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Abstract

The innovation of artificial intelligent powered *service robots* has rapidly revolutionized the service sector by increasing competitiveness and maximizing efficiency. Therefore, an increasing number of service organizations are employing service robots to deliver services that advance customer experience. However, research on customers' psychological motivations and barriers in adoption of service robots remains fragmented and sparse. Thus, this study specifically analyzes factors that motivate Norwegian service customers and what barriers impede their service robot adoption. In this context, service robots are defined as an artificial intelligence robot that autonomously or semi-autonomously provides personalized services through interaction with service organizations' customers.

This study aims to improve the Service Robot Acceptance model first introduced by Wirtz et al (2018) by testing it with functional elements (ease of use, usefulness, and trust), and enhancing it by introducing rational elements (limited perception, lack of human interaction and cultural barriers) that influence Norwegian customer service robot adoption. To answer the research question and hypothesis derived from literature review, an online survey was distributed through Facebook and LinkedIn, where 189 representative respondents were attained.

Results from the hierarchical regression analysis provides evidence that factors such as ease of use and usefulness have a great positive effect that drives Norwegian service customers adoption of service robots. While trust has no statistical significance and shows a vital area that needs improvements. Furthermore, this study shows that all rational elements generate negative effects that impedes customer adoption of service robots. Lastly, this study elaborates theoretical and managerial implications with guidance based on this study's findings, in addition to suggestions for future research.

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1.0 Introduction

The service sector is regarded as the pinnacle technological frontier of innovation in automation. This is due to the rapid development and creation of new technologies, which has dramatically changed consumer experience and organization's ability to strengthen the process of service delivery (Lu et al., 2019; Huang & Rust, 2018; Wirtz et al., 2018). A major branch of this development is artificial intelligence (AI) as a service innovation, which is changing the service industry playfield. Recent market developments indicate that AI is increasing its importance and reshaping services that a company provides to its customers, through its application in forms and service contexts. Consequently, due to AI ability to process and store complex data, and processing capabilities, robotic applications are commonly used in many services marketing functions (Xiao & Kumar, 2021).

Consequently, the adoption of AI in the service sector has been rapidly evolving over the last years and has been more frequently used in service encounters, replacing direct human interaction with the customers. Additionally, AI enables an unprecedented opportunity for businesses to improve their services and strengthen the interactions with their customers (Chen et al., 2021; Meuter et al., 2000). By the same token, due to the advanced and constantly improving AI technology, many business areas are implementing AI such as service robots as a part of their business. Thus, the interest in service robots keeps rising (Gummerus et al., 2019). The increase in organizations adopting service robots can be found in many different business areas with the intention to work as a substitute for service personnel. Furthermore, service robots generate beneficial advantages to service organizations by contributing to increased productivity and lower employee costs (White at al., 2012).

In a service marketing context, service robots can be viewed as AI robotic device that can mimic human behavior to provide, autonomously or semi-autonomously, service to an organization's customers (Haidegger et al., 2013; Lechevalier et al., 2014; Chiang & Trimi, 2020). By utilizing service robots, organizations can provide customizable service to their customers at home or in other specific service environments (Jorling et al., 2019; Thrun, 2004). Therefore, the nature of customer experience is being revolutionized by organizations enabling service robots to either support or provide services (Chuah & Yu, 2021). To illustrate the continuing advancement and utilization of service robots: today hotels are introducing humanoid service robots that guide their guests and provide them with relevant information, restaurants have robots to take orders and payments, airports use service robots to help passengers find the right gates and scan their boarding passes, and hospitals use medical service robots to take over disinfection work (Wirtz, 2021). This shows that AI operated service robots are widely spread in many business areas and has changed the concept of customer service by expanding customer interactions from human-to-human interactions to human-to-robot interactions (Park, et al. 2021).

The Covid-19 pandemic has inevitably influenced the service robot market significantly. With all the previous government restrictions and limitations being enforced globally, there was a need for more advanced AI service robots to replace humans-to-human contact as much as possible. Thus, many businesses were urgently looking for ways to restrict direct contact between their employees and their customers. However, despite great efforts of implementation, the customer adoption rate of service robots remained contradictingly low (Pozharliev et al., 2021). Ergo, this has created a confusion concerning the utility and meaning of employing service robots for services (Liu et al., 2022). The low rate of adoption can be attributed to customers' barriers of using service robots, which may cause resistance and reduction in their adoption intentions (Ivanov & Webster, 2019). This has led to the need for more understanding of consumers' psychological motivational acceptances and barriers of these types of AI services. As the process of how customers adopt the use of AI services is critical to marketers in the service domain (Park et al., 2021).

1.1 Service robot market

The practice of using service robots in the service sector is expected to increase its importance within marketing function over the coming years (Jorling et al., 2019; Wirtz et al., 2018; Xiao & Kumar, 2021; Li & Wang, 2021). This development will have a global impact on performance, competitiveness, and resilience for all service industries (Kunz et al., 2018). This rapid innovation revolution within the service sector also has a major impact on the customer perspective. As customer experience, service quality and productivity combined will be dramatically improved (Wirtz et al., 2021). Hence, service robots are widely used during customer-facing parts of large and integrated service systems, such as CRM-systems (Wirtz et al., 2018). Furthermore, organizations can also employ service robots virtually through advanced algorithms (e.g., investment services), text/chatbots (e.g., DNB & Telia chatbot), and voiced-based digital assistants (e.g., Siri, Bixby, and Google home) (Paluch & Wirtz, 2020).

Consequently, the service robot market is expanding rapidly, and generated a market valued at 37$ billion between 2019 and 2021 globally (Automate, 2021). By 2027 the service robot market worldwide is estimated to be valued at $164.9 billion, growing at a CAGR of 38.5% between the analysis forecast period 2020-2027 (Reportlinker, 2021). Thus, increasing numbers of service organizations are moving the service delivery from frontline employees to service robots. The intention in their effort is to lower prices, increase consumer consumption and improve the quality of the service delivery (Wirtz et al., 2018).

The introduction of the robots-as-a-service is a major factor in the promising future of professional service robots (Automate, 2021). Market reports indicate that larger companies are more likely inclined to use service robots, compared to smaller service companies (Sostero, 2020). Furthermore, the growth rate of implementation and utilization of service robots in Norway is considered as midcore (Mordor Intelligence, 2021). Therefore, the Norwegian service robot market is one that is characterized to be limited. Since Norwegian companies offer different varieties of industrial and collaborative robots, but lack service robots in industries like hotels, restaurants, and health care (Sostero, 2020). Thus, it appears that service robots in the Norwegian market are mainly limited to *Chatbots* and *Digital Voice Assistance*. Seemingly, Norwegian service companies' utilization of service robots is one that is intended to create utilitarian value for both the customer and the company itself.

1.1.1 Chatbots

Service robots in the form of chatbots are used to stimulate conversations with the customer and are primarily employed as text-based conversational agents (Ashfaq et al. 2020). Chatbots can also be defined as automated programs communicating with humans through written chat exchange (Przegalinska et al. 2019). Service organization utilizes chatbots due to their ability to provide quick and efficient customer service and enhance users service experience. These conversational agents are usually available 24/7 and can therefore offer support to customers at their convenience. Additionally, chatbots are used by companies and end-users, because of the low cost, easy accessibility, and flexibility (Przegalinska, et al. 2019). Moreover, chatbots are commonly used for performance of sales functions (41%), for customer support (37%) and for marketing purposes (17%) (Forbes, 2019).

Furthermore, due to chatbots' ease of flexibility and utility, customers can interact with them through different devices such as smartphones, tablets, or laptops (Araujo, 2018). In a service environment, chatbots work as company representatives and assist consumers from any location at any time of the day (Chung et al, 2018). The continued innovation of AI has led to chatbots becoming more advanced, resulting in them no longer being limited to only provide customers with information, but rather take a role as a personal assistant trying to solve customers' problems (Chung et al, 2018). Therefore, chatbots in today's service market work as virtual agents and can provide customer service with no interruptions, while also reducing time-to-response, which is a big factor of user's service satisfaction and experience (Radziwill & Benton, 2017).

1.1.2 Digital Voice Assistance

Digital Voice Assistant (DVA), which relies on AI technology, is a feature that is commonly found in handheld smart devices (mobile phones, tablets, smart watches), smart speakers (Google Home, Apple Home pod, Amazon Alexa) and on social messaging platforms (Fernandes & Oliveira, 2021; Guzman, 2019). Service robots using DVA as an interface, interact with customers in a virtual community or through face-to-face interactions. Thus, DVA service robots provide services in various sectors by acting as an AI service agent (Lu et al., 2019; Huang & Rust, 2018). Consequently, DVA as a service robot is one that can either be autonomous (have no physical form) or have a physical form that relies on control by the customer (Jörling et al., 2019; Li & Wang, 2021).

The rise in usage and commonality of DVA means that customers are increasingly communicating with both humans and human-like service robots through their service navigation (Guzman, 2019). Market reports estimate that by 2024 there will be roughly eight billion DVA in use (Statista, 2022). To exemplify, Norwegian companies such as VG and Telenor are incorporating this type of service robots into their services to provide greater customer experiences (Schibsted, 2018; Telenor, 2021). However, the utilization and further advancement is dependent on customer adoption intentions and user habits.

1.2 Research Objective

AI within the service marketing field will continue to increase its importance over time, which is why there has been an increase of academic literature that explores the theoretical underpinnings ranging from: job replacement, coordination towards technology acceptance and co-creation. Lu et al (2020) found that most research in general lacks a comprehensive analysis of service robots and their impact on customers. This is due to prior research utilizing a "down-stream" approach towards a service organization perspective. Resulting in a lack of focus towards the customers actual motivations and potential barriers, which ultimately affects their adoption of service robots.

Furthermore, research also highlights that customers' AI robot acceptance depends on how they can deliver a service that meets their functional needs and the social emotional/ relational needs (Heerik et al, 2010). Additionally, Xaio & Kumar (2021) found that research in service robots within service marketing is one that can be categorized as sparse and fragmented. As existing literature focuses on customer-robot interaction and performance. Thus, there is a need for an academic paper that focuses on factors that impact customers' acceptance of service robot adoptions in a service marketing context and factors that impede adoption. Especially when it comes to customer-robot interaction, since service robots are employed with the intent of serving the customers (Xaio & Kumar, 2021). Additionally, findings from previous research within service robot adoption, may not be generalized and applicable for other cultures that are outside of the origin research population.

Hence, this research objective is to focus on Norwegian service consumers' acceptance of service robots by analyzing their willingness to adopt it (usage) and what critical factors impede the adoption. In other words, we intend to investigate which factors have a positive influence on Norwegians' service consumers' motivation to proceed with the adoption and identify what kind of consumer barriers impede the adoption of service robots.

1.3 Research Question

The proposition of this thesis paper is through relevant theories to identify and explore what motivates Norwegian service consumers to adopt service robots, and what kind of barriers limit the adoption of it. Additionally, this paper intends to discuss how the barriers can be mitigated, since service robots will have an incremental implication on the individual customer experience and for future advancement it its utilization. Hence, this has led us to the following research question:

What are Norwegian service customers' motivators and barriers (and how the latter can be mitigated) of service robot adoption?

1.4 Contribution

The aim with our research is to contribute to the already existing research in the AI and service robotics field and provide valuable information regarding Norwegian consumers' willingness to adopt service robots. Moreover, what kind of factors motivate their decision process to proceed with the service robot adoption, and what kind of barriers have a negative impact on their adoption behavior towards service robots. Furthermore, this research will also help marketers in the service domain by highlighting and providing a deeper understanding of consumers' psychological adoption and barriers towards service robots. Additionally, we believe this research will help marketing managers to understand what kind of factors are important to consider meeting Norwegian consumers expectations and to maximize the value creation. The theoretical framework of service robots is adopted from prior literature on this domain and the conceptual model is created based on this foundation.

The following sections create the structure of this thesis paper. First, a literature review provides important summarized information on service robots employment in services and introduces the customers' acceptance of service robots' model. Second, the theoretical framework then describes customers motivations and barriers customers towards adoption. Third, the methodology of this study will be addressed. Fourth, the conceptual model and hypotheses are tested based on collected statistical data from online questionnaires. Lastly, identified theoretical and managerial implications, study limitations, future research directions, and conclusions will be discussed.

