McCarthy (1998) warns that since an organisation is a "complex system, there may be many subcultures" (p. 178). However, organizational culture is ubiquitous and embraces all actors (stakeholders) related to it.

It is also important to answer the question of how to embed community building practices into organization in order to share culture. A renowned historian Yuval Noah Harari in his popular science book "Homo Deus" (2016) mentions the concept of intersubjectivity, initially introduced by Edmund Husserl, in a cultural context. The intersubjective level of reality is claimed to exist alongside objective and subjective levels of reality and is created by human cooperation. Onto the intersubjective level of reality are placed all society-related artefacts, whose value exists as long as people believe in it. The examples include money, gods, cultures, and multiple stories that convey the value of these things. Harari maintains that they allow people to cooperate in large numbers, and thus be superior to other animals. Hence, it can be concluded that the importance of community building in organizations lies in storytelling as its tool, since storytelling is capable of explaining "how we do things around here" in a narrative form. The narration of organizational values could be conveyed via, for example, such elements of a cultural web as organizations' paradigm, control systems, organizational structures, symbols, rituals and routines, stories and myths (Johnson, 1988).

However, the question that is relevant for conducting research on OC is how it is possible to understand and decipher organization's culture from the observer's viewpoint. Edgar Schein (1986; 1990; 2016) is one of the few scholars who answer this question. He introduces a three-layered model of OC, which allows to fully understand the reasons behind people's behavior in an organization. In order to operationalize the concept of organizational culture for the purposes of this research, it appears relevant to undertake analytical descriptive approach to culture, which implies breaking down the concept and discovering the elements of organizational culture to be applied in the case study. Schein's approach to OC allows for such an analysis, and it will be followed for the purpose of this study, because his framework provides an in-depth analysis of this social phenomenon.

Since this study utilises Schein and Schein's (2016) model of organizational culture, it is important to find out how he explains this concept. According to Schein (2016), organizational culture is "the accumulated shared learning of that group as it solves its problems of external adaptation and internal integration, which has worked well enough to be considered valid and, therefore, to be taught to new members as the correct way to perceive, think, feel, and behave in relation to those problems" (p. 6). As it can be observed, Schein's definition is in line with the aforementioned explanation of culture. Schein, however, emphasizes that culture is a product of a shared social learning, and that exactly these positive experiences of what works well within shared learning lead to the formation of culture. This approach demonstrates the importance of organizational knowledge management for a fruitful development of the organization. Organizational culture is also about how knowledge is shared, stored and used, which corresponds with cultural studies because culture does provide knowledge about the world. Freiling and Fichtner (2010) even suggest a metaphor "organizational culture as a glue" between people inside it, as a form of organizational knowledge sharing.

Cultures are agreed by many scholars to be dynamic since culture is constantly shared and negotiated during social interactions. While many researchers agree that culture is "what we do", culture may also be explained as "why we do things", depending on the level and depth of analytical approach to culture. For example, Schein's approach implies three levels of analysis of organizational culture, the top-level being artifacts, second – espoused beliefs, and the deepest one – underlying basic assumptions. Artifacts can be tangible and intangible but visible and feelable phenomena, for example, physical environment, products, website, clothing, myths and stories, observable rituals. They are the easiest to observe but the most difficult to decipher without insiders' help. Remarkably, Schein places utilized technologies on the level of artifacts. On the next level are espoused beliefs, which are company values it claims to have and exercise. The power of these values lies within social validation, which "means that certain beliefs and values are confirmed only by the shared social experience of a group" (p. 20), and lead to the formation of an abstract ingroup vs. outgroup division. Finally, the deepest level of OC analysis is underlying basic assumptions, which Schein demonstrated in his case studies to be invisible from cursory observation but explanatory of people's behaviors, perceptions, thoughts and feelings in the organizations (1986; 2016). Schein underscores that these underlying basic assumptions are learned by people through time of organization's existence, solidified with positive experience of them being effective, and with time drop out of awareness. Therefore, he claims that this layer of OC cannot be understood with such methods as interviews or questionnaires but should be found out by the researcher via thorough observations of people's behavior within the organization. Additionally, according to Schein, espoused beliefs and underlying basic assumptions may not always be in congruence, which can cause internal tensions and anxieties. The level of underlying basic assumptions is what distinguishes Schein's model from other explanations of organizational culture since it digs deep into the reasons behind people's behaviors and perceptions, which are often overlooked by organizational change specialists and coaches.

It may be assumed that the analysis of organizational cultures will be easier provided that the most salient characteristics of various OCs are identified and classified. Noticeably, Schein (1986) was against classification of organizational cultures. He was convinced that organizational cultures are unique and that not enough of them have been studied, so that it would be possible to work out a classification. While Schein's claim appears to be valid considering his experiences with extensive case studies, and it certainly is valuable to approach cultures with an open mind, it should be noticed that this was proposed around four decades ago. Perhaps modern research has managed to tackle this issue. Even though it is not the goal of this study to discover all possible OC classifications, it seems important to discuss a recently proposed type of a digital organizational culture.

2.2.2 Digital organizational culture

Digital organizational culture term was proposed by Duerr, Holotiuk, Wagner, Beimborn and Weitzel (2018). They applied Schein's model of OC to discover the effects digitalization may have on digital enterprises and their organizational culture. Their research is relevant for this study because the case study company of this study can be classified as a digital organization. The authors mention that "this analysis is the first to identify the facets of OC in digitalizing firms" (p. 5133). The topic of organizational culture seems to gain even more relevance during the era of digitalization. Duerr et al. emphasise that "to successfully develop digital innovations, organizational culture is supposed to be a prerequisite" (p. 5126). Similarly, Alvesson (2012) indicates that "innovative and knowledge intensive industries pay more attention to organizational culture" (p. 7).

Duerr et al.'s application of Schein's OC model to a number of digital organizations, that is, organizations actively deploying information technologies, revealed specific features of a digital organizational culture (see Figure 1).

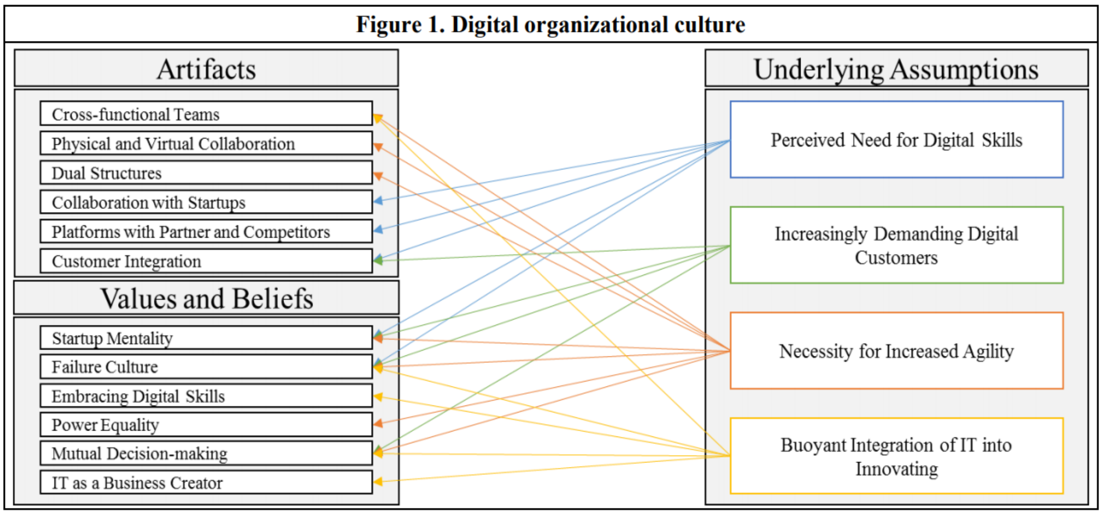

Figure 1. Schematic depiction of Schein's OC model applied to a digital enterprise. From Duerr, Holotiuk, Wagner, Beimborn and Weitzel (2018).

The authors propose that on the level of artifacts of a digital organizational culture are novel ways of internal collaboration (namely: cross-functional teams, physical and virtual collaboration, and dual structures) and external collaboration (start-ups, platforms with competitors and partners, and customer integration as well as on sharing, transparency, and integrity of data) (p. 5129). Similar to the feature of cross-functional teams, Brougham and Haar (2018) suggest the ambiguity of the jobs: "the impact from STARA is also likely to increase the prominence of the boundaryless career. Boundaryless careers are seen and defined as 'the opposite of "organizational careers" – careers conceived to unfold in a single employment setting'" (p. 241).

On the level of espoused beliefs, they place higher adaptiveness to change, strong customer focus, further development towards a failure-accepted culture, and a start-up mentality, which is conceptualized as a very collaborative way of working with little to no formalization, and less hierarchy (p. 5130-5131). Likewise, Wisskirchen, et al. (2017) see digital changes in the organization in the form of better connectivity of the departments, with prevalent IT department, which leads to flattening of the organizational structure.

Finally, the underlying basic assumptions in a digital firm, according to Duerr et al. (2018), are represented by the integration of IT into innovating, necessity for increased agility, increasingly demanding digital customers, and a perceived need for digital skills.

While the comprehension of a digital organisational culture is important for the understanding of the case study organization, more theoretical evidence needs to be presented on the human-AI relations in the workplace.

2.2.3 Organizational culture as a network. Integrating ANT in Schein's OC model

To deepen the understanding of the AI integration into organizational culture, the philosophy of technological determinism should be introduced. Technological determinism implies that the utilization of technology and its affordances determine society's development and its cultural norms. Even though this philosophy suggests only one-way influence of technology on society, it allows to witness the impact of AI on the social and cultural aspects (on social structures and interactions) of societal development, which are the focus of this research. The importance of studying the impact of technologies on the society was also emphasised by Latour (1996): "to understand what holds society together is impossible without reinjecting in its fabric the facts manufactured by natural and social sciences and the artefacts designed by engineers" (p. 370).