2.0 Theoretical Background

Traditionally, service encounters between a service organization and its customers are composed of a series of mutually dependent services roles, with subsequent coordinated actions. Through these service encounters, customers generate expectations of the service interactions, which further impacts their evaluation of the service experience (Solomon et al., 1985). Today, the service sector is at an inflection point with regards to innovation and customer experience. This is mainly due to the emergence of AI service robot technology that has reshaped how customers interact with various service providers. As different stages of service encounters are affected by the various levels of human factors and technology infusion. Thus, companies today need to evaluate the interplay of the service encounter stages and how this changes the customer-company relationship (Fan & Mattila, 2021).

Customarily, the service encounter stages involve a form of an interaction between customer and a service provider through a face-to-face setting. However, the adoption of service robots is changing this interaction (Bitner, 1990). Writz et al (2018) define service robots as a "*system-based autonomous and adaptable interface that interacts, communicates and delivers service to an organization's customers"*. The design of service robots can have (1) virtual or physical representation (AI software that works autonomously and learns over time), (2) service robots can incorporate humanoid or non-humanoid appearance, (3) can perform cognitive-analytical tasks and emotional-social tasks (Writz et al., 2018).

The aforementioned functions all together are expected to increase and be perfected over time. Thus, it is expected that service robots will be increasingly adopted in services and may replace the traditional customer-employee human interaction. Resulting in an expected paradigmatic shift in the service sector (Kumar et al., 2015; Marinova et al., 2017). Furthermore, academic research has indicated that companies that are able to adopt AI, such as service robots, will ultimately be able to achieve more personalized and efficient services (Van Doorn et al., 2017). The customization of the service robot can be done physically, as well as non-physically, since it is able to do tasks with a high degree of autonomy (Jörling et al., 2019). Thus, the implementation of service robots for a service organization can be seen as a significant innovation and is a tool that has the potential to increase revenues and reduce costs (Huang & Rust, 2018; Davenport et al., 2020). Further, this also has a direct consequence on service organizations' customers in terms of acceptance, quality perceptions and satisfaction (Paluch & Wirtz, 2020).

Consequently, the service sector is evolving from human-driven to technology-driven to create value both for the customer and the service provider. Therefore, the adoption of service robots leads to a reconfiguration of relevant service roles (the role that service provides employees, customers, and service technology plays), as the service encounter is becoming increasingly multidimensional. Subsequently, this reshapes the customer's motivation and barriers towards service robots (Larivière et al., 2017). Furthermore, service robots are now being deployed in services with any degree of cognitive complexity and are commonly found in services that require low emotional/ social complexity (Paluch & Wirtz, 2020).

Conversely, due to the human social nature and the continuous development of service robots, services that require high emotional/social complexity are predominantly delivered by frontline employees. This is due to service robots not being able to engage in deep humanlike emotions. However, future innovation will further develop this attribute to a more adequate level. Thus, services with both high task and emotional complexity tend to be delivered in a combination with service providers employees with the support of service robots (Writz et al., 2018).

2.1 Customer Acceptance of Service Robots

Customer adoption of service robots can be elaborated by applying the Service Robot Acceptance model (sRAM), which is an extension of technology acceptance model (TAM). Service robot acceptance model provides good insights and understanding of how customers interact with robots (Fuentes-Moraleda et al. 2020; Wirtz et al., 2018). sRAM aims to examine customers' perceptions, beliefs and behavioral intentions towards services that are provided by service robots. Furthermore, Fernandes & Oliveira (2021) stated that sRaM has been empirically validated and is able to have high predictive power by roughly explaining 88% of the variance of consumers acceptance.

Prior research mainly used TAM first introduced by Davis (1998) to explore variables that have a significant impact on customers usage intentions of new innovative technological products within the service marketing field (Fernandes & Pedroso, 2017). The baseline of TAM is that the acceptance of new technology can be attributed to variables such as ease of use and usefulness, elements of which will be addressed later in this paper. However, TAM has been repeatedly criticized by researchers due to the lack of other influential variables and not being comprehensive enough to explain customers willingness to adopt new innovative technology (McLean & Osei-Frimpong, 2019; Fernandes & Oliveira, 2021). This has led to the continuing evolution to gain a better theoretical foundation that will explain customers' adoption of any new technology (Dwivedi et al., 2019; Fernandes & Oliveira, 2021). Therefore, studies such as Wirtz et al (2018), van Doorn et al (2017) and Heerik et al. (2009) has collectively expanded sRAM to explain customers' acceptance through elements of: functional performance, social-emotional and relational needs, and lastly rational elements.

There are three types of elements that influence consumers' acceptance of service robots according to sRAM (Fuentes-Moraleda et al. 2020). The three elements are functional (like in the TAM model), emotional and relational. All these elements contribute to consumers' acceptance of the robots, depending on how well the robots deliver on functional, social, and emotional needs to achieve congruence (Wirtz et al, 2018). The first functional dimension refers to ease of use, usefulness, and adherence to social norms (Fuentes-Moraleda, et al. 2020). Usefulness and perceived ease of use are the main elements of the TAM model, which will be discussed in the section below. These elements refer to goals of new technology use (Wirtz, et al, 2018). According to Wirtz et al. (2018) customers' technology acceptance is greater when there is a relationship between the functional elements and social norms. Additionally, trust plays an important part when it comes to customers' technology acceptance, and is the key to retaining customers (Gefen, et al. 2003).

A rational dimension is also a part of the sRAM model, which equally determines consumers acceptance of new technologies. Three major elements in this dimension are perceived humanness, perceived social interactivity and perceived social presence (Fuentes-Moraleda, et al. 2020). Furthermore, the social dimension is important since one of the main bases for willingness to adopt is rooted if the customer's action is accepted by their references and culture (Schepers & Wetzels, 2007). Service robots' ability to detect and interpret events that occur and their ability to respond to customers' commands is described as human-oriented perception (Tung & Au, 2018). Moreover, Wirtz et al. (2018) argues that service robots cannot be implemented before customers' needs and perception of the robots are well aligned for. Lack of human interaction, different cultures and norms regarding service robot market, and lack of perception can be influencing factors that might prevent adoption of service robots.

2.2 Motivators of service robot adoption

The major functional elements that motivate consumers to adopt a service robot are perceived use of ease, perceived usefulness, and trust. Perceived usefulness and perceived ease of use are elements from a technology acceptance model and are factors that can influence consumers’ willingness to accept new technologies (Davis et al. 1989). While trust is an important factor in many transactional relationships, most importantly those containing an element of risk, including interacting with a service robot (Grefen et al, 2003).

2.2.1 Perceived ease of use

Perceived ease of use is the extent to which a person accepts as true that using an exacting method would be at no cost to that individual (Davis et al.1989). Rogers (1983) stated that perceived ease of use is the degree to which consumers perceive a new service as better than its substitutes (Jahangir & Begum, 2008). Moreover, Rogers (1962) stated that perceived ease of use refers to the degree to which an innovation is perceived not to be difficult to understand, learn, or operate. Similarly, Zeithaml et al. (2002) stated that perceived ease of use can be defined as the degree to which an innovation is easy to understand or use (Jahangir & Begum, 2008). Perceived ease of use refers also to the ability of consumers to experiment with an innovation and evaluate its benefits easily, without having to put a lot of effort into it (Consult, 2002).

According to the technology acceptance model, perceived use of ease has an impact on consumers behavior and attitude intentions (McCloskey, 2006). Perceived ease of use might be an important factor in determining whether a person will be willing to adopt a service robot or not. The service robots ease of use should be equivalent or more superior to direct human interaction in a service encounter to provide a valuable experience, without losing any quality of the service.

Furthermore, previously conducted research has shown that there is evidence indicating that consumers are more likely to use new technology if they perceive it useful and easy to use (Elliot et al, 2014). This is important in this field because AI´s primary role is to help customers complete tasks in an effective and efficient manner (Kim, et al. 2021). Moreover, according to McCloskey (2006), perceived use of ease can be linked to perceived usefulness. Based on this, the following hypothesis has been formulated:

Hypothesis 1 (H1): *Consumers perceived use of ease has a positive effect on service robot adoption*

2.2.2 Perceived usefulness

The importance of perceived usefulness has been widely recognized in different fields (Jahangir & Begum, 2008). Many researchers have defined usefulness as the subjective likelihood that using the technology will improve the way a user completes a given task. Based on social psychology theories such as the theory of reasoned action and technology acceptance model (Jahangir & Begum, 2008). Furthermore, according to Davis's (1989) TAM, perceived usefulness influences consumer behavior and attitude intentions. TAM defines perceived usefulness as the degree to which a person believes that using a specific system would improve his or her job performance. Consumers' perceptions of the outcome of the experience are referred to as perceived usefulness. According to Davis (1989), perceived usefulness is the individual's belief that using new technology will enhance or improve their performance (Jahangir & Begum, 2008).

Previous research argues that perceived usefulness is significant because it is directly related to an individual's attitudes toward a specific technology. Perceived usefulness is found to have stronger links to the various mechanisms that influence technological adoption when compared to other technology-related perceptions, such as perceived ease of use (Davis, et al. 1989). Tan and Teo (2000) suggested that the perceived usefulness is an important factor in determining adaptation of innovations. Consequently, the greater the perceived usefulness, the more likely it will lead to adaptation (Jahangir & Begum, 2008). The perceived usefulness of technology is concerned with how practical it may be in everyday interactions (Davis, 1989).

Lastly, the customer advantage of using service robots compared to human employees is also directly tied to the perceived usefulness. This is because usefulness impacts the service robot's ability to perform a task efficiently in service encounters where service robots are more competent and quicker. Therefore, customers are more willing to adopt service robots based on its performance in a service encounter, which creates advantages compared to human interaction, in the extent that usefulness goes beyond the ability to perform a service task (Lu et al., 2019). Hence, we wish to test whether:

Hypothesis 2 (H2): *Consumers perceived usefulness has a positive effect on service robot adoption*

2.2.3 Trust

Trust is a factor of great importance in AI-human interactions, especially due to the increased adaptation of service robots that take over tasks previously handled by humans (Oksanen, et al. 2020). Trust is essential in human interactions; it provides a feeling of security and builds relationships between people. This allows consumers to bond with companies and their employees during service encounters, which leads to customer satisfaction and loyalty (Wirtz et al., 2018). However, challenges occur when human handled service encounters are replaced by service robots. This is because trust is equivalently important in technological interactions, and people are more likely to adopt new technology if they have sufficient prior knowledge and experience (Oksanen, et al. 2020).

Moreover, how a service robots' abilities are presented also affects how the level of trust in the robot is perceived during the service encounter. Customers tend to trust robots more when they see likable features, such as positive emotional expressions. Further, this has also a positive effect on the adoption intention (Cameron et al., 2021). Physical characteristics are usually what the robots are defined by, and the more consumers are exposed to visual images of a robot the more it will affect their perception of it, which might lead to more trust (Oksanen, et al., 2020). Furthermore, trust is essential since service robots rely on user data and customers tend to be averse to artificial intelligence algorithms when mistakes are made (Wirtz et al., 2018; Chattaramman et al., 2019).

Consequently, if service organizations can transmit the confidence that their service robot is able to generate reliable trustworthy services, their customers will be willing to adopt it (Fernandes & Olivera, 2021). Hence, we assume that:

Hypothesis 3 (H3): *Consumers perceived trust in robots has a positive effect on service robot adoption*

2.3 Barriers of service robot adoption

The elements that create customers barriers and impediments to service robot adaptation are *limited perception* of service robots, *cultural barriers*, and *lack of human interaction*. This dimension is quite crucial as customers tend to have reservations against service robots, especially when mistakes are made (Wirtz et al., 2018). Additionally, AI functions such as service robots tend to use personal data and advanced algorithms to deliver the service, which tends to create customer aversion (Chattaraman et al., 2019). The customer adaptation of service robots relies on customer satisfaction of the provided service (Xiao & Kumar, 2021). Customer barriers are then considered as rational elements that has the power to contradict and impede service robot adoption, despite positive motivational factors.

2.3.1 Limited perception

The first barrier towards customer adaptation is the customers *lack perception of service robots.* The customer limited perception barrier is expected to be one of the main reasons for why customer adoption of service robots in previous research is generally low. This is largely due to perceived uncertainty mediates effect on service type and adoption intention. The uncertainty is rooted in lack of customer understanding and creates unpredictability for strategic implementations of service robots (Liu et al., 2022). Mende et al (2019) found that service robots that resemble the human body in shape (anthropomorphic robots) generate a sense of discomfort and threat, which leads to negative customers´ perceptions and acceptance. Furthermore, research and academic literature found that older people tend to be more negative towards service robot adoption intentions due to skepticism about AI technology. While younger people tend to be more predisposed to be technology inclined and open to widen their technology perceptions (Broadbent et al., 2009).

Consequently, customers' perception of AI driven service robots is grounded in their fundamental understanding and knowledge, which builds their foundation of crucial reference and context for interpretation (Chen et al., 2022). Thus, customers are more inclined to use services provided by trustworthy providers due to the familiarity on how the service is produced (Shin, 2021; Rai, 2019). Furthermore, when negative service encounters occur, the lack of perception can result in customers being angry, which generates negative service evaluation and lower satisfaction (Kalamas et al., 2008; Iglesias, 2009; Jörling et al., 2019). Therefore, customers will be disinclined to adopt service robots and be more inclined to generate negative word of mouth. This also has a widespread effect that negatively effects the customer perception on the service provided by an organization.

Subsequently, lack of perception makes consumers have a negative understanding of service robots when evaluating the service encounter and taints the overall experience. Witch also has negative side effects that impacts the entire service organization. Based on this, we hypothesize the following:

Hypothesis 4 (H4): *Limited perception of service robots has a negative effect on adoption.*

2.3.2 Cultural barriers

Cultural barriers have the potential to impact the convergence of humans and AI machines in services (Kaplan, 2004). Cultural barriers in service robot adaptation generates implications in various service fields utilization (Li et al., 2010). Research on human robot interaction suggests that customer interaction with service robots is affected by existing experiences and expectations. Cultural acceptance of AI robots affects customers' thoughts and feelings, which also gives future predictions of service robot interactions (Zanatto et al., 2019). Furthermore, research has found that cultures that are not AI robot inclined, tend to have more negative associations and customers have more negative feelings towards service robots. Additionally, this also supports previous research that has concluded that customer acceptance of service robots will vary depending on culture (Lu et al., 2019; Nomura, 2017).

Moreover, uncertainty avoidance within a culture is found to have a tremendous effect on acceptance of new technologies such as service robots. This explains the disparity in the customers attitude, satisfaction, and their difference in behavioral intention (Daewon & Suwon, 2021; Nistor et al., 2014; Reimann et al., 2008). Furthermore, cultural differences cause customers to perceive and engage with service robots differently. Customers who are in cultures that are robot adverse, rely on their personal decision to adopt to service robots based on how it mediates membership in their social group and will be less inclined to use services exposed to service robots (Lim et al., 2020). Therefore, due to the Norwegian culture and general lack of service robot, we posit that:

Hypothesis 5 (H5): *Cultural barriers has a negative impact on Norwegian service customers adaptation of service robot*

2.3.3 Lack of Human interaction

Lastly, *lack of human interaction* is deeply rooted in customer acceptance of service robots and is affected by functional considerations such as interactions (De Kervenoael et al., 2020; Wirtz et al., 2018). Interactions is a vital condition of which customers evaluate the service encounter and creates expectations (Solomon et al., 1985). Service robots operate autonomously by relying on complex AI to give directions, without the need for instructions or support of employees (Colby & Parasuraman, 2016). Thus, customers are interacting with service robots without humans in a service setting. To date, service robots are not able to match or surpass human intuitiveness and empathy. Therefore, due to the AI limitations, service robots are unable to perform complicated service tasks that require intuition, judgment, wisdom based on experience and human emotion (Huang & Rust, 2018). Consequently, research has highlighted the gap that exists between the level of service provided by a service robot and that of a human. This gap is large enough to render certain complex services useless (Gale & Mochizuki, 2019). Moreover, the lack of human interaction can create a lack of trust and acceptance towards service robots (Talk & Lew, 2020).

In conclusion, human interaction in services brings social and relational elements that drive AI-based application adoption, combined with customer experience and the need for human interaction in services (Fernandes & Oliveira, 2021). Hence, we expect that:

Hypothesis 6 (H6): *Lack of human interaction leads to a barrier in Norwegian customer service robot adoption.*

2.4 Conceptual Model

To answer our research question and hypothesis, a conceptual model that illustrates elements that can affect consumers' willingness to adopt a service robot and elements that impedes the adoption has been created (figure 1). The conceptual model is based upon the sRAM research framework adopted from Wirtz et al. (2018). However, the model has been modified to represent motivations and the introductions of barriers that are more suitable for the Norwegian service customers. The functional elements are motivational factors that represent a positive variable that is expected to create customer acceptance of service robots and thus more inclined to adapt to this type of service. While the rational elements on the other hand, represent variables that negatively affect service robot adoption. Our main interest is to study how each construct affects customers' willingness to adopt service robots. Thus, the model has been modified with the intent to use quantitative research, which will be presented in chapter 3.

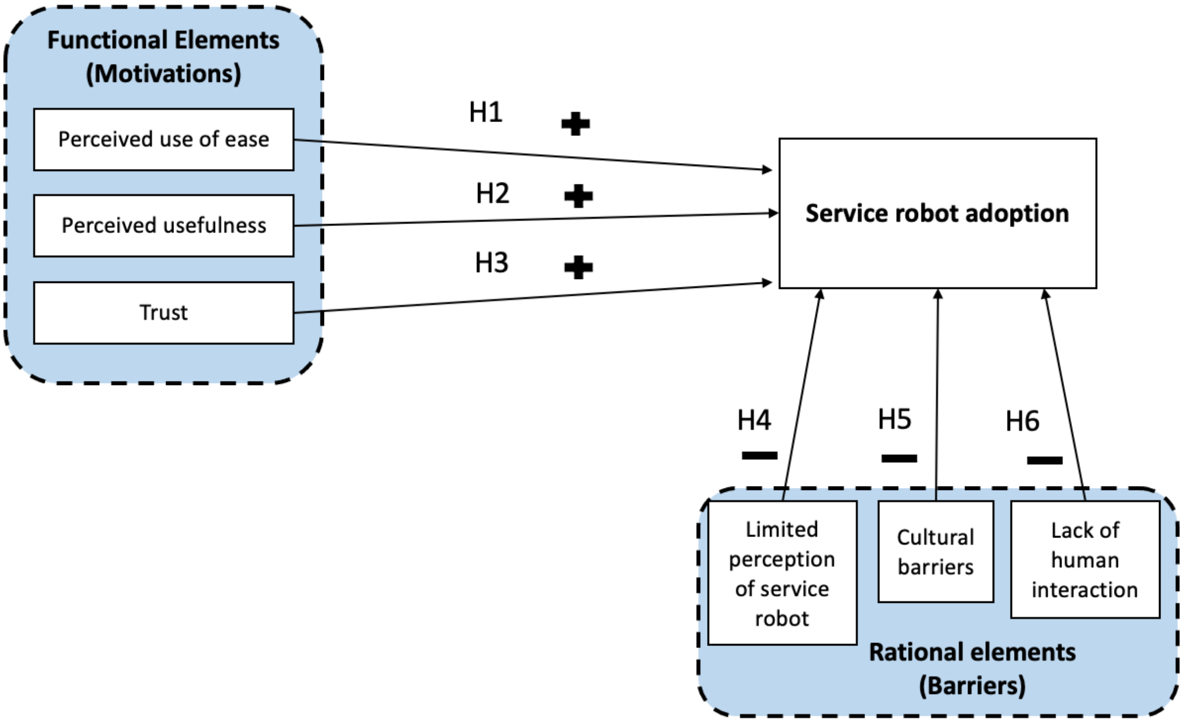

Figure 1: Conceptual Model

3.0 Methodology

The primary goal of this paper is to evaluate the proposed conceptual model of Norwegian customers' motivations and barriers towards service robots. In addition to testing the subsequent formulated hypotheses. This will be done through a quantitative research design, which will generate statistical data to be derived according to the conceptual framework. The utilization and analysis of numerical data using specific statistical techniques, will work as evidence for additional documentation and further research analysis (Apuke, 2017; Gripsrud et al., 2016).

3.1 Research Design

Selecting research design depends on knowledge in theory, experience on topic and level of ambition set, which shapes the analysis and intention to explain contexts (Gripsrud et al., 2016). Thus, a cross-sectional survey design was used for this quantitative research, as it is the preferred research design. This method involves gathering data collection of information from any given sample from the population only once (Malhotra, 2010). Furthermore, this study also utilizes a descriptive approach within the quantitative study. This approach identifies applicable attributes of a particular phenomenon through an observational basis, and explores the correlation between one or more phenomena (Williams, 2007). This allows for formulation and testing of specific hypotheses, as the information needed is clearly defined (Malhotra, 2010). Moreover, as quantitative research generates large amounts of statistical data, it is crucial that the processing and collection ensures generating accurate data that allows for correct interpretation and insight (Gripsrud et al., 2016). This will collectively create value for the research, as we intend to explain the phenomenon through quantitative data in numerical form.

3.2 Population

Selection of respondents needs to be selected in accordance with representativity. This is because results gathered from the sample need to be representative for the entire population (Gripsrud et al., 2016). Furthermore, it is imperative for this study to have a population which includes a collection of elements that shares a common set of characteristics that aligns with the purpose of our research (Malhotra, 2010). Therefore, the chosen population are Norwegians ranging from 18-65 years in age. This selection has been chosen since the younger generations have greater predisposition towards AI technology, are trend updated, and tend to be early adopters of new AI technologies (Liebana-Cabanillas et al., 2014). Literature review also shows that the younger population is adopting new AI technologies at a faster rate, while the older population tends to use the technology more often as they have higher purchasing power (Fernandes & Oliveira, 2021). In conclusion, the population for this study are Norwegian consumers who previously had encounters with different types of service robots.

Furthermore, the appropriate approach for this study is to utilize purposive and convenience-based sampling to gather statistical data from the appropriate sample subjects. This implies that the selection of the sample group is based on the choice of elements and is primarily determined by what is feasible to achieve (Gripsrud et al., 2016). Thus, the randomly selected sample group is one that is drawn based on its convenient accessibility, whose characteristics are defined for the purpose of this study (Andrande, 2021). Hence, the sample subjects who have had prior experiences with service robots are only targeted. This is done by having a control variable that segregates the survey by those who answered “no” if they have had any prior experiences with service robots. These respondents will be selected out and not be able to further participate in the survey. This is done to ensure higher external validity in our research, as the sample group's experience with service robots is essential for them to give valid answers. Subjects who have no prior experience with service robots have no reference points and thus no expectations of the service.

3.3 Data Collection

To answer the initial research question and to gather statistical data to test our hypothesis, the internet questionnaire-based tool Qualtrics was used to design the survey and distribution of it to gather data (appendix 1). Within descriptive research design, the primary methodology for data collection is to use structured surveys with a representative sample form the population (Gripsrud et al., 2016). Therefore, the data gathered for our study was collected through a standardized survey and digitally distributed through social media (Facebook and LinkedIn). By doing so, we can generate significant findings in our data with the adequate number of samples. Moreover, Norwegian culture is becoming more diversified, and the communicated language is becoming increasingly multidimensional. Thus, to avoid any linguistic misinterpretations and to strengthen construct validity in our study, the survey was written and conducted in English.

3.4 Questionnaire Design

The designed survey consists of three main parts. The first part introduces the respondents with a general introduction thanking them for taking part and reminding them participation is voluntary, the purpose of the study, and the requirements of anonymity. The second part of the survey involves a demographic questionnaire. The main purpose is to mainly gather information on the targeted sample subjects' gender, age, place of residence, educational background, and employment status. Lastly, the third part of the questionnaire consists of the control variable, the independent variables, and the dependent variable. The third part corresponds with the presented theories and the conceptual model from chapter 2, as this is the core part of our research and the survey. The independent variables in the questionnaire are perceived ease of use, perceived usefulness, trust, limited perception of service robots, cultural barriers, and lack of human interaction.

Due to the limited offering and advancement of service robots in the Norwegian market, the context of our questionnaire was applied based on our research population's familiarity. This is done to reduce the possible difference in the targeted sample subjects' understanding of service robots, which is caused by the difference of exposure and experience. Furthermore, to avoid any inconsistencies between the answers from the respondents, the questionnaire defined the concept of service robots. Consequently, the applied context focuses namely on service encounters through *Chatbots* and *digital voice assistants*.