It was mentioned earlier that organizational culture unites all its stakeholders into a whole unit. Also, it was discussed that Schein views technologies as artifacts of the organization. However, it is not clear how to approach the relationship between employees and smart technologies at the workplace. One possible way to understand this relationship is by introducing Actor Network Theory (ANT) proposed by Latour

(1988) and integrating it with Schein's (1986; 2016) organizational culture model. The peculiarity of ANT is that it expands the content of an organizational culture and redefines it as a "network of heterogeneous actors", where actors can be "social, technical, textual, naturally occurring, etc." (Whittle and Spicer, 2008, p. 112). This framework has been utilized to study information systems implementation into organizations and may help to address the issues of the coexistence of AI and humans within organizations.

Actor Network Theory may be viewed as a fundamental theory for understanding the relationships of human and non-human actors (in the case of this study - AI) occurring within a particular organizational culture. A crucial insight from this theory is that human and non-human actors exist in networks of relationships and are seen as equal actors within an organization. They both affect the network as a whole, the network in turn affecting them: "objects, ideas, processes, and any other relevant factors are seen as just as important in creating social situations as humans" (Latour, 1988). This is also in line with the approach to the organization as a system, in which the introduction of a new element impacts the whole system.

The application of ANT in the context of work automation and augmentation is not a new phenomenon, but it has started to gain more attention recently. For example, Boyles and Meisinger (2020) apply ANT theory to study the interaction between human and non-human actors in a newsroom library. This article is also one of the few attempts so far to combine AI, organizational culture, and ANT. The authors mention that "institutional memory formulates shared organizational culture" (p. 4). Their findings demonstrate that advanced technological assistants indirectly restructure the roles and responsibilities of the librarians (people seek tasks proactively, without supervision), as well as change the impact and importance of their work to others and to the organization in general. Boyles and Meisinger (2020) also put forward that the introduction of technologies flattens the organizational hierarchy and networks.

To study the impact of AI introduction on the organizational culture and social interactions within it, it seems valuable to combine Schein's (1986) OC concept with ANT. Firstly, AI can be placed on Schein's level of artifacts, being an observable asset of the organization. Secondly, it is important to remember that Schein's levels of OC influence each other in a particular way: basic underlying assumptions influence espoused beliefs and artifacts, or espoused beliefs can also influence artifacts. However, considering ANT's interconnectedness of all actors of the network and their mutual influence on each other and on the network in general, it can be suggested that AI (and its affordances) as an artifact may affect basic underlying assumptions that represent human reasoning behind their behaviours and indirectly change human-human interactions in the organization. The findings of this case study will also demonstrate this influence (AI-chatbots reinforce the assumptions that each case study organization's employee is an expert of their job, absence of managers lead to independence and high personal responsibility, absence of micro-managing that is outsourced to chatbots creates kind relationships between employees and people persons, thus reinforcing the culture of freedom and individual initiative). This seems to be in line with Schein's approach as well, as he acknowledges that the OC is shaped by, among other factors, the technologies the company uses. The integration of Schein's model and ANT will be speculated further in the Discussion section.

To sum up, the consequences of successful introduction of smart technologies to the workplace appear to lead to the flattening of organizational structure, ambiguity of work roles, higher personal freedom, responsibility and initiative, and consequently to the need for more effective communication and interconnectedness of the community. However, the mere introduction of AI to the workplace does not necessarily determine the employees' acceptance of AI. Thus, it would be beneficial to examine AI features and functions that have been proven to make human-AI collaboration comfortable and effective.

2.3 Designing Human-AI relations

It appears also vital to consider AI developers' points of view on the design of artificial intelligence software and its impact on human-AI interaction and humans' attitudes toward these intelligent technologies. This viewpoint will be approached from the aspects of AI's image and design, humans' relation to AI, interaction, and people's expectations from AI. The field of human-computer interaction (HCI) seems to be potent in helping answer questions related to comfortable human-AI collaboration.

The question how an AI-solution should look like to nudge a person to start using it seems to be pivotal in HCI research and IT-design. For example, Araujo (2018) underpins, that anthropomorphic design cues must be present in AI-based technologies, especially those fulfilling conversational agent function and facilitating discussions with humans (e.g., chatbots), because in that case people will be willing to engage into interactions with them and feel comfortable in these interactions. On the other hand, Liberati and Nagataki (2019) argue that the AI should be embodied (have a human-like body) to make people feel comfortable in the interactions with the machines. They explain this by the viewpoint that a human-like body of AI allows people to predict the embodied AI's behavior, since they know how their own body functions, and this may help reduce overwhelming uncertainty caused by new unknown intelligent technologies. Interestingly, the authors propose that when AI-based technologies are disembodied, that is, are not put into some sort of physical robot-type machine resembling a human but are rather created in the form of a software, these design cues are especially crucial. They may include human-like communication style and a recognizable name. These insights provide a vital source for the interview questions that are to be conveyed further in this research. The abovementioned design cues are to be addressed in the interviews.

However, research mentioned in the news article "Study: nobody wants social robots that look like humans because they threaten our identity. Humanlike robots may make us feel less human" (Ackerman, 2018) presents the opposite opinion. It claims that humans tend to dislike anthropomorphic social robots (embodied AI) because of the identity theft issue. The more human-like they look, the less people are able to draw a line between a human and a robot, which leads to unsettling feelings and a blurring of the concept of what is human. In research this phenomenon is widely referred to as uncanny valley (Mori, MacDorman and Kageki, 2012) and was put forward as an implication for robotic design in 1970. Masahiro Mori, the author of the concept, argues that there is a gap, or a valley, in a graphic model of an individual's sense of affinity, in which the affinity plummets for the things that have high human likeness, and robots are one of them. Mori believes it is the deception of one's expectations in a human-robot interaction that turn people's affinity into eerie, scary sensations. Even though the research mentioned in the Ackerman's article has several limitations that need to be undressed in the future (small sample; providing participants with images of the robots, not videos), the uncanny valley topic seems to be more relevant to be discussed in the context of robots than of unembodied AI. Nevertheless, the uncanny valley research may be important to be considered in an ethical usage of unembodied AI (e.g., chatbots) to answer a debatable question of whether a human interacting with a chatbot should be informed that they are interacting with a machine, not a human.

As it can be seen, scholars propose different views on the image an AI-based technology should have to make human-AI interaction comfortable and effective. Nevertheless, those hypotheses unveil little about the way people relate to AI. An important dimension in understanding human-AI relations is whether AI solutions are treated simply as a tool or as something intelligent. This might have something to deal with the so-called AI effect. According to the description of this paradox, when people understand how a technology functions, they no longer consider it intelligent. For example, calculators used to be considered intelligent in the past but are no magic today. Perhaps sometimes it is all about naming things right or according to the agenda behind the message. Some IT experts even recommend toning down the ubiquitous use of the term AI to avoid future AI winters and to focus more on the opportunities of the technology rather than on the trending name.

Regarding research on human-AI interactions, CASA (Computers As Social Actors) theory seems to be very pertinent (Nass and Moon, 2000). According to it, people tend to mindlessly apply behavioral scripts that are normally appropriate only within social interactions to interactions with the machines. In other words, treating a machine as if it was a living being, because they call to mind similar social attributes as humans. Traeger, Sebo, Jung, Scassellati, and Christakis (2020) emphasise that "CASA theory stresses that social responses to machines are independent of the conceptualization of a machine as human-like" (p. 176:17). It seems that there have been attempts to apply the implications of this theory to practice. For example, Liberati and Nagataki (2019) conducted a phenomenological study on the example of a trash collecting robot in Japan, which side-goal was to nudge people to unlearn a habit to litter on the street. They found out that people are more likely to collaborate with robots if those express vulnerability (for example, ask for help: e.g., "can you help me recycle this?"). Since vulnerability is seen as a very human characteristic, it had a positive effect on people being more willing to collaborate with a robot, as opposed to the attitude "it is a machine, it works perfectly without me, it will pick up the trash if I drop it anywhere". This study demonstrates how vulnerability in robots can change human perception of them and help develop good habits or behavior in humans: "the perception of the fact there is an entity needing help is more than enough to turn the subject into something different" (p. 340). Perhaps the concept of vulnerability could enrich CASA theory.

Similarly, there is a "study demonstrating the ability of a robot to significantly shape human–human interaction" (Traeger, Sebo, Jung, Scassellati, and Christakis, 2020, p. 6370). The robots in this study were found to improve discussions in a group work by exercising vulnerable speech: "it is not just the presence of a speaking robot in a hybrid system that changes human–human communication, but rather the nature of the robot's speech – specifically, speech that is vulnerable" (p. 6373). Both aforementioned studies illustrate the application of human characteristics to robots in order for the latter to have a social impact. However, this factor is one of the many that affect the likelihood of a person to start or continue collaborating with a robot or AI solution. Humans' expectations of AI-based technology appear to impact that a lot. Nagy and Neff (2015) propose a concept of imagined affordances. They first define technological affordances as "what a material artefact allows, its actionabilities and its perceived usability" (p. 51). Consequently, imagined affordances are what people perceive a piece of technology can do and in what way. These perceptions not only shape people's experiences but can also determine whether a person will continue using this technology or not, in case its imagined affordances do not coincide with its real affordances. Boyles and Meisinger (2020) provide the following example: "in their daily practice, newsroom librarians are not entirely fearful of automation's impact upon practice; rather, they are doubtful of its potential in connection to the newsroom's archive" (p. 11). Though imagined affordances may not always reflect reality, such perceptions may be important for future development of these technologies, because "to design something, it has to be imagined" (Traeger et al., 2020, p. 51). Additionally, Traeger et al. (2020) posit that this "concept offers scholars a middle ground between technological determinism and social constructivism" (p. 48). This approach may have a significant relevance for research on AI in the workplace.