Moreover, to encompass variables that may influence this research understanding of the relationship between the designed independent variables and the dependent variable, control variables were created. Thereby increasing internal validity of the study, as confound variables could impede accurate results (Malhotra, 2010). Thus, the control variables in our survey include gender, age, place of residence, educational background, and employment status. Most importantly, the main control variable in our survey is if the respondents have had any previous experiences with service robots. As this can capture extraneous influences on the desired effect, which could independently affect the study's results (Carlson & Wu, 2012). Consequently, respondents who reported "no" to any experiences with service robots, were screened out to the "Thank you" page and were not included in the data collection.

Conjunctly, to adjust for respondents' biases in their answers and survey fatigue, randomization of question in part three of the questionnaire was utilized. Since the general order in which the questions are presented can have a significant effect on the data results (Arslan et al., 2021; Lavrakas, 2008). The responses collected in the survey and the subsequent analysis benefits from avoiding instant attitudes switching from positive to negative, and by having respondents answer as truthfully as possible.

3.5 Measurements

The survey questions were adapted from previous research with validated scales and minor adjustments were made to correspond with the objective of this study. This ensures validity and reliability of our survey. The core items in the survey are assessed by using a 7-point Likert Scale ranging from Strongly Disagree (1) to Strongly Agree (7) with maximum of five items. The usage of a 7-point Likert Scale in our survey ensures that the various aspects of the measured variables are expressions of the same underlying statements that the respondents are asked to decide on (Gripsrud et al., 2016). The complexity and experience ultimately affect the respondent's ability to choose which answer alternatives is closest to their view. The measurement items are in table 1 below.

Measurement Items-Sources & Constructs		
Sources	**Construct**	**Items**
Lu et al. (2019)	Motivator: *Perceived ease of use*	Interaction with service robots is easy to understand
		I think using service robots are easy to use
		I think I can use the service robot without any help
		I see the need for service robots
Heerik et al. (2009)	Motivator: *Perceived usefulness*	I think the robot is useful to me
		It would be convenient for me to interact with a service robot
		I think the service robot can assist my needs
Heerik et al. (2009)	Motivator: *Trust*	I would trust the service robots' recommendations
		I would follow the advice the robot gives me.

		I can rely on the service robot to deliver the service it is supposed to do
		I can rely on the service robot to provide me with accurate information
Carpinella et al. (2016)	Barrier: *Limited perception of service robot*	I would feel uncertain interacting with a service robot
		I have negative impression of service robots
		I feel that if I depend on service robots too much, something bad might happen
		I would feel uneasy if robots really had emotions
Daewon & Suwon (2021)	Barrier: *Cultural barriers*	I do not like handing over control to a service robot to deliver the service
		I feel uneased entering personal data or payment details to service robots
		My associations towards service robots are negative
		My past experience with serve robot has been unsatisfactory
		I tend to get anxious easily when I do not know the outcome
		Interacting with service robots makes me concerned
Lu et al. (2019)	Barrier: *Lack of human interaction*	I prefer human interaction rather than service robots
		Artificially intelligent devices such as service robots are intimidating to me
		I would not accept artificially intelligent devices such as service robots even if a significant proportion of my social network uses it
Fernandes & Oliveira (2021)	Service robot adoption	I intend to use service robots in the future if I have access to it

Table 1**:** *Measurement Items*

3.6 Validity & Reliability

Conclusions drawn from this study on will be invalid or biased unless measurement of validity and reliability reflect the concept of the theory being tested. For research data to be valuable and useful, it must be both valid and reliable for us to be able to measure what we intend to measure in the best possible way (LoBiondo-Wood & Haber, 2014; Gripsrud et al., 2016; Malhotra, 2010). In other words, this tells us how "good" our planned analysis is to investigate our service robot adoption phenomenon.

3.6.1 Validity

The degree to which measures accurately represent the concept of interest is defined as validity (Hair et al, 2011). In other words, it tells us about the accuracy of our means to which we measure customers' motivations and barriers towards service robots. Content validity applies to which extends the data's measurement method used to cover the indented theoretical concepts (Gripsrud et al., 2016). For our research, it is important that the survey items explain the desired construct characteristics. The assessment of the correspondence between the item and the construct can be done through rating by expert judges (Hair, 2010). Hence, the constructs in this study are from well-established theories, as demonstrated in the measurement section above, and the items are accepted to reflect the constructs' characteristics in previous studies. This reduces the threat of potential biases and ensures relevant constructs in the test.

Construct validity focuses on the utilized measurements accurately measuring what they are intended to measure. Furthermore, it also addresses the connection between the theoretical concept and the operationalization of it (Gripsrud et al., 2016; Malhotra, 2010). For this study, it is sufficient to discuss convergent and discriminant construct validity. Firstly, convergent validity measures are the extent to which the used scales correlate positively with other measures in the same construct (Malhotra, 2010). Thus, convergent validity is useful for determining the strength of the relationship between the items (Hair et al, 2011). Hence, high correlation indicates that the variables are measuring the constructs in our survey and establishes the strength of the relationship of these constructs. Secondly, discriminant validity is a vital sub-branch of construct validity which addresses whether our indicator measures do not correlate with other constructs (Gripsrud et al., 2016; Malhotra, 2010). Hence, the constructs in our data should have a low correlation, as they are intended to differ. Subsequently, further analysis will be conducted on validity and reliability in the analysis result section.

Lastly, different questions from the motivational and barriers variables are included in our survey. Questions regarding customer motivations towards service robots are positively loaded, while the questions concerning barriers are negatively worded. Therefore, the questions in the survey were randomized to maintain high internal validity. Internal validity is the accuracy of the manipulation of the independent variables that has a caused effect on the dependent variable (Malhotra, 2010). Furthermore, by including control variables described in 3.4 Questionnaire Design section, we are limiting potential confounds and thereby maintaining internal validity. Moreover, the external validity of our research is anticipated to be generalized, as results can be applicable beyond the sample group and representative for the Norwegian population group.

3.6.2 Reliability

Reliability is the extent to which findings for our study can be consistent and replicable if repeated or similar measurements are made. In other words, reliability tells whether similar observations and conclusions can be made by other researchers at different times and under different conditions, and whether there is transparency in how conclusions are drawn from raw data are all referred to as reliable (Hair, 2010; Gripsrud et al., 2016: Malhotra, 2010). Thus, to examine the internal reliability consistency of the independent variables, the Cronbach's alpha test will be conducted. By taking the current situation in today’s service market in Norway and the continued evolution into account, it is expected that customer behavior will change over time. Therefore, the respondent’s current level of knowledge and perception of the survey questions will vary. Consequently, this will have a fluctuating impact on the reliability in the measurements from gathered quantitative data.

3.7 Pre-test

The pretest is conducted prior to the final distribution of the questionnaire to the target population (Reynolds, et al. 1993). By conducting a pretest of our initial designed survey allows for all aspects of it to be tested. This includes: the question content, wording, sequences and form, the questions difficulty, and instructions (Malhotra, 2010). Hence, a pre-test was conducted on a group of 15 respondents drawn from the defined population. This allows us to check the content validity of our survey, test if respondents understand the questions and given information, and be able to answer the questions accordingly. At the end of the pre-tested survey respondents were able to comment on any improvements, provide any information on misunderstandings and general feedback.

The gathered feedback enables appropriate improvements of the survey and initially showed that respondents misunderstood the question with regards to previous experience with service robots. Respondents reported that they wanted a quick reminder of what the definition was or examples of it, although the previous page had already given them the definition and common examples. Further, by utilizing Cronbach Alpha analysis, we tested the internal consistency and reliability of the scales included in the survey. A rule of thumb is that Cronbach Alpha should not be under the limit of 0.6 to 0.7 (George & Mallery, 2003; Malhotra, 2010). From the reliability statistics table, the actual scale value of Cronbach Alpha is 0.703. Therefore, we can conclude that the scales have an acceptable level of reliability and work as anticipated for the purpose of our study.

3.8 Sample

The sample group was representatively randomly drawn from the population and the data collection lasted a period of one month. As a result, the gathered data consists of 220 respondents. However, after the data cleansing involving removing extreme outliers, missing data, and selection of the control variable, we were left with 189 valid responses. A descriptive analysis on demographics shows that 104 respondents were male (54.7%) and 85 were female (45.3%), they have a bachelor's (47.8%) or master´s (25.8%). The most frequent age of our respondents were 24 years old, the majority lived in Northern-Norway (31.45%) and Eastern-Norway (29.6%).

Furthermore, the respondents on average reported that they interact with service robots 1-3 times per month (71.7%). Appendix 2 shows further demographic information of the survey respondents.

3.9 Data Analysis

To conduct statistical analysis and follow the statistical analysis process, this study will use SPSS to analyze and interpret the gathered data. The validity of our variables is assessed through factor analysis and then average variance extracted will be calculated to evaluate convergent validity. Further, the Fornell-Locker criterion will be used to estimate discriminant validity. Then the reliability of our gathered data is estimated based on Cronbach's alpha and composite reliability. Moreover, analysis on multicollinearity and common method bias will be conducted. Lastly, to test our formulated hypothesis introduced in chapter 2.2 and 2.3, we will use regression analysis to evaluate the relationship between the independent variables (motivations and barriers) and the dependent variable (service robot adoption) (Gripsrud et al., 2016). This is because regression analysis as a statistical tool enables assessment of the casual relationship and the magnitude of the strength between the variable relationship. In addition, it also explores the direction of impact between the variables and the value of them (Malhotra, 2010; Zhao et al., 2018).

3.10 Ethical Considerations

The information obtained from the quantitative data will only be used for the purpose of this thesis and not in any other contexts. Therefore, prior to participating, the respondents were informed about the purpose of the survey, what the collected data will be used for, and that participation is voluntary. Respondents were also ensured that their data will only be used for the purpose of this research, and that it will not be possible to trace answers back to them. Moreover, all the collected material will be anonymous and treated confidentially. This ensures that our study is aligned with the Privacy ACT (GDPR). Lastly, all responses collected by our questionnaire will be deleted in August.

4.0 Results

The fundamental of this section is to analyze data and to derive information related to the components of the research questions, hypotheses, and thus, provide input into both theoretical and managerial implications (Malholtra, 2010). Since this study utilizes a cross-sectional survey design, the data is analyzed in several stages.

4.1 Descriptive

After collecting data from Qualtrics and subsequent data cleansing was performed, we were left with 189 valid responses to use for further analysis in SPSS. For the motivations for adoption, the variable Ease of Use “I think I can use the robot without any help” (M=5.55, SD= 1.399) and Ease of Use “I see the need for service robots” (M=5.94, SD=1.429) has the greatest effect. Interestingly, the variable Trust had the lowest score of the variables motivation to adopt, with an average mean of 3.86. For the barriers towards adoption variables, Lack of Human Interaction “I prefer human interaction rather than service robots” has the greatest effect on impeding adoption (M=5.76, SD=1.319), followed by Limited Perception “I have negative impressions of service robots” (M=5.34, SD= 1.409), and Cultural Barrier “My experience with service robots has been unsatisfactory” (M=5.36, SD=1,371).

Furthermore, the skewness and kurtosis for all the items in our data set were also examined to further understand the nature of the distribution of the variables. Skewness in the data measures on the tendency of the deviations from the mean to be larger in one direction than the other in a normal distribution. Thus, skewness that ranges outside the value between -1 to +1 indicates a significant skewed distribution (Malhotra, 2010). The variable Ease of Use “I think I can use the service robot without any help” can be determined as significantly skewed. The descriptive analysis shows it has a skewness of -1.312 and will have correspondingly small values and tails to the left in the distribution.

Moreover, kurtosis measures the relative peakedness or flatness of the curve defined by the frequency distribution (Malhotra, 2010). For the kurtosis analysis, a normal distribution at zero. Therefore, a positive kurtosis value over 0 indicates a peaked distribution and a negative value under 0 suggests a distribution that is flat. The analysis shows only two variables have a peaked distribution, while 23 variables have a flat distribution. More detailed information on the results of the descriptive analysis which includes the mean, standard deviation, skewness, and kurtosis can be found in appendix 3.

4.2 Test of Validity & Reliability

4.2.1 Validity

To test both convergent and discriminant validity of the finalized instruments, an exploratory principal component analysis with Varimax rotation method in SPSS was utilized. This is an approved method used in research used to both evaluate and improve these two factors (Hurley, 1997). Consequently, the item retention will be determined, and further unfit items are intended to be removed (Malhotra, 2010). Since this study uses a cross-sectional survey that relies on participants to measure on self-report, we find it adequate to have a retained item factor loading of at least 0.5 and higher for the factors to be considered important (Malhotra, 2010).
Thereby, we are reducing the threat of confound measures and being able to contend with discriminant validity.

The examination of the sample appropriateness of conducting exploratory principal component analysis was done through inspecting Kaiser-Mayer-Olkin (KMO) and Bartlett's Test of Sphericity. High values that range between 0.5 and 1 indicate that factor analysis is appropriate (Malholtra, 2010). The first analysis indicates a KMO of 0.858, approx. Chi-square of 2133, degrees of freedom 276 and a significant value less than 0.001. Subsequently, we can conclude exploratory principal component analysis on our measurements is appropriate. Furthermore, the number of factors is determined by evaluating factors that have an eigenvalue higher than 1 criterion (Kaiser, 1960). The analysis indicates that 6 the factorial structure has an eigenvalue higher than 1 criterion and initially explains 69% of the total variance. Thus, exceeding the rule of thumb of minimum desirable criteria of 60% (Hair, 2010; Malholtra, 2010). Moreover, a total of 5 items were removed for not meeting the set inclusion criteria of 0.5 and for loading on other factors. These five items are namely: "I think I can use Service Robot without any help" (Ease of use), "I feel that if I depend on service robots too much something bad might happen" (Limited

Perception), “I tend to get anxious easily when I do not know the outcome” (Cultural Barrier), “I do not like to hand over control to a service robot to deliver the service (Cultural Barrier), and lastly “I would not accept artificially intelligent devices such as service robots even if a significant proportion of my social network uses it “(Lack of Human Interaction). Thereby, the validity of convergence and discriminant is thus increased, and hence the rotated matrix component is considered significant (Appendix 4)

Further assessment of convergent and discriminant validity is done by evaluating Average Variance Extracted (AVE). This is because AVE indicates the variance in the indicators or observed variables that is explained by the construct (Malholtra, 2010). A general principle is that AVE of 0.5 and above indicates a satisfactory level of convergent validity. As table 2 below shows, all the variables meet the minimum requirement of AVE equal or greater than 0.5. Thus, on average the included latent constructs in our data account for more than 50% of the explained variance in the observed variables, and thus we have an acceptable level of convergent validity.

	AVE
Ease of Use	0.54
Usefulness	0.63
Trust	0.64
Limited Perception	0.53
Cultural Barriers	0.52
Lack of Human Interaction	0.56

Table 2*: Reliability & Validity*

Lastly, discriminant validity is assessed by the Fornell-Locker criterion. This analysis is done by evaluating if the square root of every AVE belonging to each latent construct is much larger than any correlations among any pair of latent constructs (Fornell-Locker, 1981; Malhotra, 2010). From appendix 5, discriminant validity is achieved for all the latent variables, as the square root of AVE is larger than the correlation coefficients (Malhotra, 2010).

4.2.2 Reliability

In conjunction with the pre-test, Cronbach Alpha tests the reliability of the internal consistency of our survey through SPSS. Internal-consistency reliability reflects the consistency of individual measurement items across replications from the same data source (Li & Wang, 2021). A general guideline for Cronbach Alpha is that the value should not be under the limit of 0.6 to be considered reasonable (George & Mallery, 2003; Malhotra, 2010). Table 3 shows that the variables in the survey have a fluctuating value. The variables *Usefulness* and *Trust* have values above 0.8, while *Ease of use* is above 0.7. Therefore, these can be considered as variables that have optimal Cronbach Alpha values. While variables such as Limited Perception, Cultural Barriers and Lack of Human Interactions are above 0.6. Furthermore, the overall Cronbach's alpha was 0.899. Thus, taking the findings from the analysis into consideration, the variables used in our survey provide an acceptable level of reliable measurement.

Moreover, analysis on the Composite Reliability (CR) will further assess internal consistency. CR is the total amount of true score in relation to the total score variance and does not assume that all factor loading is equal (Malhotra, 2010). Thus, a CR score of 0.7 and above is considered good, while a CR score between 0.6 and 0.7 is acceptable. As shown in table 3, variables such as Ease of Use, Usefulness and Trust exceed the score of 0.7. While variables such as Limited Perception, Cultural Barrier and Lack of Human Interaction score above 0.6. Therefore, in correlation with the estimates of the model validity, the reliability of our measurements is considered satisfactory.

Factors	**Cronbach´s α**	**CR**
Ease of Use	0.732	0,720
Usefulness	0.903	0,913
Trust	0.876	0,690
Limited Perception	0.640	0,709
Cultural Barrier	0.696	0,698
Lack of Human Interaction	0.621	0,768

Table 3*: Test of Reliability*

4.3 Assumptions Checking

4.3.1 Multicollinearity

Before we can be confident that motivational and barrier variables are able predict service robot adoption, we need to ensure that the variance explained is not highly overlapping. Since high intercorrelation among the predictors can cause inflation in variance explained and r squared (Malhotra, 2010; Hair, 2010). Therefore, analysis on the variance inflation factor (VIF) will be conducted with a commonly cut-off point of 10. Moreover, a tolerance value below 0.10 is an indication of Multicollinearity (Pallant, 2010; Malhotra, 2010). From the multicollinearity analysis (appendix 6), no variables are over VIF of 10 and no variables are over the threshold of 5. Additionally, no variables had a tolerance level below 0.10. Conclusively, the multicollinearity analysis suggests that the included factors are not highly correlated with one another and does not warrant corrective measures.

4.3.2 Common Method Bias

Since this study involves a cross-sectional survey design and is reliant on respondent's self-report, there is naturally an element of potential measurement error. This is because of bias effects that influence the respondents desire to provide optimal or satisfactory answers to the questions (MacKenzie & Podsakoff, 2012). This effect is known as common method bias (CMB), which has the potential to influence item validities, item reliabilities, and the covariation between latent constructs (MacKenzie & Podsakoff, 2012; Malhotra, 2010). Therefore, we have examined this by performing Harman's Single Factor Test in SPSS. The results from the Harman's Single Factor Test shows that the total variance explained by one factor is 35.88%, which is below the critical criteria for CMB of 50%. Thus, we can statistically conclude that there are no CMB issues in our data.

Conclusively, the soundness of our data measures has been established on the sections above and thus, subsequently warrant further analysis to test the hypotheses. In other words, the measurements included in our conceptual model for this study meets the expected requirements of scale design and can be used as a measurement for Norwegian service customer service robot adoption.

4.3 Hypothesis Testing

For hypothesis testing, a regression analysis will be conducted to explain how changes in the independent variables (motivations and barriers) explains the changes in the dependent variable (service robot adoption). Thus, a hierarchical multiple regression analysis method is utilized. For the hypothesis testing, the significance level is set at 5%.

4.3.1 Hypothesis 1

First, we perform the regression analysis on the ease-of-use independent variable. Here we are interested in the mediating effect between ease of use and service robot adoption. Following from the analysis, the standardized regression coefficient of ease of use is 0.308 and the passed F-value is 16.510. As table 4 shows, the regression effect of ease of use on service robot adoption is significant with a positive coefficient. Furthermore, the explanatory value of Ease of Use through adjusted R square is 8.9%. Thus, hypothesis 1 "*Consumers perceived use of ease has a positive effect on service robot adoption*" is validated. In conclusion, the ease of use has a significant positive effect on Norwegian service customers when all other factors remain unchanged. The easier the interaction and usage of the service robot makes it easier to use and yields a positive motivation for service robot adoption.

	Standardized Coefficient	
Variable	***β***	**Significance**
Ease of Use	0.308	＜0.001
F	6.012	
R^2	0.095	
Adjusted R^2	0.089	

Table 4: *Regression analysis on Ease of Use & Service Robot Adoption*

4.3.2 Hypothesis 2

The second hypothesis states that usefulness will have a positive effect on service robot adoption. Results from the regression analysis shows that the variable Usefulness has a standardized regression coefficient of 0.405 and has a significant

F-value of 34.150. Thus, as shown in table 5 below, we have statistical evidence to conclude that Usefulness has a positive impact on service robot adoption when other factors remain unchanged. Additionally, the examination of adjusted R-square indicates that usefulness explains roughly 16.5% of the variance in service robot adoption. Hence, hypothesis 2 is validated, meaning when usefulness is perceived to have a high value, Norwegian service customers are more likely to adopt service robots.

	Standardized Coefficient	
Variable	***β***	**Significance**
Usefulness	0.405	＜0.001
F	34.150	
R^2	0.181	
Adjusted R^2	0.16.5	

Table 5: *Regression analysis on Usefulness & Service Robot Adoption*

4.3.3 Hypothesis 3

Next, we report on the last motivational variable which is trust and its statistical impact on service robot adoption. The results from the regression analysis shows that the standardized coefficient of the variable trust is 0.2975. The reported and passed F-value is 143.241. However, evidence indicates that trust does not have any statistically significant effect on service robot adoption, since the p-value is greater than the significance level of 5%. The results from the analysis are shown in table 6. Consequently, we can conclude that hypothesis 3 "*Consumers perceived trust in robots has a positive effect on service robot adoption"* is not verified. Hence, when Norwegian service customers are not able to trust the service robot to provide a service offered by the company, they are more inclined to have a negative attitude towards service robot adoption. This should also have a correlation between what type of service offering an organization uses service robots for and the range of complexity of the service provided. The lack of trust will ultimately create a worse experience and thus negatively impact customers' adoption willingness towards service robots.

Variable	Standardized Coefficient		
	β		Significance
Trust	0.2075		＞0.073
F		143.241	

Table 6: *Regression analysis on Trust & Service Robot Adoption*

4.3.4 Hypothesis 4

The first barrier variable to be examined by the regression analysis is limited perception of service robots. The results are shown in table 7 below, which demonstrates the standardized coefficients of limited perception is -0.815 and a F-value of 4.916. Since the significance level of 0.028 is less than alpha at 0.05, the F-test is passed. Furthermore, the value of adjusted R-square is 0.22, meaning that limited perception explains 22% of the variance in barriers to service robot adoption. Thus, we have statistical evidence to conclude that hypothesis 4 "*Limited perception of service robots has a negative effect on adoption*" is validated. Hence, with a negative standardized coefficient, the limited perception that Norwegian service customers have will ultimately impede service robot adoption. Larger perceived limited perception will generate a greater mediation effect on the service offered by an organization and have a negative effect on the service adoption intention by the customers.

Variable	Standardized Coefficient		
	β		Significance
Limited Perception	-0.815		＜0.028
F		4.916	
R^2		0.29	
Adjusted R^2		0.22	

Table 7: *Regression analysis on Limited Perception & Service Robot Adoption*

4.3.5 Hypothesis 5

The fifth hypothesis focuses on Norwegian service customers' cultural barriers towards service robots. The subsequent results regression analysis indicates that the standardized coefficient for cultural barrier -0.48 with a significant F-value of

14.585. Moreover, the adjusted R-square shows that this variable has 7.6% of the explanatory value of barriers towards service robot adoption. Thus, hypothesis 5 *"Cultural barriers have a negative impact on Norwegian service customers' adaptation of service robots*" is consequently validated. Therefore, we have statistical evidence that shows cultural barriers with a negative standardized coefficient have a significant effect on the mediation effect on service robot adoption. The Norwegian service customers' cultural barriers creates negative thoughts and feelings, which in return gives a negative prediction on service robot acceptance and adoption. Results of the regression analysis are shown in table 8.

	Standardized Coefficient		
Variable	$\boldsymbol{\beta}$		**Significance**
Cultural Barrier	-0.48		$<$0.003
F		14.585	
R^2		0.099	
Adjusted R^2		0.076	

Table 8: *Regression analysis on Cultural Barrier & Service Robot Adoption*

4.3.6 Hypothesis 6

Lastly, we will report on the regression analysis on lack of human interaction and service robot adoption. As shown in table 9, the standardized regression coefficient for the variable lack of human interaction is -0.444. The F-value is 9.404 and has passed the necessary F-test. Furthermore, the analysis shows that the regression effect is significant, and the adjusted R-square is 10.1%. In conclusion, we have statistical evidence to state that hypothesis 6 "*Lack of human interaction leads to a barrier in Norwegian customer service robot adoption*" is supported. Therefore, the lack of human interaction creates a lack of trust and subsequent service robots' adoption is impeded by this barrier. Not surprisingly, customers prefer interactions with human employees from the organization who is providing the service, which is also rooted in the level of service provided between a service robot and that of a human.