This chapter introduced the most important aspects of design of the smart technologies. However, most of the mentioned research articles focused on embodied AI, robots, and further research may be necessary to understand the same design aspects of disembodied AI, such as chatbots. The following study attempts to contribute to this topic.

3 CASE STUDY

3.1 Research methodology

This study relies on the research philosophy of social constructivism. It views reality and knowledge as socially constructed through the prism of personal experiences and thus, understands them as ontologically subjective, rather than ontologically objective (from Searle, Dennett, and Chalmers, 1997). The social constructivism paradigm is relevant because the focus of the case study is on individual perceptions and experiences of a phenomenon. Additionally, the fundamental assumptions of this paradigm require the use of qualitative data collection and data analysis methods, which in this study are represented by semi-structured interviews and qualitative content analysis.

The selected paradigm also provides a useful approach to social reality, according to which the way people perceive reality affects the reality around them. This insight is especially important in relation to exploring attitudes of the employees towards AI-assistants and the ways they perceive the effects of AI on their organizational culture.

The research design of this study is cross-sectional qualitative and is based on the case study of a Finnish enterprise. The purpose of the case study is to answer the following research question (RQ): "How do the employees view the impact of AI (Slack chatbots) on their company's organizational culture?".

It should be clarified how the study conductor ended up with the RQ. Since the topic of AI and organizational culture is relatively new and understudied, it was decided to begin with discovering what people in the studied context think, feel and tell about having an AI assistant at the workplace that performs a part of their tasks. It was assumed that these first-hand insights would provide initial insights into the studied phenomenon. Next, the choice of the qualitative research design and social constructivism paradigm shaped the way the research question should be formed.

3.1.1 Qualitative data collection method

The applied data-gathering method is semi-structured interviews. The advantage of the semi-structured interview approach lies in the fact that while the study controller has an assumption of what questions to seek answers to in the empirical part, there is still a leeway for the interviewees to share their experiences and insights that can be relevant for the study but may not be expected by the researcher. It is especially relevant in the context of social constructivism. This approach has a potential to increase the quality and the scope of the findings. In total, about ten open-ended questions were asked during each interview, occasionally followed by new questions based on the participants' answers.

In total, five interviews in English language (that served as a lingua franca) were conducted with the employees of the Finnish case study organization in March 2021. The interviews were conducted using an online conferencing software Zoom, in four cases including the video and in one case audio only. This particular organization was chosen because they have already implemented an AI-based solution, specifically, Slack chatbots, into their internal work. The company has developed and utilizes three Slack chatbots, that will be referred to as chatbot 1, chatbot 2, and chatbot 3. Importantly, some of the organizations' employees' tasks are delegated to these chatbots on the voluntary basis, which implies that the AI-solution is basically functioning as an optional "co-worker". As the findings eventually revealed, these chatbots were found to be reinforcements of the company's organizational culture, which renders this case study relevant to this research topic.

The interviewees for the data collection were found via contacts provided by the supervisor from the company's side. In the beginning the wish to interview employees with specific duties was communicated to them. Therefore, the type of sampling in this study is non-probability snowball sampling combined with purposive sampling. Regarding the demographics of the participants, one female and four male employees were interviewed, both young and middle-aged participants. Additionally, both managers and subordinates were in the sample. The sample is also represented by software developers who worked on the creation of studied chatbots, software developers not involved in the creatin process, and a marketing professional. All interviewees are active users of the studied chatbots. There were approximately seven hours of recorded interview data.

The interviews were transcribed manually by the researcher resulting into about 25 pages of written data. The transcription was done in details, including every topic that the participants brought up, with occasional improvement of the grammar and omission of lexical hedges and interjections. Additionally, irrelevant speculations (e.g., about the weather, what they are doing at the moment of speaking) were not included in the transcripts. Since the chosen data analysis method is qualitative content analysis, not discourse analysis, word-by-word transcription was not conducted. The manual transcription method was selected due to the sensitivity of the data that may have been jeopardized when employing online automatic transcription software.

Finally, it should be mentioned that even though this study does not rely on the method of triangulation, it has some elements of it. In the process of getting to know the context of the case study company the study conductor needed to familiarise themselves with the general information about the company, which was done by skimming through the website, company's blog, and social media pages. Some of the extracted information informed the interview questions, however, the case study findings were not re-evaluated with the help of triangulation method. Moreover, though the aforementioned company's artifacts were created collectively, the focus of this case study is on the employees' individual perceptions and interpretations of these artifacts and work experiences.

3.1.2 Qualitative data analysis method

The selected data analysis method for this study is qualitative content analysis (QCA) (Krippendorff, 2018; Schreier, 2012). This choice was justified by several reasons. Firstly, the RQ of this study is descriptive, that is, asking "how", with the focus on people's opinions and experiences about a particular social phenomenon. Secondly, the material of the study is qualitative and deals with the meaning that is not obvious, therefore, it needs to be systematically described and interpreted. Thirdly, QCA seems to pair up well with the social constructivism paradigm, because according to QCA, the meaning is not given in data, but needs to be constructed with the help of systematic analysis method. Additionally, QCA allows to conduct exploratory work on an unknown or poorly studied phenomena, which is the case with the RQ of this study. This fact also necessitates the use of the data-driven coding frame (inductive method). Finally, QCA helps reduce large amounts of data and explore the phenomenon from a particular angle identified by the RQ. Only written transcripts of the interviews were analyzed, excluding the videos of the recordings.

The QCA was applied to the transcriptions of the five interviews, and the goal was to arrive at a valid and reliable descriptive data-driven coding frame. However, latent meaning or inferential leaps were not the objectives of this content analysis. At the beginning of QCA the material was coded for relevant and irrelevant using a simple complexity coding frame. Relevant material was defined as the material that helps to answer the RQ, that is, reflects the interviewees' perceptions of the impact of AI Slack chatbots on their organizational culture (OC), expands this topic and helps understand the context of this phenomenon. Irrelevant material was defined as the material that does not help to answer the RQ. Only relevant material was analysed further. Next, progressive summary strategy was applied to a part of the material (about 1,5 interviews) to help arrive at the initial draft of the coding frame. The extracts from the interviews were identified on the basis of themes (but not as specific as during the segmentation stage), summarised and then ascribed a more general and shorter paraphrase. These general paraphrases served as the basis for subcategory names, some of them were shortened or edited more. About 26 paraphrases were turned into a coding frame with five dimensions and 18 subcategories in total, which made a medium complexity data-driven coding frame. This stage was followed by the pilot phase. The first step in the pilot phase was the segmentation of all material on the basis of thematic criterion. Thematic criterion was selected because the material did not have an inherent structure. That step resulted in 189 units of coding. After all material was divided into segments, trial coding of the part of the material was conducted. The material for trial coding was taken from several transcribed interviews to include various topics. Each unit of coding was ascribed to a subcategory. This material was recoded 10 days after the first coding to evaluate the consistency of the initial coding frame (reliability). The reliability of the initial coding frame was found to be satisfactory because there were only a few minor inconsistencies between the coding rounds, and it was possible to arrive at the final meaning of the inconsistent units of coding. Additionally, the level of validity of the initial coding frame was assessed according to face validity type and considered acceptable. This step followed the same procedure for the evaluation of validity as in the main coding phase.

The outcomes of the pilot phase required the coding frame to be improved and expanded, which led to the creation of the final coding frame with high complexity structure, five dimensions and 22 subcategories total (see Figure 2). The coding frequencies were counted after the main coding was completed and the matrix created.

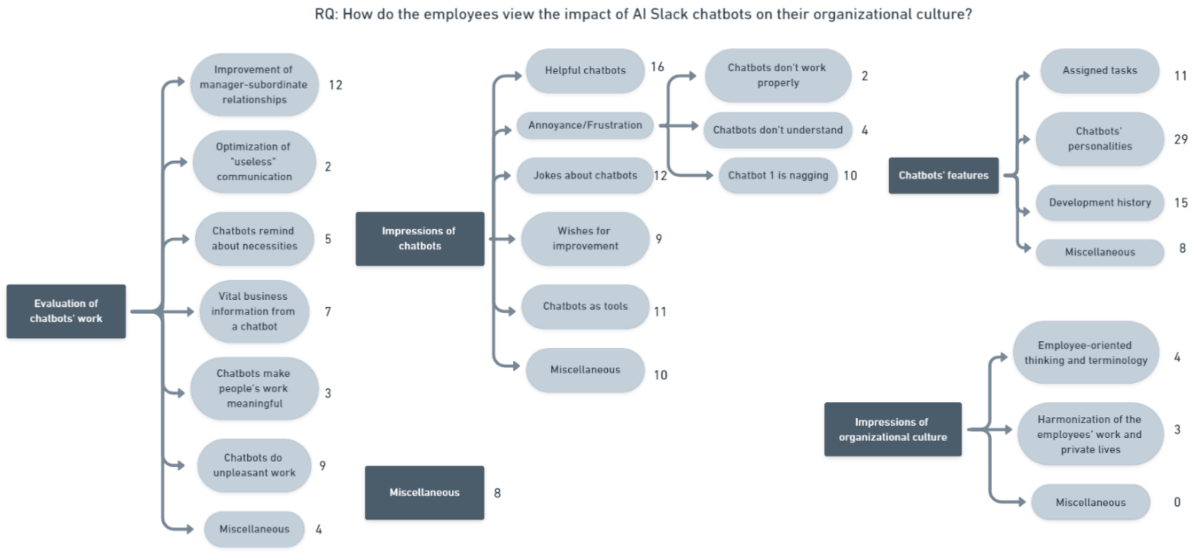

Figure 2. Final coding frame with the coding frequencies of the subcategories. Dimensions are represented by dark gray boxes and subcategories – by light gray ones.

All dimensions and subcategories were given definitions and examples (see Appendix 1). The final coding frame met the requirements of unidimensionality, mutual exclusiveness, exhaustiveness, and saturation (Schreier, 2012, p. 71). Residual subcategories were introduced within each dimension to meet the criterion of exhaustiveness. The criterion for saturation was not met only by the miscellaneous subcategory of the "impressions of organizational culture" dimension, but the dimension was not considered critical for answering the RQ.

The final coding frame allowed to start the main coding phase, during which each unit of coding of all of the material was ascribed to a subcategory (or to a dimension in case with the "miscellaneous" dimension). All units of coding were recoded 10 days later to evaluate the reliability of the final coding frame. The number of units of coding that were coded differently during the second round of coding was insignificant, and the final meaning was ascribed to them. Therefore, the level of reliability of the final coding frame was found to be satisfactory.

Finally, the validity of the final coding frame was assessed. The goal of this content analysis was to deal with descriptive meaning of the data and to avoid inferences going beyond the text; hence, face validity type was selected. First, the number of the units of coding that were coded for residual categories (miscellaneous dimension and miscellaneous subcategories within other four dimensions) constituted around 15% of all units of coding and was not significantly large compared to the recurrencies of other subcategories. Second, the coding frame appears to be differentiated enough because the subcategories within a dimension are not too large compared to other subcategories in this dimension. There is one exception, the subcategory "chatbots' personalities” is larger than other ones in the dimension “chatbots' features”, but since the expansion of this subcategory would not bring new important information (it would be the information about ascribed personalities of the three different Slack chatbots, which is already known), a decision was made not to extend it further. Finally, the level of abstraction of the coding frame was found to be sufficient since the subcategories have shown to be differentiated enough, to cover the meaning of all material, and to represent the concepts of the RQ well. Considering these factors, the level of validity of the final coding frame was deemed satisfactory. Consequently, the content analysis part was concluded.

After the main coding phase, a matrix for presenting the results was created (appendix 2). The matrix is important for bringing the meanings from the level of units of coding to the level of interviews. It also demonstrates a number of times each subcategory recurred in the material. For further presentation of the results in the findings section a strategy of describing and illustrating findings using continuous text was selected.

Before proceeding to the main findings, it is necessary to comment on the process of identifying the subcategories that made it to the main findings. It is a common practice in QCA to select several subcategories as the main findings based on their level of recurrency, where a few most recurrent subcategories are discussed further. However, in the case of this study the most recurrent subcategories constituted a large portion but were rather predictable and did not provide new information. The goal of the study conductor with the QCA was to identify and present unique findings, that answer the RQ well but are the least expected to be discussed or show up within the topic of the RQ. This also justifies the use and demonstrates the advantage of the data-driven coding frame as opposed to the concept-driven one. Moreover, QCA and social constructivism are both interpretative method and paradigm and allow the researcher to apply particular interpretations of their findings. Consequently, based on this uniqueness of information criterion, three subcategories are presented as major findings. Some of the remaining subcategories that present less unique but thought-provoking answers to the research question are considered in the discussion section.

3.1.3 Research ethics

The case study has been conducted in an ethical manner because it is based only on the data provided by the interviewees who consented to participate in the study (Byrne, 2016). The non-disclosure agreement (NDA) was signed with the company prior to the conduction of the case study and a supervisor from the company's side was assigned to the study conductor. According to the NDA, the name of the company, their supervisor and participating employees may not be mentioned in the study. The NDA also implies that full transcripts of the interviews must not be published. The interviewees were provided with three research documents before the interview. The documents included a research notification, which describes the study and data collection in general, a research consent form, which, after being signed by the participants, proves that obtained data can be uses in the study, and a research privacy notice, which explains how the interviewees' data is processed. The interviewees also expressed their written consent to participate in the study via official emails. The privacy of the company and the interviewees is taken seriously in this study and all excerpts from the interview data are presented anonymously.

3.2 Findings

Systematic qualitative content analysis of the data combined with after-analysis identification of the most unique and relevant for the RQ information, allowed to point out three subcategories within the final coding frame that will be presented as the major findings and explained and illustrated further in this section. The findings are named impacts since they describe the ways the employees of the case study organisation view the impact of AI (three Slack chatbots) on their company's organizational culture. The findings illustrate how people of the case study company describe their understanding of this phenomenon through their daily personal experiences of collaboration with AI at the workplace rather than constitute a universal answer to the RQ.

3.2.1 Impact 1: Chatbots improve manager – subordinate relationships

The subcategory "improvement of manager-subordinate relationships" provides a valuable and unique insight into the way AI-powered chatbot affects human-human interaction and group dynamics at the workplace.

Chatbot 1, that was discussed in this subcategory of the coding frame, has, among others, the following function: to weekly or daily remind employees to report their billable hours to the chatbot itself. Before the introduction of this chatbot this menial but important task was done by the managers who are responsible for their subordinates. The reason behind delegating this task to the chatbot lied in the optimization of the managers' time and easier reporting and data storage system affordances of the chatbot. However, the descriptions of the case study participants' experiences revealed a more interesting and initially unintended effect of this task delegation. Since frequent reporting reminders communicated by the manager to the subordinates may bring up power disbalance associated with the manager's role, tensions or unpleasant feelings between a manager and a subordinate may arise. Yet, when these reminders are communicated by a chatbot, the power disbalance in a team seem to be alleviated and tensions mitigated.

> “Chatbot 1 is the middle manager who takes the burden off our shoulders, so we don’t have to nag about these things, that make our relationships not so nice.” (Participant 5).

> “When you have middle managers in organizations, you recognise them as nagging and managing people. But when these things are outsourced to AI, you can focus on more humane interaction with a people person.” (Participant 3).

Even though Chatbot 1's impact does not cancel power-related dynamics in a team completely, it seems to help to mitigate tensions associated with the communication of continuous mundane tasks that are important for the managers.

Remarkably, all internal Slack chatbots of the case study organization are endowed with personalities. That means that each of them has a specific graphic image, communication style, character traits emergent from the communication style, approximate age group and sometimes a gender. According to the study data, Chatbot 1 is perceived as a slightly grumpy middle-aged male middle-manager, who is usually nagging people about reporting their hours. It may be that the presence of this particular personality plays a crucial role in the discovered impact. When the messenger is a chatbot, these unpleasant emotions are not associated with the people-person, but with the chatbot's personality. Therefore, it might be assumed that it is possible to "outsource" unpleasant emotions to a chatbot. That, in turn, makes people chat and joke about the chatbots and serves a community building function (see Impact 2).

Finally, this impact of the chatbot aligns with one of the core values of the case study company, according to which the company wants to create a welcoming workplace for their employees.

3.2.2 Impact 2: Chatbots carry cultural value and spur emotional response

The subcategory “jokes about chatbots” sheds light on the chatbots’ contribution to community building in the organization. As discussed in Chapter 2.2, community building activities are vital for sustaining organizational culture.

By being endowed with memorable and distinctive personalities chatbots present cultural value as mascots of the company and objects of jokes and memes and free-time discussions among the employees. This fact makes these AI-powered chatbots shared artifacts of the organization and demonstrates how they play a community building role.

> “Chatbot 1 is sort of a designated asshole, but that’s something everybody can hate and joke around without anyone being offended.” (Participant 1).

"Chatbot 1 is an inside joke, for example, so they have a cultural value for the employees." (Participant 3).

Additionally, it was noticed that the messages coming from chatbots with personalities appear to spur a greater emotional response to the message itself compared to a situation where the messenger is a faceless chatbot. This emotional response seems to make it likely that the addressee will respond to the message. This could be taken into account in future chatbot design and development.

"I can't pinpoint why but there's something nice about having a face on that reminder. Even if it's someone like Chatbot 1. Maybe there is a certain power in that annoyance of the reminders Chatbot 1 sends." (Participant 1).

Even though the units of coding in this subcategory of the coding frame mostly referred to Chatbot 1, other chatbots were found to contribute to community building as well.

3.2.3 Impact 3: Chatbots optimize "useless" communication

The subcategory "chatbots optimize "useless" communication" reveals further advantages of chatbot implementation. It appears that chatbots can optimize not only particular menial labor tasks that do not bring value to humans, but also "useless" communication. Though some communication scholars may not agree with the existence of such a phenomenon, in the context of this case study "useless" communication is understood as unnecessary communicative exchange that, unlike Malinowski's (1967) phatic communion, is not aimed at bonding, or knowledge sharing but rather distracts one's colleagues from work. These are such inquiries as, for example, "where can I find this thing/person?", "who is responsible for this?", "whom should I contact about this?", etc. Such information inquiries are important but may distract co-workers from their own tasks. Hence, when the chatbots are able to handle these inquiries, employees can focus on their more important and creative tasks or on more meaningful free-time interactions with colleagues. In the case study organization this function is fulfilled by a Q&A-based chatbot.

"It (chatbot) reduces labor for me and for someone else whom I would have to ask for these things." (Participant 3).

> “I don’t think chatbots are directly improving human-human communication in terms of asking personal stuff, etc., but it can do that indirectly, because if you use them, you will have more time to interact with employees who have breaks and chat with them.” (Participant 2).