Variable	Standardized Coefficient	
	β	Significance
Lack of Human Interaction	-0.444	< 0.001
F	9.404	
R^2	0.106	
Adjusted R^2	0.101	

Table 9: *Regression analysis on Lack of Human Interaction & Service Robot Adoption*

4.3.5 Summary of Hypotheses

By conducting the analysis on sections 4.3.1 to 4.3.6, we present table 10 which gives a summary of the hypothesis findings.

Number	Hypothesis	Supported/Not Supported
H1	Consumers perceived use of ease has a positive effect on service robot adoption	Supported
H2	Consumers perceived usefulness has a positive effect on service robot adoption	Supported
H3	Consumers perceived trust in robots has a positive effect on service robot adoption	Not supported
H4	Limited perception of service robots has a negative effect on adoption.	Supported
H5	Cultural barriers have a negative impact on Norwegian service customers' adaptation of service robots	Supported
H6	Lack of human interaction leads to a barrier in Norwegian customer service robot adoption	Supported

Table 10: *Summary of Hypothesis Findings*

From table 10 above, it is evident that all hypotheses, except for hypothesis 3, are supported and are in conjunction with introduced theories on the variable's topic. This implies that the majority of the independent variables in the conceptual model, introduced in chapter 2.4, has an influential impact on Norwegian service customers service robot adoption. Hence, the statistical conceptual model in figure 2.

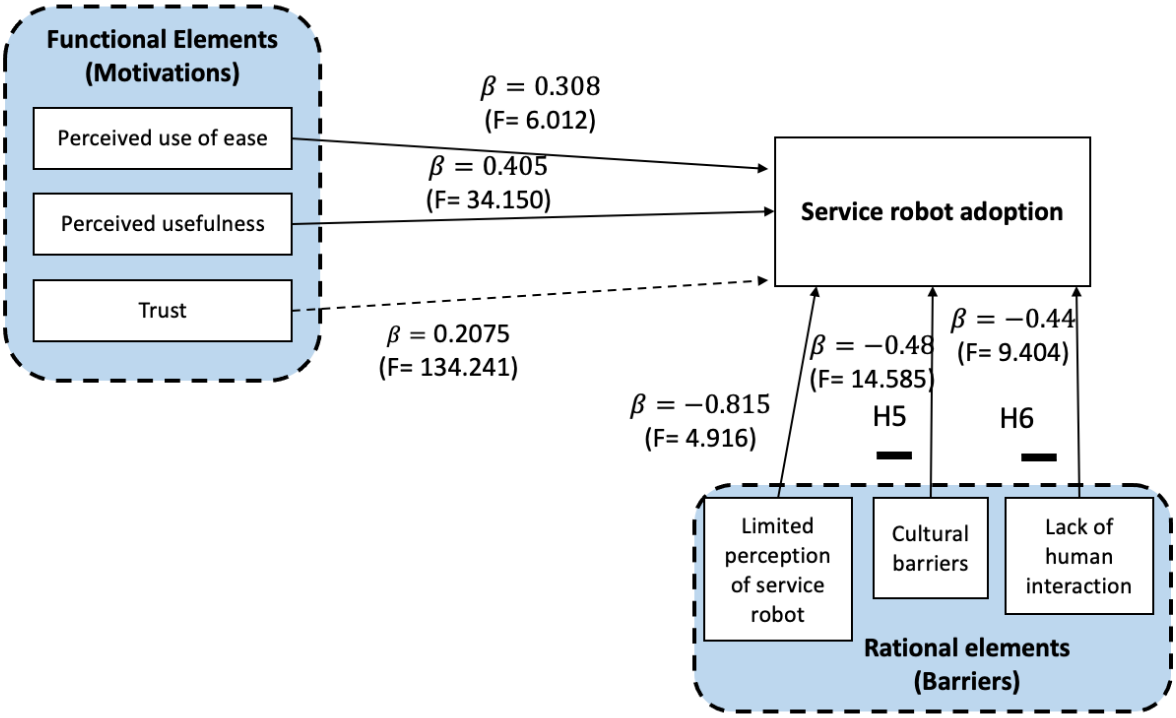

Figure 2: Results for the original conceptual model (dotted line indicates non-significant coefficient)

4.4 Control-Variable Analysis

Norwegian service customers' intention to adopt service robots may be related to some other attributes that have a confound effect that is not measured in our conceptual model. Therefore, in this section we will conduct further analysis on our control variables in our data set with the intention to measure their statistical influences. The control variables we are interested to further report on are gender and educational level.

First, we conducted an independent sample t-test to analyze if there are any statistically significant differences in the means between men and women in terms of service robot adoption. Results from the analysis shows that women in group two have a greater mean, respectively 6.68 (group 2), compared to men in group 1 5.07 (group 1). Furthermore, by looking at equality of means, we find that there is a statistical difference in the means between the two groups in terms of service robot adoption. Since the two-sided p-value is < 0.001. Additionally, by analyzing equal variance assumed, the p-value is < 0.001. Thus, there is also statistical evidence to conclude that there are significant variances between men and women. More detailed information on the results from the independent sample t-test analysis can be found in appendix 7.

The second analysis focuses on the descriptive on the respondent's educational level and the respondent's invention to use service robots in the future. Results from this analysis shows that customers who have a master's degree (M=6.85, SD=3.404) and PhD (M=6.40, SD=3.847) have the highest intention to use service robots in the future. Therefore, Norwegian service customers who either have a master's degree or PhD have a higher willingness to adapt to service robots. Furthermore, customers who have a bachelor's degree (M=5.39, SD=2.935) and only completed high school (M=5.29, SD=2.739) have a neutral stance in terms of service robots' adoption. Therefore, these customers are potentially more skeptical and could have higher values in terms of the identified barriers in our conceptual model. The full results of this analysis can be found in appendix 8.

5.0 Discussion

For this chapter we are going to discuss the theoretical implications based on our findings from the quantitative research analysis, which will be anchored in the presented theories from chapter 2. The main purpose is to create the foundation of which will answer the thesis statement and the end conclusion of our study.

5.1 Discussion & Theoretical Implications

The service sector is at the forefront of innovation and is the sector where AI has seen rapid development. Service robots are one of the main branches within AI innovations that have been adopted by organizations and will play an increasingly important role to provide customers with services expeditiously. However, to date service robots in Norway are relatively new and are limited in their advancement.

Yet the quantity of businesses in Norway employing service robots continues to increase and has become an important topic within the service marketing field. Furthermore, research on customers' psychological motivational acceptance and barriers towards AI service robots has been fragmented and is one that is still in its infancy stage. Therefore, the main purpose of this study was to examine what Norwegians service customers' motivations and barriers towards service robot adoption. Hence, our study will contribute by providing a further understanding by drawing on the conceptual Service Robot Acceptance model first introduced by Writz et al. (2018) and further develop it by introducing barriers. Thus, our introduced conceptual model has incorporated theories that respectively have been investigated before, both separately and some collectively.

First, we acquired a comprehensive understanding of relatively new research that has been conducted on the topic of service robots and customers' acceptance of this new AI technology. Moreover, we also attained knowledge of how service robots are changing the service field in terms of implications it has on customers' experience and expectations, which has an incremental effect on adoption. This was done as an initial step to investigate customers' psychological factors that influences their willingness to adopt service robots. Thus, we can capture customers' evaluation of motivational and barriers elements towards service robot adoption. Based on the conceptual model, we hypothesized six assumptions in accordance with theory that would influence Norwegian service customers service robot adoption. All but five were supported and one was determined not to be significant by subsequent data analysis in SPSS. The general findings, based on gathered data collected from 189 respondents, underscore that despite positive functional elements that positively affects motivations of service robots, rational elements generate greater barriers in Norwegian service customers that directly impede adoption. Thus, potentially limiting further advancement and development of service robots in the Norwegian service sector.

Previous applied theory supports our findings in our research regarding the different variables affecting consumers' willingness to adopt service robots. First, we will discuss the motivators and their impact on Norwegian customers' willingness to adopt a service robot. Regarding hypothesis one on ease of use, the main motivator for service robot adoption is the fact that customers see the need for service robots.

Customers tend to seek easy solutions that reduce the minimum effort to perform, which can help them solve their problems (Venkatesh & Davis, 2000). Based on our results, we believe that Norwegian consumers find it essential that technology they are using is easy to understand and easy to use. This can be explained by considering customers' needs in a service encounter, and how in some cases there is a need for a service robot that could be more efficient and effective than a human. Consumers might be more willing to proceed by using AI digital assistance than human employees. Furthermore, the results show that they find it important to have an interaction that is easy to understand. Additionally, the standardized regression coefficient of ease of use is 0.308, which shows a positive interaction. Hence, our study supports the findings of Fernandes & Olivera (2021) and Lu et al. (2019). The ease of use of service robots helps to positively influence both the customer experience and the interaction between the service providers. Since it helps to reduce both the effort expectancy and the technological skills needed to be able to create value in a service encounter. Moreover, the easier service robots are to use and understand, the better customer experience becomes and will result in a stronger perception of usefulness.

With regards to the second hypothesis of usefulness, results from the regression analysis showed we have statistical evidence to conclude that usefulness has a positive impact on Norwegian service customers service robot adoption with a standardized regression coefficient of 0.405. This further supports the findings of Heerik et al. (2009). Therefore, when the usefulness of service robots increases, it also increases the performance of the service which in return positively affects adoption. Usefulness is strongly correlated to the convenience of using service robots. However, it is important to note that usefulness is a term which measures how consumers perceive service robots' ability to perform certain functions (Chan et al; 2017; Lu et al., 2019). Thus, we believe that usefulness is rated high among Norwegian service customers when the performance of service robots has a higher advantage than interacting with humans in terms of service delivery. However, a descriptive analysis on usefulness shows that there is a need for further improvements, as this also has the potential to influence consumers' trust.

Previously discussed theory states that trust is a very important factor in AI-human interactions. This is due to providing the sensation of a feeling of security (Oksanen et al., 2020). However, our results do not support and contradict the findings of Heerik et al. (2009). The level of trust in service robots is incremental for the utilization of deploying them in services and the level of trust Norwegian service customers have been low. This is because customers tend to be skeptical of something they don't know or lack experience with, which in turn can result in a negative attitude towards the matter. Our findings show that the quality of service that a service robot delivers is not meeting customers' expectations, nor do they create adequate levels of trust. Customers do not trust the service robot to deliver reliable service, nor do they feel like they are given accurate information which leads to them not trusting the given recommendations. We argue that the level of trust in service robots is expected to be fluctuating, since AI technology is constantly evolving and is getting more advanced. We can also assume that trust can come after interacting with the service robots and experiencing their service delivery and base their trust on the service delivery outcome. Thus, the negative outcome of the delivered service is a factor that disconcerts the level of trust customers have towards service robots. Nevertheless, the lack of level in trust found in our analysis is expected to be rooted in the barriers towards service robot adoption.

This study also extends the sRAM model by introducing and validating rational elements that creates customers barriers towards service robot adoption. The results from analyzing the variable limited perception (H4) enables us to understand how this element creates a vital customer barrier. The results showed that limited perception has the highest standardized coefficients of -0.81. This is largely due to respondents indicating that they have negative impressions towards service robots and that they would feel uneased if it had emotions. Therefore, our findings are consistent with Carpinella et al. (2016) and Liu et al. (2022). As previous research claims, the overall lack of understanding and knowledge that the customer has of AI driven service robots, creates unpredictability, and negatively affects their perception (Chen et al., 2022). Our research indicates this has a correlation with the limitation of which Norwegian businesses utilize service robots, where chatbots and digital voice assistance are predominantly present in-service settings. Thus, Norwegian service customers' limited perception of service robots is rooted in their psychological uncertainty and understanding which impede adoption. Furthermore, customers' limited perception also creates a perception of disadvantage of using service robots, which also affects their intention to adopt and creates negative attitudes.

The fifth hypothesis included the variable cultural barrier. The aim of this hypothesis was to measure the degree of expectations, thoughts, feelings, and association towards service robot adoption. We expected that since service robots in Norway are limited, the Norwegian service customer culture would be more disinclined towards this new AI technology. Since the origin culture that the customer is surrounded by, ultimately influences their consumer behavior and psychological judgment towards service robots. This is also evident based on previous research that has found customer acceptance of new technology will vary depending on culture and that this will also impact future prediction of service robot interactions (Nomura, 2017; Kaplan, 2004). Results from our analysis shows that cultural barrier is the second largest factor impeding service robot adoption with a standardized coefficient of -0.48. This is largely due to customers' previous experience having been unsatisfactory compared to their expectations and thus creates negative associations. Another important factor in cultural barriers is uncertainty avoidance, where our results explain the disparity in the customer's attitude is due to feeling uneased entering personal data or payment details to an AI robot.