3.3 Case study conclusion

The case study is an illustrative example of the cultural benefits that stem from the integration of AI and organizational culture. The major findings demonstrate that the use of the internal Slack chatbots carries a positive impact on people's wellbeing at the workplace. It seems however, that these benefits were not initially intended or foreseen before chatbot implementation, but with the help of this study and the application of social constructivism philosophy of science it was possible to discover these valuable insights. Nevertheless, there are a few other noteworthy topics stemming from the case study, that may bring more insights when evaluated at the backdrop of this study’s literature review.

4 DISCUSSION

This section is dedicated to the overall discussion of the case study findings. Firstly, the case study findings will be connected to the previous theoretical review to investigate how the findings relate to it. Secondly, the discussion of two coding frame subcategories at the backdrop of the literature review helped bring two more noteworthy insights to the surface and will be presented here. Thirdly, theoretical and practical implications of the findings will be presented. Additionally, the directions for the follow-up research will be suggested. Finally, the perspective shift that occurred during the research process will be outlined.

4.1 Discussion of the findings

To find out whether the major findings of the case study support, contradict or expand previously discussed theoretical review, each of them needs to be evaluated separately.

4.1.1 AI may affect Basic Underlying Assumptions within OC

Impact 1 seems to be a new contribution to the field of AI and organizational culture. There have been studies demonstrating how robots improve human-human communication in teams (Traeger et al., 2020), but no articles citied in this research appear to have found that AI-powered chatbots can improve human-human relationships in the workplace, specifically, manager-subordinate relationships. If to connect this finding with Schein's (2016) OC model, an interesting insight is discovered. While the interviews revealed people's interpretations of the artifacts and espoused beliefs (values), specifically, how the interviewees describe their perception of the artifacts and espoused beliefs, it was not possible to find out underlying basic assumptions via an interview method (see Chapter 2.2.1). However, the approach of integrating Schein's model with ANT may allow to suggest a hypothesis that could potentially expand and reinterpret Schein's theory. Schein places technologies on the level of artifacts, so it is possible to place AI on that level. Improved manager-subordinate relationships, described in Chapter 3.2.1, may be placed on the level of basic underlying assumptions because not all employees may notice the change or be aware of the reasons behind their improved manager-subordinate relationships, which is a characteristic of the basic underlying assumptions. Hence, it can be proposed that not only basic underlying assumptions influence espoused beliefs and artifacts, but also the artifacts (in the form of AI such as chatbots form the case study) may influence basic underlying assumptions (positive perception of one's manager), (see Figure 3). However, the follow-up research is necessary to test this hypothesis.

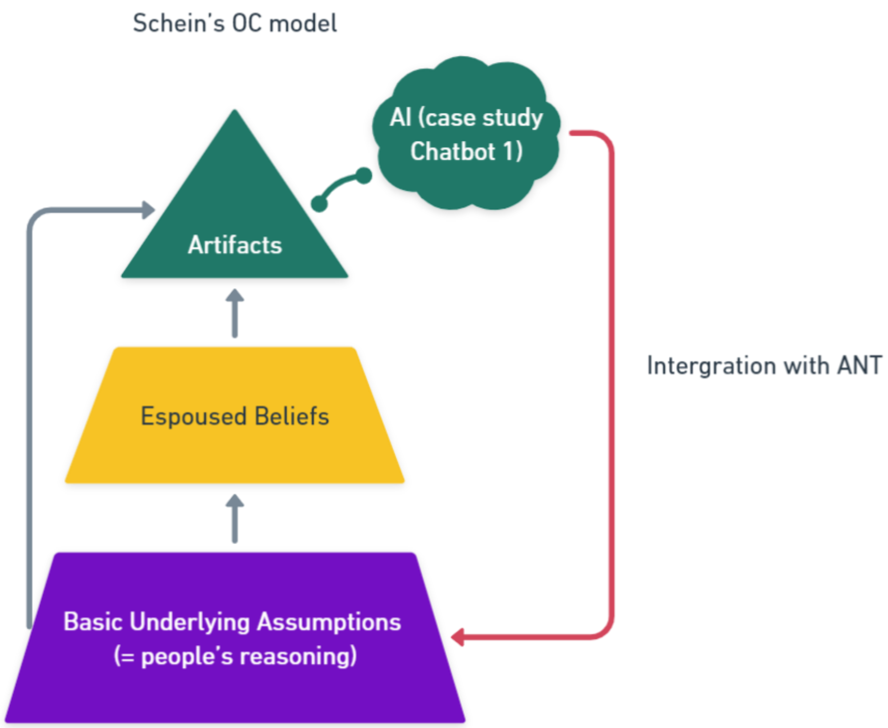

Figure 3. Suggested integration of Schein's OC model and ANT is demonstrated by the influence of the artifacts in the form of AI on the basic underlying assumptions (red arrow). Impacts of the OC levels on each other are shown with arrows.

This insight yields practical implications for discovering other ethical ways the AI can improve social dynamics and organizational atmosphere, and perhaps planning and implementing these positive influences as a part of the organizational culture change and transformation.

4.1.2 Negative responses to chatbots are also effective

Impact 2 seems to also be in line with Schein's (2016) theory. Since chatbots are visible artifacts of the organization, they contribute to the workplace culture. It was discussed in Chapter 3.2.2, that the presence of a memorable image and ascribed personality of a chatbot seems to spur more emotional response to its messages compared to a faceless chatbot. However, the data analysis revealed that these emotional responses were not always positive. The subcategory "annoyance/frustration" within "impressions of chatbots" dimension had a high coding frequency within this dimension and illustrated employee's negative feelings towards chatbots. It needs to be noted, that these emotions were responses to chatbots' messages or answers, (not a biased fear of AI as a competitor). The reasons for such responses were usually that the chatbots do not work well or do not understand inquiries, but the most common reason was when Chatbot 1's messages were perceived as nagging (see Chapter 3.2.1). It must be emphasised that it was the presence and manifestation of the chatbot's personality that provoked such emotional affect. One of the interviewees even said:

> "It's a part of our culture that Chatbot 1 is an asshole" (Participant 2).

Hence, nagging is seen as a part of Chatbot 1's personality, it is widely recognised in the organization and thus, carries a shared cultural value. Nevertheless, when talking about these negative emotions the study participants acknowledge that this chatbot is helpful, which is proven by the coding frequency of the subcategory "helpful chatbots" (16) of "impressions of chatbots" dimension and happens to be the same coding frequency for "annoyance/frustration" subcategory (16). Therefore, it can be concluded that both positive and negative emotional affects spurred by chatbots are effective and make the addressee more likely to respond to the message.

The discussion of Impact 2 correlates with the CASA theory (Nass and Moon, 2000). On the case study examples it can be seen that a chatbot is not simply perceived as a piece of code, but it becomes something more in the context of human-AI interaction, primarily because of the chatbots' distinctive attributed personalities. According to CASA theory the applications of social scripts to machines happens without a person's conscious effort to conceptualize machine as human. On the one hand, this effect seems to be enhanced by the presence of a chatbot's attributed personality, and the chatbots are less spoken of as machines or tools and more referred to according to their names and ascribed genders. On the other hand, if AI effect is brought into this discussion, a new hypothesis can emerge. A subcategory "chatbots as tools" within "impressions of chatbots" dimension has a relatively insignificant coding frequency but reveals that sometimes chatbots were perceived as tools, rather than an assistant or coworker. Such responses were coming from advanced software developers most of whom worked on these chatbots. It can be assumed that when people perceive chatbots as a tool or algorithms the emotional affect of the chatbots' messages may not be spurred and thus, the presence of chatbots' personalities may have no effect, same as in the case of faceless chatbots. Remarkably, the subcategory "chatbots' personalities" has the highest coding frequency (29 units of coding) among the rest of the subcategories of the coding frame. The coding frequency and the contexts in which chatbots' personalities have been discussed in this study demonstrate the importance and value of the memorable and distinct ascribed personality of a chatbot. It is also in line with Araujo's (2018) article, illustrating that conversational agents should be endowed with anthropomorphic design cues to encourage people to engage into interactions with them and feel comfortable in these interactions.

4.1.3 AI may make the concept of useless communication emerge

Impact 3 appears to make a new contribution to the field of AI and organizational culture. Wisskirchen, et al. (2017) discussed the impacts of smart technologies introduction on organizational culture and claimed that "the cross-linking of single employees by new technologies allows easier communication and enables a better exchange of information" (p. 49). It can be assumed that better exchange of information can also lead to elimination of "useless" communication. However, the concept of "useless" communication applied in this study needs to be studied further. Perhaps the rise of the field of AI and organizational culture will make the discussion of this concept relevant in the context of digital communication. The use of AI chatbots may also even solidify the concept of "useless" communication in the future since there will be a distinction between the communicative inquiries meant for humans and those meant for AI-based assistants. Thus, considering the purpose of AI as the automation of unnecessary or unpleasant tasks, communicative inquiries meant for AI assistants will be considered as "useless" communicative exchanges among humans.

4.1.4 Chatbots may affect organizational structure

It looks like by reviewing this study's coding frame in connection to the literature review it is possible to identify one more insight stemming from the data. It has been discussed in Chapter 3.2.1 that Chatbot 1 basically substitutes middle management of the case study organization. The study participants described their organizational hierarchy as flat:

> "Fairly flat organization as a whole" (Participant 2).

> “And they [employees] have this really high freedom and responsibility compared to maybe more traditional organizations, where you have more managers or middle-managers.” (Participant 2).

While it is difficult to claim to what extend particularly Chatbot 1 has contributed to the flattening of the organizational hierarchy (there may be other factors), it seems that the chatbot can help flatten organizational hierarchy by placing more responsibility on the employee and taking away monitoring activities from the manager. Boyles and Meisinger (2020) and Wisskirchen, et al. (2017) put forward as well that the introduction of technologies flattens the organizational hierarchy and networks. Additionally, flat hierarchy was listed as a feature of a digital organization (Duerr et al., 2018), which is accurate for the case study company. Therefore, it can be assumed that one of the chatbots helps create digital organizational culture of the case study company.

4.2 Implications of the findings

It is crucial to understand theoretical and practical implications of the findings of this study. From a theoretical point of view, the findings of this study have shown to be in line with and expand existing scientific literature. This study made a contribution to research on conversational agents (chatbots) and their impact on organizational culture. A number of directions for the follow-up research have been mentioned throughout the study. From a practical point of view, by understanding and educating company’s stakeholders (especially customers and partners) about the aforementioned impacts of AI on the organization, companies can help shift general public’s perception of AI from AI as a threat toward AI as a helper. Additionally, the findings emphasize the benefits of endowing chatbots with personalities, which is a practical implication for chatbot design.

4.3 Evolution of this study

Ultimately, it should be mentioned how this study’s perspective evolved with its progress. The initial focus was on perceptions of AI as a threat to employment and biased attitudes to collaboration with AI caused by that. The goal of the study was to find out how to help employees working alongside AI overcome this fear via the introduction of the OC concept. The study would then focus on how to integrate AI into organizational culture to nudge people into liking it. However, further study of scientific literature helped the study conductor to change their own perception of AI. Based on the previously demonstrated studies, it turned out that AI-assistants and robots perform tasks outsourced to them by humans that the later are unwilling or unable to perform (Wisskirchen, et al., 2017). The interviews with the case study company revealed the same attitudes, and it was decided to shift the focus towards the impact of smart technologies on organizational culture, while discussing perceived employment threat connected with AI in a socio-cultural context. Even though the first subchapter of this study is about fear of technologically induced unemployment, the major focus is on the open-minded approach to the impacts of AI on OC.

5 LIMITATIONS

Credibility of the research is demonstrated not only by the evaluation of the method's reliability and validity but also by acknowledging its limitations. In this section the limitations determined by the scope of the study, socio-cultural context, sampling, theoretical framework, and data analysis method will be considered.

Firstly, the scope of this study was determined by its purpose as a master's thesis. The limited time and financial resources did not allow to conduct a full-fledged in-depth phenomenological study on the selected topic. That dictated a necessity to approach the studied phenomenon from a particular angle and to limit the perspective of the study to a single vantage point. This explains the choice of an interview method and the qualitative content analysis method.

Secondly, as it was discussed in the Chapter 2.1.4, varying socio-economic, cultural, and political realities of the countries have a great potential to influence people's perception of AI-assistants and their feelings regarding collaboration with them in the workplace. For this case study only employees of a Finnish enterprise were interviewed. Therefore, the findings of this study need to be applied with caution to organizations in a differing cultural context, and the cultural distance (Smelser and Baltes, 2001) needs to be considered. To avoid compromised results, the findings may need to be reinterpreted in a different cultural context. Equally important is the understanding that AI-driven solutions constitute a wide family of different software, and their impact on organizational culture may be different depending on the solution's features and affordances (see Chapter 2.1.4). This case study revolved around AI-driven chatbots.

Thirdly, certain theoretical aspects stemming from organizational studies were omitted in this case study. For example, since the design of this research is cross-sectional, it was not investigated how the case study's organization's culture had been evolving throughout its history or how it was influenced by economic, political and technological changes (Schein and Schein, 2016). Additionally, organizational culture plays different roles during different life cycle stages of a company, stable companies often having subcultures within them. The case study company's culture life cycle stage was not considered, and the focus on subcultures was thought irrelevant. Moreover, regional differences between the offices of a company (even within one country) may cause varying interpretations of the organizations' corporate culture. In the case study mostly employees of the Jyväskylä office were interviewed, while the company has offices in other Finnish cities as well. Minor cultural differences between the offices were acknowledged by the interviewees but were not deemed crucial for this study.

Fourthly, the chosen research paradigm certainly determines both the study method and its outcomes. This study's paradigm is social constructivism since it is useful for studying social phenomena of perceptions and attitudes. However, the adjacent research philosophies may bring more insights to the research topic. For example, social constructionism combined with focus groups may shed light on the group's perceptions of AI at work, and phenomenology can help provide a holistic overview of this research topic.

Fifthly, the soundness of the research depends on the relevance and accuracy of its methods. Regarding data collection method of this study, the biggest problem with the interviews is the possible wish of the interviewees to create a favorable image of their workplace and work experiences, which leads to them not revealing their real feelings or possible bottlenecks to the interviewer. Another methodological limitation related to the interview method is connected with the application of Schein's (1986, 2016) Organizational Culture model and Actor Network Theory (Latour, 1996). Both Schein's and ANT approaches to studying organizational contexts emphasize the importance of observing people's actual behavior. As it was discussed in Chapter 2.2.1, Schein warned against the use of the interviews as ultimate solutions for the investigation of OC and underscored, that the deepest level of Underlying Basic Assumptions that guides people's behavior can be discovered with the help of observations and other ethnographic methods, but not with the interviews alone. Therefore, an ethnographic research method of observation combined with, for example, triangulation, might improve the findings. Even though the presence of a researcher in the group would not eliminate participants' possible inclination to maintain a certain image, the researcher would be able to observe participants' interaction with each other and their nonverbal behavior. Since due to Covid-19-related restrictions it was possible to host interviews only via online conferencing software, this is a possible direction for future research. This study could be expanded and refined in the future by adding a dimension of people's observable behavior in the workplace.

Sampling methods also have their limitations. Non-probability sample, as used in this study, may not be representative enough and it may be difficult to estimate sampling variability and possible bias of the participants. Though it was not the focus of the research question to look into different groups within the population. Additionally, snowball sampling has the same limitations. However, in the case study the research conductor had to rely on their scarce initial contacts with the case study company, and non-probability sampling was the optimal solution. Yet, this study relied on a limited dataset, and the population's demographic data was not analyzed.

Data analysis method plays a crucial role as well. Though qualitative content analysis has numerous advantages, there are also a few shortcomings of this method that may impact the research outcomes. For example, QCA does not provide a holistic overview of the material, that is, does not allow the researcher to describe the full meaning of all their data and arrive at a holistic overview of the material. Rather, it provides them with a specific angle from which to look at the data. A wholistic overview of the data would be beneficial for describing new or understudied phenomena, but in case the scope of the research does not enable such efforts, it is more important that the data analysis method allows to answer the research question adequately. Even though the goal of the QCA in this study was to arrive at an inductive coding frame, the final coding frame was not fully inductive since the RQ narrowed down the topic a bit. One disadvantage of the QCA is that the segmentation of the data involves decontextualization. A lot of context-dependent nuances of the units of coding may be lost thereby. The QCA method could be improved by introducing codes for the context around units of coding, that would be evaluated based on the thematic criterion and written next to each code, allowing units of coding with the same code to have different context codes, thus enabling the variability of the meanings to be carried to the later stages. This could be applied in cases when the researcher considers the context of the units of coding to be important for answering the RQ.

Another inconvenience is that the distinctions within the data not covered by coding frame are not visible in the final stage and are lost. Even though it is the purpose of QCA to reduce data and produce systematized information, a lot depends on the researcher's interpretation and evaluation of the relevance of the emerging findings to the RQ.

That brings up the question of the researcher's reflexivity, rather than of the objectivity of qualitative research. According to social constructivism and QCA, data does not carry inherent meaning, but the researcher and research participants construct it during a research process. The reflexivity of this study during data collection was achieved by treating the participants as experts in the topic of a chosen RQ, partners and co-producers of data together with the study conductors. During data analysis stage the thesis supervisor assisted in interpretation of the subcategories of the coding frame and their importance for the RQ, which helped to overcome the limits of the study conductor's own background and assumptions during interpretation of the coding frame and findings.

Moreover, the goal of QCA is to go beyond individual understanding of the phenomenon and arrive at a socially shared understanding of the material (Schreier, 2012). In QCA it is achieved by creating a coding frame and making the definitions of the subcategories transparent to the readers (page 27, figure 2); and by assessing the consistency of the interpretations: the reliability of the coding frame was assessed in Chapter 3.1.2.

CONCLUSION

To conclude this study, the use of AI at the workplace on the example of internal Slack chatbots was found to have much more valuable consequences for the employees than previously thought. The case study chatbots not only automate repetitive menial labor, but also improve human-human interactions and by doing so, reinforce the values of their organizational culture and, to some point, create it. Consequently, it is important to approach technological non-human actors that augment employees' performance in the organization as a part of its organizational culture. That also draws implications for the AI development in accordance with the culture of an organization of deployment. A way to integrate AI into organization culture seems to lie in the development of its functions and features so that they contribute to the support of the claimed organizational culture. Different combinations of features and affordances of different types of AI may impact workplace dynamics, human-human and human-AI relations differently, which calls for further investigation.

By presenting three major findings the case study helped answer the research question and demonstrate how the employees of a Finnish enterprise perceive the impact of AI-powered chatbots on their organizational culture. The most important implication of the findings lies in the potential of the AI-powered chatbots to support employee wellbeing by improving manager-subordinate relationships (see Chapter 3.2.1). This opens the possibilities to further study other potential ways AI could positively affect social dynamics at the workplace. Thus, AI-based chatbots not only help automate menial repetitive tasks, but also improve the workplace's atmosphere. Not less significant is the chatbots' potential to bring cultural value to an organization, which seems to be directly connected with the chatbots' ascribed personalities (see Chapter 3.2.2). This implication paves the direction to research AI design in connection with the understanding of the organizational culture of a company the solutions are being designed for. That, in turn, calls for the development of more practical and manageable measures to investigate organizational cultures. Ultimately, the literature review and the case study of this research hope to be of assistance in shifting negative societal perception of AI (AI as a ubiquitous substitution of human workers) towards a fruitful collaboration of humans and AI.