Conclusively, this supports our fifth hypothesis and is consistent with Daewon & Suwon (2021) and Lu et al (2020) research. Therefore, we argue that Norwegian culture creates a preconception of service robots which dramatically weakens satisfaction and attitude on intention to adopt services by this type of AI technology. When customers are in a service setting where they are interacting with service robots, their pre-expectations are already low and will have more negative feelings. Furthermore, when service robots are unable to provide an adequate level of service that is expected or does not meet the customer's needs (service failure), customers will generate a greater negative attitude, future expectations in terms of trust will be low and the experience will be negatively impacted. Thus, creating a prominent barrier with a considerable threshold for adopting service robots.

Another important insight gained from this study is results from hypothesis six, which showed that lack of human interaction in a service encounter has a negative impact on consumers' willingness to adopt a service robot. The regression analysis indicated that the standardized regression coefficient for this variable is -0.444 and the descriptive analysis showed that the respondents considerably preferred to have service interaction with a human rather than a service robot. This supports our assumption and previous research such as Lu et al (2019) and Talk & Lew (2020) regarding lack of human interaction being a significant barrier to AI service robot adoption.

Furthermore, hypothesis six connects with the variable cultural barriers (H5) and can awaken negative feelings towards the service robots because of different underlying factors, such as lack of trust (H3) and limited perception (H4). Like De Kernevoael et al. (2020) and Wirtz et al. (2018) mentioned, lack of human interaction is deeply rooted in customer acceptance of service robots and is affected by interactions. We believe Norwegian customers prefer human contact when in a service encounter rather than AI powered service robots, due to lack of trust and because customers feel like they will not receive high enough quality service from a service robot. When compared to the level of expected quality service they would receive from a company's employees. Much of this is anticipated to be related to the fact that customers tend to want human interaction in a service setting since it fills the social needs and creates a relationship between the organization and the customer. However, future advancement in service robots will enable this technology to match human intuitiveness, empathy, and other human like emotions. Thus, being able to create a more human-like interaction (Huang & Rust, 2018).

5.2 Managerial Implications

This study has managerial implications that are noteworthy to discuss related to Norwegian service customers service robot adoption. AI driven service robots have and will continue to change the service marketing field. However, despite clear optimistic advantages of utilizing service robots from an organizational perspective, there are major implications from a customer’s perspective which limits future predictions. Automated forms of interaction such as AI driven service robots in a service setting causes impediments on customer preference, attitude, and experience. Which in return affects customers' willingness to adopt these new technologies, to the extent that service organizations are crucially reliant on it for future success (Kaplan & Haenlein, 2020). Therefore, Norwegian service organizations managers can use the findings from our study to strengthen their endeavors to better understand Norwegian service customers' motivations and barriers towards service robot adoption. More importantly, how service organizations can mitigate customer barriers that are impeding adoption.

On the one hand, our study has revealed that Norwegian service customers endorse service robots through ease of use and usefulness as motivational factors for adoption. These two factors greatly motivate and are seen as the main foundation of which Norwegian service customers use to base their expectations and positively influences their experiences. However, managers need to be aware that service robots that are utilized in the Norwegian service market are perceived as not being trustworthy by the customers. Hence, this requires managers to carefully monitor services that are delivered by service robots and allocate resources to further advance the interaction with the customer. Especially when it comes to giving advice and recommendations that solves the customers problems and needs. Which is also rooted in the service robot's ability to be reliable and accurate. Continued advancement in ease of use, usefulness and notably trust, will further improve expectations and experiences that enhance more widespread adoption. These improvements need to be done in consideration of customers' demands and expectations. Subsequently, this also provides an encouraging environment for customers to have a positive attitude and create positive behavioral adoption intentions. This is particularly important for service organizations operating in the airline and hotel industry, since services here are more utility driven and positive emotions trigger service robot adoption (Lu et al., 2019).

On the other hand, it is crucial that managers are aware of prominent barriers influencing service robot adoption and gain understanding of how-to mintage them. Firstly, to combat limited perception of service robots, calls for managers to assure their customers are aware of the utilitarian value associated with using service robots. For example, the wide variety of tasks it can perform and the convenience in terms of generating personalized services. Essentially, managers and the marketing department need to be aware of their customers preferences and integrate their expectations as a part of the service delivery by the service robot. Moreover, service organizations need to increase customers' familiarity and understanding of service robots. This includes better understanding of the potential value of using it, what benefits it will create and how it can generate personalized services (Li et al., 2021). Thus, the most efficient way is to use marketing to better understand the organization's customers' expectations and communicate the benefits of service robots.

Secondly, to counter cultural barriers, managers need to strengthen the service personalization ability of service robots in accordance with customer characteristics and expectations. Service robots need to be accessible and efficiently targeted towards a diverse demographic group. This will collectively create positive emotional responses which ultimately generates positive experience which leads to adoption (Chen et al., 2021). Managers also need to work with their marketing department to generate incentives that enables multiple positive word of mouth for influencing attitudes and create contingency plans with countermeasures to solve potential setbacks caused by cultural barriers. Additionally, service organizations need to communicate on the aspect of security to strengthen consumers' perception of the service robots.

Lastly, lack of human interaction creates implications that divert managers attention towards developing service robots that can mimic human responses and behavior. This enables a “relationship” to be established between the customer and service robot. Although service robots cannot replace the social presence of humans, managers can use the attributes to mimic the perception of the existence of it. Leading to customers generating trust, satisfaction and positively influencing their experience (Fernandes & Olivera, 2021). Hence, managers need to be aware that increasing the humanness of the service robots contributes to reducing dissatisfaction. Furthermore, managers need to ensure that the deliverance of the service can be done combined with a human employee and service robots. This is to meet the social need of the customers, a factor that is more important in case of service recovery.

Furthermore, results from our study also show that most of the Norwegian participants, who would be willing to adopt a service robot, have a higher level of education. This indicates that populations with a higher educational level are more acceptable towards artificial intelligence service robots and are more motivated to adopt such a service. Moreover, the younger generations tend to be more trustworthy and have a more positive attitude towards artificial intelligence service deliveries. While older people tend to be more conservative and cautious regarding new advanced technologies. Therefore, the interaction preferences of Norwegian service customers and demographics creates a major factor for segmentation with regards to the utilization of service robots. It is essential for adoption that consumers believe the use of service robots will be worth their while and creates value for them.

6.0 Limitations & Future Research

6.1 Limitations

This study contributes to the service marketing field by gaining further understanding of consumers' psychological motivational acceptances and barriers towards service robot adoption. However, there are three noteworthy limitations involved in our study that need to be presented.

First, our research involves using a cross sectional survey design which is dependent on respondent's self-report. This makes it easier for respondents to lie about their true opinions. Additionally, potential biases based on knowledge and experiences could have an underlying influence for which answers the respondents give in the survey. Furthermore, our study only targeted those who have prior experience with service robots, but the respondent's evaluation of the questions is reliant on their knowledge. This has led to the concerns that, despite the best effort to easily define what a service robot is, respondents may not fully comprehend and grasp what they are answering due to lack of knowledge.

Second, respondents for our survey were included based on convenience sampling through social media. Therefore, the data that has been gathered stems from a small sample size, which makes it more difficult to receive generalizable results.

Additionally, many of our respondents can be categorized as belonging to the millennial generation, which makes our study slightly lacking in variation of respondents in terms of age. Thus, our results are not necessarily cross validated for other age groups. Furthermore, our research focuses on Norwegian service customers, which causes our findings potentially not being transferable for other cultures.

Lastly, the conceptual model constructed for this study uses previous research and existing literature as its foundation. Thus, the validity and theoretical systematicity of our model remains to be verified. Furthermore, we only tested the effects of six variables in terms of them being statistically significant. The path coefficients which further analyze the impacts in our model remains yet to be tested. Additionally, there are variables that are not included in our conceptual model that would give an even further understanding on customers motivations and barriers towards service robot adoption.

6.2 Future Research

Results from this research and conceptual model creates areas for further research on service robots with interest in the service marketing field. We have identified four new areas that require to be further addressed. First, further research is needed to apply our model in different service contexts. We find that there is especially a need to address how customers' psychological motivations and barriers influence their willingness to adopt service robots when service failure and recovery occurs. The complexity of the survey should also have an influence and creates an interesting perspective on how the motivations and barriers will differently affect customer adoption. Future research should also apply the model to the different phases in a service encounter (pre- vs post-service).

Second, future research using a qualitative experimental design will help to further find new motivational aspects and more importantly identify barriers that have not yet been established. The experiment should focus on applying service robots in a service encounter and measure customers reaction. This could also be done by using a pre and posttest in the experiment to compare how motivations and barriers values will fluctuate. Conversely, researchers could implement a scenario-based approach.

By doing so, they could present respondents with a real-life scenario, and then monitor their responses/behavior in accordance with the presented scenarios involving an interaction with a service robot. Another interesting aspect future research should experiment on is how customers evaluate their motivations and barriers when encountering a human interaction compared to service robots.

Third, service robots do not only affect customers, but it also affects the employees. Thus, there is a critical need for future research to address what are the employees' motivations and barriers towards working with service robots, and how the perceptual dynamic is influenced through the employee's perspective. Future research needs to address staff and managers' willingness to adopt. Lastly, results from this study should be cross validated among other age groups of Norwegian service customers. Survey responses should be collected from different parts of Norway and consist of different age groups. This will contribute to greater results that can be more generalized to the Norwegian population.

7.0 Conclusion

The aim of this research was to gain valuable understanding of Norwegian service customers' psychological motivations and barriers towards service robot adoption. In addition, this research also intended to discuss how the barriers could be mitigated by business managers.

The result for our research indicates that motivational factors such as ease of use and usefulness have a significant positive effect that drives Norwegian customers adoption of serve robots. However, trust was not found to be significant and shows implications that need to be improved. Furthermore, our study discovered that lack of human interaction, limited perception and cultural barriers have a significant negative effect that impedes Norwegian service consumers' willingness to adopt service robots.

Based on the findings from our analysis, to mitigate factors impeding adoption, managers in service organizations should carefully monitor services that are delivered by service robots and allocate resources to further advance customer experience. Furthermore, the utilitarian value associated with using service robots needs to be communicated through carefully planned marketing and integrate customers' expectations as a part of the service delivery. It is important that companies build trust that encourages service robot adoption. Likewise, marketing needs to be used for generating multiple positive word of mouth for influencing attitudes and for contingency plans to solve potential setbacks due to customers' psychological barriers.

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9.0 Appendix

Appendix 1: *Qualtrics Survey*

Master Thesis: Service Robot

This survey is made in context with our final master thesis of Master of Science degree in Strategic Marketing Management at BI Norwegian Business School.

Participation in this study is voluntary and there are no right or wrong answers. We are only interested in your honest opinion. To ensure your data privacy is respected, every answer will be anonymous and will only be used for the purpose of our research. No personal data such as such as e-mail, IP-addresses or names that can be traced back to you.

Please take your time to read and answer the questions as honestly as possible.
This survey will only take approximately 5-6 minutes to finish.
We appreciate you taking the time to help us.
Thank you!

Q1 How old are you? (Numbers only)

____

Q2 To which gender do you most identify with?

- ○ Male (1)
- ○ Female (2)
- ○ Non-binary / third gender (3)
- ○ Prefer not to say (4)

Q3 Where in Norway do you live?

- ○ Northern Norway (1)
- ○ Trønderlag (2)
- ○ Western Norway (3)
- ○ Eastern Norway (4)
- ○ Southern Norway (5)

Q4 What is the highest degree or level of school you have completed?

- ○ Primary/Secondary School (1)
- ○ High School (2)
- ○ Bachelor’s degree (3)
- ○ Master’s degree (4)
- ○ PhD (5)

Q5 Employment status

- Full-time (1)
- Part-time (2)
- Student (3)
- Unemployed (4)

This part of study will focus on service robots. A service robot is an artificial intelligence program that stimulates human interaction through voice commands or text chats or both. Chatbots and digital voice-assistants are some of the examples of service robots that are commonly used in Norway. For example:

- When contacting DNB through their chat services, you will initially be interacting with their chatbot that will try to assist your specific personal needs.