The evidence of the impact of AI on OC also implies that the use of advanced technology in the organizations should be meaningful and follow the purpose of the organization and its cultural values, and not simply be implemented because of the current trendiness of these technologies.

Finally, the research outcomes of this study demonstrate the importance and relevance of bridging the research fields of organizational studies, smart technologies and HCI to further investigate how a comfortable workplace of the future can be created with the assistance of smart technologies.

REFERENCES

Ackerman, E. (2018). “Study: Nobody Wants Social Robots That Look Like Humans Because They Threaten Our Identity. Humanlike robots may make us feel less human”. Published 8.02.2018. Retrieved from https://spectrum.ieee.org/study-nobody-wants-social-robots-that-look-like-humans

Alvesson, M. (2012). *Understanding organizational culture*. Sage.

Araujo, T. (2018). Living up to the chatbot hype: The influence of anthropomorphic design cues and communicative agency framing on conversational agent and company perceptions. *Computers in Human Behavior, 85*, 183-189.

Borenstein, J. (2011). Robots and the changing workforce. *AI & society*, *26*(1), 87-93.

Boyles, J. L., & Meisinger, J. (2020). Automation and Adaptation: Reshaping journalistic labor in the newsroom library. *Convergence*, *26*(1), 178-192.

Brain, D. (2004). Placemaking and community building. *Presentation at the University of Miami School of Architecture, Coral Gables, Florida*.

Brougham, D., & Haar, J. (2018). Smart technology, artificial intelligence, robotics, and algorithms (STARA): Employees' perceptions of our future workplace. *Journal of Management & Organization*, *24*(2), 239-257.

Byrne, D. (2016). *Research ethics*. SAGE Publications, Inc.

Cao, Y., Vasek, J., & Dusik, M. (2018, July). Design Towards AI-Powered Workplace of the Future. In *International Conference on Distributed, Ambient, and Pervasive Interactions* (pp. 3-20). Springer, Cham.

Cath, C., Wachter, S., Mittelstadt, B., Taddeo, M., & Floridi, L. (2018). Artificial intelligence and the ‘good society’: the US, EU, and UK approach. *Science and engineering ethics*, *24*(2), 505-528.

Cialdini, R. B. (1987). *Influence* (Vol. 3). Port Harcourt: A. Michel.

Deal, T.B., & Kennedy, A. (1982). Corporate Culture: The Rites and Rituals of Corporate Life. AddisonWesley, London

Duerr, S., Holotiuk, F., Wagner, H. T., Beimborn, D., & Weitzel, T. (2018, January). What is digital organizational culture? Insights from exploratory case studies. In *Proceedings of the 51st Hawaii International Conference on System Sciences*.

Fast, E., & Horvitz, E. (2017, February). Long-term trends in the public perception of artificial intelligence. In *Proceedings of the AAAI Conference on Artificial Intelligence* (Vol. 31, No. 1).

Frey, C. B., & Osborne, M. (2013). The future of employment.

Given, L. M. (2008). *The SAGE encyclopedia of qualitative research methods* (Vols. 1-0). Thousand Oaks, CA: SAGE Publications, Inc. doi: 10.4135/9781412963909

Harari, Y. N. (2016). *Homo Deus: A brief history of tomorrow*. Random House.

Hodson, H. (2019). DeepMind and Google: the battle to control artificial intelligence. *The Economist, ISSN*, 0013-0613.

Huang, M. H., Rust, R., & Maksimovic, V. (2019). The Feeling Economy: Managing in the Next Generation of Artificial Intelligence (AI). *California Management Review*, *61*(4), 43-65.

Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons*, *61*(4), 577-586.

Johnson, G. (1988). Rethinking incrementalism. *Strategic Management Journal*, *9*(1), 75-91.

Kagermann, H., Wahlster, W., Helbig, J., Hellinger, A., Stumpf, V., & Kobsda, C. (2013). Umsetzungsempfehlungen für das Zukunftsprojekt Industrie 4.0 -Abschlussbericht des Arbeitskreises Industrie 4.0. Berlin.

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons*, *62*(1), 15-25.

Kravchenko, A. (2019). AI, Robotics, and the Workplace of the Future. *Editorial Board*, 38.

Krippendorff, K. (2018). *Content analysis: An introduction to its methodology*. Sage publications.

Latour, B. (1988). Mixing Humans and Non-Humans Together: The Sociology of a Closed Door. *Social Problems*, *35*, 3.

Latour, B. (1996). On actor-network theory: A few clarifications. *Soziale welt*, 369-381.

Liberati, N., & Nagataki, S. (2019). Vulnerability under the gaze of robots: relations among humans and robots. *AI & SOCIETY, 34(2),* 333-342.

Malinowski, B. (1967). The problem of meaning in primitive languages. *Meaning in Meaning*.

Mavridis, N., Katsaiti, M. S., Naef, S., Falasi, A., Nuaimi, A., Araifi, H., & Kitbi, A. (2012). Opinions and attitudes toward humanoid robots in the Middle East. *AI & society*, *27*(4), 517-534.

McCarthy, E. (1998). The dynamics of culture, organisational culture and change. *AI & SOCIETY*, *12*(3), 155-184.

McClure, P. K. (2018). "You're fired," says the robot: The rise of automation in the workplace, technophobes, and fears of unemployment. *Social Science Computer Review*, *36*(2), 139-156.

Mori, M., MacDorman, K. F., & Kageki, N. (2012). The uncanny valley [from the field]. *IEEE Robotics & Automation Magazine*, *19*(2), 98-100.

Nagy, P., & Neff, G. (2015). Imagined affordance: Reconstructing a keyword for communication theory. *Social Media+ Society*, *1*(2), 2056305115603385.

Nass, C., & Moon, Y. (2000). Machines and mindlessness: Social responses to computers. *Journal of social issues*, *56*(1), 81-103.
Oosthuizen, R. M. (2019). Smart technology, artificial intelligence, robotics and algorithms (STARA): Employees' perceptions and wellbeing in future workplaces. *Theory, Research and Dynamics of Career Wellbeing*, 17-40. Freiling, J., & Fichtner, H. (2010).
Organizational culture as the glue between people and organization: A competence-based view on learning and competence building. *German Journal of Human Resource Management*, *24*(2), 152-172.
Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review*, *46*(1), 192-210.
Rogers, E. M. (1962). Diffusion of Innovations the Free Press of Glencoe. *NY*, *32*, 891-937.
Saner, M., & Wallach, W. (2015). Technological unemployment, AI, and workplace standardization: The convergence argument. *Journal of Evolution and Technology*, *25*(1), 74-80.
Schein, E. H. (1986). What you need to know about organizational culture. *Training & Development Journal*.
Schein, E. H. (1990). *Organizational culture* (Vol. 45, No. 2, p. 109). American Psychological Association.
Schein, E. H., & Schein, P. A. (2016). *Organizational culture and leadership*. ProQuest Ebook Central https://ebookcentral.proquest.com (Retrieved 04.04.2021)
Schiff, D., Ayesh, A., Musikanski, L., & Havens, J. C. (2020, October). Ieee 7010: A new standard for assessing the well-being implications of artificial intelligence. In *2020 IEEE International Conference on Systems, Man, and Cybernetics (SMC)* (pp. 2746-2753). IEEE.
Schoeneborn, D., Blaschke, S., Cooren, F., McPhee, R. D., Seidl, D., & Taylor, J. R. (2014). The three schools of CCO thinking: Interactive dialogue and systematic comparison. *Management communication quarterly*, *28*(2), 285-316.
Schreier, M. (2012). *Qualitative content analysis in practice*. Sage publications.
Searle, J. R., Dennett, D. C., & Chalmers, D. J. (1997). *The mystery of consciousness*. New York Review of Books.
Sebo, S., Stoll, B., Scassellati, B., & Jung, M. F. (2020). Robots in groups and teams: a literature review. *Proceedings of the ACM on Human-Computer Interaction*, *4*(CSCW2), 1-36.
Siitonen, M., & Aira, A. (2019). Technology-Mediated Communication in the Workplace. *Workplace Communication*.

Sirén-Heikel, S., Leppänen, L., Lindén, C. G., & Bäck, A. (2019). Unboxing news automation: Exploring imagined affordances of automation in news journalism. *Nordic Journal of Media Studies*.

Smelser, N. J., & Baltes, P. B. (Eds.). (2001). *International encyclopedia of the social & behavioral sciences* (Vol. 11). Amsterdam: Elsevier. – Definition of Cultural difference. Retrieved 25.09.2021 13:25

Song, F. W. (2003). Being left behind: The discourse of fear in technological change. *The Hedgehog Review*, *5*(3), 26-43.

Su, G. (2018). Unemployment in the AI Age. *AI Matters, 3(4)*, 35-43.

Tracy, S. J. (2019). *Qualitative research methods: Collecting evidence, crafting analysis, communicating impact*. John Wiley & Sons.

Traeger, M. L., Sebo, S. S., Jung, M., Scassellati, B., & Christakis, N. A. (2020). Vulnerable robots positively shape human conversational dynamics in a human–robot team. *Proceedings of the National Academy of Sciences*, *117*(12), 6370-6375.