- If you need assistance to find a good restaurant or accommodation, you might ask for recommendations from your digital voice assistant Siri or Bixby on your phone.

Please take your time to read the questions carefully and answer as honestly as possible.

Q6 Do you have any previous experience with a service robot? (E.g. Chatbot or Digital voice assistance)

- Yes (1)
- No (2)

Q7 How many times per month do you interact with a service robot?

- ○ 1-3 times (1)
- ○ 4-6 times (2)
- ○ 10 or more (3)
- ○ Never (4)

Q8 Evaluate how the below statements you think are consistent with your perception of Service Robots ease of use

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
Interaction with service robots is easy to understand (1)	○	○	○	○	○	○	○
I think using service robots are easy to use (2)	○	○	○	○	○	○	○
I think I can use the robot without any help (3)	○	○	○	○	○	○	○
I see the need for service robots (4)	○	○	○	○	○	○	○

Q9 Evaluate how the below statements you think are consistent with your perception of Service Robots usefulness

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I think the robot is useful to me (1)	○	○	○	○	○	○	○
It would be convenient for me to interact with a service robot (2)	○	○	○	○	○	○	○
I think the service robot can assist my needs (3)	○	○	○	○	○	○	○

Q10 Evaluate how the below statements you think are consistent with your perception of trust with regards to Service Robots

	Strongly Disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I would trust the service robots' recommendations (1)	○	○	○	○	○	○	○
I would follow the advice the robot gives me. (2)	○	○	○	○	○	○	○
I can rely on the service robot to deliver the service it is supposed to do (3)	○	○	○	○	○	○	○
I can rely on the service robot to provide me with accurate information (4)	○	○	○	○	○	○	○

Q11 Evaluate how the below statements you think are consistent with your viewpoint of Service Robots

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I would feel uncertain interacting with a service robot (1)	o	o	o	o	o	o	o
I have negative impression of service robots (2)	o	o	o	o	o	o	o
I feel that if I depend on service robots too much, something bad might happen (3)	o	o	o	o	o	o	o
I would feel uneasy if robots really had emotions (4)	o	o	o	o	o	o	o

Q12 Evaluate how the below statements you think are consistent with your judgment of Service Robots

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I do not like handing over control to a service robot to deliver the service (1)	o	o	o	o	o	o	o
I feel uneased entering personal data or payment details to service robots (2)	o	o	o	o	o	o	o
My associations towards service robots are negative (3)	o	o	o	o	o	o	o
My experience with serve robot has been unsatisfactory (4)	o	o	o	o	o	o	o
I tend to get anxious easily when I do not know the outcome (5)	o	o	o	o	o	o	o

Q13 Evaluate how the below statements you are consistent with your perception of interactions with Service Robots

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
Interacting with service robots makes me concerned (1)	○	○	○	○	○	○	○
I prefer human interaction rather than service robots (2)	○	○	○	○	○	○	○
Artificially intelligent devices such as service robots are intimidating to me (3)	○	○	○	○	○	○	○
I would not accept artificially intelligent devices such as service robots even if a significant proportion of my social network uses it (4)	○	○	○	○	○	○	○

Q14 Evaluate how the below statement you think is consistent with your intention to use Service Robots in the future

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I intend to use service robots in the future if I have access to it (1)	○	○	○	○	○	○	○

Q15 Anything else you would like to add?

____

End of Block: Default Question Block

Appendix 2: *Respondents demographic information*

Variables	**Categories**	**Frequency**	**Percentage**
Age	24 years old	37	19.5%
Gender	Men	104	54.7%
	Women	85	45.3%
Place of residence	Northern-Norway	59	31.45%
	Trøndelag	32	16.9%
	Western-Norway	13	6.92%
	Eastern-Norway	56	29.56%
	Southern-Norway	28	15%
Education	Primary/Secondary	2	1.25%
	High School	42	22%
	Bachelor's Degree	90	47.8%
	Master´s Degree	49	25.8%
	PHD	6	3.14%
Employment	Full time	99	52.8%
	Part time	30	15.7%
	Student	56	29.6%
	Unemployed	4	1.9%

Interaction with service robot	1-3 times a month	136	71.7%
	3-6 times a month	25	13.2%
	10 or more a month	6	3.14%
	Never	22	11.9%

Appendix 3: *Descriptive Analysis*

Variables	**Mean**	**Std. D**	**Skewness**		**Kurtosis**	
			Statistic	Std. Error	Statistic	Std. Error
Ease of use - 1	5,60	1.423	-.580	.192	-.503	.383
Ease of use - 2	5,64	1.429	-.441	.192	-.661	.383
Ease of use - 3	5,55	1.399	-1.312	.192	1.459	.383
Ease of use - 4	5,94	1.429	-.809	.192	.397	.383
Usefulness - 1	4,28	1.547	-.370	.192	-.491	.383
Usefulness - 2	5,31	1.526	-.458	.192	-.535	.383
Usefulness - 3	5,13	1.479	-.243	.192	-.659	.383
Trust - 1	3,94	1.286	-.134	.192	-.452	.383
Trust - 2	3,99	1.250	-.224	.192	-.074	.383
Trust - 3	3,64	1.403	.199	.192	-.628	.383
Trust - 4	3,87	1.355	-.035	.192	-.550	.383
Limited Perception - 1	4,58	1.442	.091	.192	-.815	.383

Limited Perception - 2	5,34	1.409	-.073	.192	-.516	.383
Limited Perception - 3	4,18	1.545	.473	.192	-.398	.383
Limited Perception - 4	4,26	1.663	-.311	.192	-.564	.383
Cultural barrier - 1	5,11	1.463	.023	.192	-.510	.383
Cultural barrier - 2	5,20	1.558	-.127	.192	-.638	.383
Cultural barrier - 3	5,01	1.482	.013	.192	-.459	.383
Cultural barrier - 4	5,36	1.371	-.146	.192	-.473	.383
Cultural barrier - 5	4,42	1.481	.274	.192	-.576	.383
Lack of human interaction - 1	4,18	1.297	.413	.192	-.363	.383
Lack of human interaction - 2	5,76	1.319	-.991	.192	.161	.383
Lack of human interaction - 3	4,09	1.420	.473	.192	-.263	.383
Lack of human interaction - 4	4,37	1.461	.332	.192	-.537	.383
Service Robots adoption	5,80	3.109	.637	.192	-1.027	.383

Appendix 4: *Rotated Component Matrix*

Variable	Item/ Factor	Comp .1	Comp .2	Comp .3	Comp. 4	Comp.5	Comp.6
Ease of Use (EOU)	Interaction with service robots is easy to understand (1)	0.625					
	I think using service robots are easy to use (2)	0.718					
	I see the need for service robots (3)	0.839					
Usefulness (USF)	I think the robot is useful to me (1)		0.817				
	It would be convenient for me to interact with a service robot (2)		0.747				
	I think the service robot can assist my needs (3)		0.824				
Trust (TRU)	I would trust the service robots' recommendations (1)			0.848			
	I would follow the advice the robot gives me. (2)			0.839			
	I can rely on the service robot to deliver the service it is supposed to do (3)			0.691			
	I can rely on the service robot to provide me with accurate information (4)			0.807			

Limited Perception (LP)	I would feel uncertain interacting with a service robot (1)	0.598		
	I have negative impression of service robots (2)	0.718		
	I would feel uneasy if robots really had emotions (3)	0.847		
Cultural Barrier (CP)	I feel uneased entering personal data or payment details to service robots (1)		0.794	
	My associations towards service robots are negative (2)		0.634	
	My past experience with serve robot has been unsatisfactory (3)		0.731	
Lack of Human Interaction (LHI)	Interacting with service robots makes me concerned (1)			0.794
	I prefer human interaction rather than service robots (2)			0.712
	Artificially intelligent devices such as service robots are intimidating to me (3)			0.772

Appendix 5: *Fornell-Locker Criterion*

Correlations	EOU1	EOU2	EOU3	USF1	USF2	USF3	TRU1	TRU2	TRU3	TRU4	LP1	LP2	LP3	CB1	CB2	CB3	LHI1	LHI2	LHI3	LHI4
EOU1	*0,7325913*																			
EOU2	.381**	*0,7325913*																		
EOU3	.714**	.334**	*0,7325913*																	
USF1	.540**	.514**	.524**	*0,7967589*																
USF2	.494**	.510**	.521**	.797**	*0,7967589*															
USF3	.496**	.531**	.477**	.762**	.712**	*0,7967589*														
TRU1	.429**	.239**	.349**	.429**	.429**	.387**	*0,7987107*													
TRU2	.418**	.251**	.406**	.420**	.485**	.377**	.775**	*0,7987107*												
TRU3	.444**	.324**	.455**	.456**	.461**	.474**	.580**	.529**	*0,7987107*											
TRU4	.403**	.241**	.387**	.465**	.525**	.378**	.674**	.653**	.644**	*0,7987107*										
LP1	-.316**	-.346**	-.273**	-.329**	-.375**	-.221**	-.373**	-.363**	-.186*	-.314**	*0,7281339*									
LP2	-.431**	-.361**	-.382**	-.520**	-.393**	-.467**	-.247**	-.157*	-.331**	-.268**	.326**	*0,7281339*								
LP3	-.129	-.239**	-.152	-.192*	-.125	-.104	-.140	-.194*	-.081	-.173*	.406**	.121	*0,7281339*							
CB1	.042	-.077	.030	-.131	-.127	-.129	-.152	-.175*	-.030	-.164*	.103	.194*	.209**	*0,7226694*						
CB2	-.371**	-.463**	-.417**	-.553**	-.488**	-.595**	-.219**	-.164*	-.358**	-.252**	.386**	.696**	.133	.232**	*0,7226694*					
CB3	-.396**	-.342**	-.476**	-.518**	-.514**	-.554**	-.321**	-.268**	-.431**	-.342**	.302**	.699**	.124	.090	.694**	*0,7226694*				
LHI1	-.369**	-.339**	-.275**	-.294**	-.329**	-.276**	-.262**	-.315**	-.120	-.249**	.468**	.260**	.189*	.204**	.348**	.176*	*0,7521899*			
LHI2	-.138	-.262**	-.173*	-.171*	-.208**	-.179*	-.210**	-.116	-.177*	-.202*	.126	.330**	.069	.168*	.318**	.437**	.015	*0,7521899*		
LHI3	-.286**	-.188*	-.090	-.256**	-.185*	-.201*	-.163*	-.181*	-.044	-.132	.309**	.130	.143	.089	.231**	.026	.586**	-.161*	*0,7521899*	
LHI4	-.245**	-.369**	-.118	-.243**	-.245**	-.259**	-.213**	-.266**	-.134	-.202*	.372**	.283**	.079	.159*	.323**	.118	.606**	.069	.588**	*0,7521899*
N	189	189	189	189	189	189	189	189	189	189	189	189	189	189	189	189	189	189	189	189

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

* Correlation is significant at the 0.05 level (2-tailed).

Appendix 6: *Multicollinearity*

Constants	Collinearity Statistics	
	Tolerance	VIF
EOU1	.544	1.839
EOU2	.668	1.497
EOU3	.537	1.861
USF1	.232	4.303
USF2	.259	3.867
USF3	.299	3.345
TRU1	.304	3.291
TRU2	.301	3.324
TRU3	.430	2.328
TRU4	.377	2.655
LP1	.512	1.951
LP2	.364	2.750
LP3	.716	1.397
CB1	.767	1.304
CB2	.306	3.272
CB3	.301	3.325
LHI1	.440	2.274
LHI2	.683	1.465
LHI3	.489	2.046
LHI4	.457	2.190

Appendix 7: *Independent sample t-test*

Group Statistics:

Variable	Gender	N	Mean	Std. D
Service Robot Adoption	Male	104	5.07	2.774
	Female	85	6.68	3.280

Independent Sample Test:

Service Robot Adoption	**Equality of variances**				**Equality of means**	
	F	**Sig**	**t**	**df**	**Two-sided P**	**Mean diff.**
Equal variance assumed	14.390	< .001	-3.357	157	< .001	-1.612

Appendix 8: *Educational Level & Service Robot Adoption*

	N	**Mean**	**Std. D.**
Education level:			
Primary/Secondary School	2	5	5.657
High School	42	5,29	2.739
Bachelor's degree	90	5,29	2.935
Master's degree	49	6,85	3.403
PhD	6	6,4	3.847
Total	**189**		