Walsh, T. (2018). Expert and non-expert opinion about technological unemployment. *International Journal of Automation and Computing*, *15*(5), 637-642.

Whittle, A., & Spicer, A. (2008). Is actor network theory critique? *Organization studies*, *29*(4), 611-629.

Wisskirchen, G., Biacabe, B. T., Bormann, U., Muntz, A., Niehaus, G., Soler, G. J., & von Brauchitsch, B. (2017). Artificial intelligence and robotics and their impact on the workplace. *IBA Global Employment Institute*, *11*(5), 49-67.

World Economic Forum. (2016). The future of jobs: Employment, skills and workforce strategy for the fourth industrial revolution. *Global Challenge Insight Report*.

Wrench, J., & Punyanunt-Carter, N. (2012). An Introduction to organizational communication. *Creative Commons: Mountain View, CA, USA*.

APPENDICES

APPENDIX 1

Description of the dimensions and subcategories of the coding frame.

Definitions of dimensions

Dimension (category) name	**Description**	**Example**
Evaluation of chatbots' work	Units of coding that describe perceived impact of the chatbots' tasks and roles on the employees, their work, intraorganizational relationships and the importance of these tasks for the employees and the organization	"…even in Finland some news are written by AI, so journalists are not really replaced because it's not a WOW work to do"
Impressions of chatbots	Units of coding that reflect emotional or evaluative responses to the collaboration with chatbots	"…sometimes maybe frustration of Seppo nagging, …"
Impressions of organizational culture	Units of coding that reflect interviewees' perception and interpretation of their organizational culture	"So, for me personally, it is that I'm allowed to be myself, that I'm respected as a person that I am, and that is so liberating also."
Chatbots' features	Units of coding that reflect the most salient features of the chatbots that are often discussed by employees	"They [chatbots] are referred to by their names.

		So, they are personalities."
Miscellaneous	Units of coding that do not fall within any other dimensions	"They might be annoyed that "damn, my billing role is low", but I've been doing other projects."

Definitions of subcategories

Dimension	Subcategory name	Description	Example
Evaluation of chatbots' work	Improvement of manager-subordinate relationships	Units of coding that describe the improvement in manager – subordinate (or people person – team member) relationships as a result of the active use of chatbots	"Seppo is the middle manager who takes the burden off our shoulders, so we don't have to nag about these things, that make our relationships not so nice."
	Optimization of "useless communication"	Units of coding that inform about the optimization of unnecessary communicative exchange that distracts from work	"…it (chatbot) reduces labor for me and for someone else whom I would have to ask for these things."
	Chatbots remind about necessities	Units of coding that describe chatbots' tasks as reminders about necessary actions to be taken	"Seppo helps to remind about the necessities (hours, vacations), …"
	Vital business information from a chatbot	Units of coding that reflect the importance of information obtained from the chatbots	"It's good for me to get info from Seppo, how things are going. …Seppo just today told all of

			us, …, the utilization rate for last week and how it's been divided between business units and group functions. Actually, the utilization rate is something that we follow very carefully in executive management team."
	Chatbots make people's work meaningful	Units of coding that demonstrate a positive impact of chatbots on the employees' quality of work and tasks	"And if they [chatbots] somehow would replace some parts of somebody's job, then they would be able to concentrate on more meaningful work."
	Chatbots do unpleasant work	Units of coding that describe work done by the chatbots as unpleasant and dull for the employees	"…even in Finland some news are written by AI, so journalists are not really replaced because it's not a WOW work to do [particular types of news]."
	Miscellaneous	Units of coding that do not fall within any other subcategories within this dimension	"Even though AI helps out in repeatable tasks, in the long run it may give more

			stress to the workers because there are no more easy tasks to do, just thinking, thinking, thinking."
Impressions of chatbots	Helpful chatbots	Units of coding that reflect positive evaluation of collaboration with the chatbots and emphasise their helpfulness	"Then I just found it very helpful to hear from Seppo that I missed something."
	Annoyance/Frustration	Units of coding that reflect negative emotions provoked by collaboration with the chatbots	"…if they [chatbots] are not working properly, if they don't understand my questions, that's when I get a bit annoyed".
	Annoyance/Frustration: chatbots don't work properly	Units of coding that reflect employees' frustration caused by chatbots' malfunction	"Well, if they are not working properly, …"
	Annoyance/Frustration: chatbots don't understand	Units of coding that reflect employees' frustration caused by chatbots' failure to understand their inquiries	"I haven't used Granny a lot, because she's a recent addition, my questions to her are too complex, she doesn't understand."
	Annoyance/Frustration: chatbot 1 is nagging	Units of coding that reflect employees' annoyance caused by chatbot 1's reminders	"Or if there is a sick leave that needs approval, then I can't mark hours, and

			Seppo is frustrating me."
	Jokes about chatbots	Units of coding that reflect chatbots being objects of joke and free-time discussions	"Seppo is an inside joke for example, so they have a cultural value for the employees."
	Wishes for improvement	Units of coding that convey employees' preferences to improve chatbots' work	"He may need an improvement when you have dozens similar projects within him, because the names are so similar, I need to input them myself."
	Chatbots as tools	Units of coding that reflect employees' attitude towards chatbots as tools	"They say it's a tool, we talk about the coffee, not the coffee machine. You talk about the output of the system."
	Miscellaneous	Units of coding that do not fall within any other subcategories within this dimension	"…But it's good that we have different opinions.]"
Impressions of organizational culture	Employee-oriented thinking and terminology	Units of coding that describe employee-centered attitudes and practices in the organization	"And you noticed that I'm talking about people persons not managers, and team members, not subordinates."

	Harmonization of the employees' work and private lives	Units of coding that reflect the organization's care for employees' work and private lives	"People can't be something only at work, and we respect people as they are and their conditions that they live in, and we try to harmonize it somehow, that everyone feels well."
	Miscellaneous	Units of coding that do not fall within any other subcategories within this dimension	(No units of coding)
Chatbots' features	Assigned tasks	Units of coding that mention chatbots' preprogramed duties	"Before I worked with Gene about train tickets…"
	Chatbots' personalities	Units of coding that reflect the ascription of personalities to the chatbots	"Granny is my favourite, she's a bit silly. Her way of talking is... the words that she uses are charming. "Oh dear,…", it's always pleasant to chat with her."
	Development history	Units of coding that demonstrate chatbots' evolution and ways in which they had been improved	"I developed her from an original FAQ bot."
	Miscellaneous	Units of coding that do not fall within any other subcategories within this dimension	"I mean, I can't really describe her fairly because she's my creation, …"

Miscellaneous	N/A	Units of coding that do not fall within any other dimensions or subcategories	"For example, there was communication workshop, it's important for a consultant but it's a soft skill. If I don't agree with it, then it's just a suggestion, I don't have to follow it."

APPENDIX 2

Matrix of the main coding for presenting the results.

How to read the matrix:

Interviewee	Dimensions
	Subcategories coded for each interview + their recurrencies

Interviewee	**Evaluation of chatbot's work**	**Impressions of chatbots**	**Chatbots' features**	**Impressions of organizational culture**	**Miscellaneous**
Interviewee 1	Chatbots remind about necessities	Chatbot 1 is nagging (4)	Assigned tasks (2)		Miscellaneous (4)
	Improvement of manager-subordinate relationships (4)	Chatbots as tools (5)	Chatbots' personalities (7)		

	Chatbots do unpleasant work	Jokes about chatbots	Development history (4)		
		Helpful chatbots (3)	Miscellaneous (3)		
		Miscellaneous (3)			
Interviewee 2	Chatbots do unpleasant work (2)	Chatbots don't work properly	Chatbots' personalities (5)	Employee-oriented thinking and terminology	
	Optimization of useless communication	Wishes for improvement (3)	Development history (4)		
	Chatbots make people's work meaningful	Chatbots as tools	Assigned tasks		
		Chatbot 1 is nagging	Miscellaneous (4)		
		Jokes about chatbots (3)			
		Chatbots don't understand			
		Helpful chatbots			
		Miscellaneous (2)			
Interviewee 3	Vital business information from a chatbot	Jokes about chatbots (5)	Assigned tasks (4)		Miscellaneous (3)
	Chatbots do unpleasant work (3)	Wishes for improvement	Chatbots' personalities (5)		
	Improvement of manager-subordinate relationships (4)	Helpful chatbots (4)	Miscellaneous		
	Optimization of "useless" communication	Chatbot 1 is nagging (2)			
	Miscellaneous (2)	Miscellaneous (3)			
Interviewee 4	Improvement of manger-	Helpful chatbots (2)	Chatbots' personalities (7)	Employee-oriented thinking	Miscellaneous

	subordinate relationships (2)			and terminology	
	Vital business information from a chatbot (3)	Chatbots don't understand	Development history (4)	Harmonization of the employees' work and private lives	
	Chatbots do unpleasant work	Wishes for improvement (4)	Assigned tasks (4)		
	Miscellaneous	Chatbots as tools (5)			
		Chatbot 1 is nagging (2)			
		Miscellaneous			
		Jokes about chatbots			
Interviewee 5	Vital business information from a chatbot (3)	Jokes about chatbots (2)	Chatbots' personalities (5)	Employee-oriented thinking and terminology (2)	
	Chatbots remind about necessities (4)	Chatbots don't work properly	Development history (3)	Harmonization of the employees' work and private lives (2)	
	Chatbots do unpleasant work (2)	Chatbots don't understand (2)			
	Improvement of manager-subordinate relationships (2)	Chatbot 1 is nagging			
	Chatbots make people's work meaningful (2)	Helpful chatbots (6)			
	Miscellaneous	Wishes for improvement			
		Miscellaneous			