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Consumer Adoption of AI-Powered Chatbots: Developing a Customized Adoption Model

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Executive Summary

Recent advancements in Artificial Intelligence have transformed the business landscape, with AI-powered chatbots playing a crucial role in enhancing customer service and automating tasks. As current literature seems to predominantly focus on the use of AI-powered chatbots in organizational contexts, this study aims to fill this gap by creating an understanding of the factors driving AI-powered chatbot adoption from a consumer perspective. To achieve this, we utilize the Theory of Planned Behavior (TPB), the Technology Adoption Model (TAM), the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), and Diffusion of Innovations (DOI), as traditional technology adoption models. Along with the constructs from these traditional models, we add the AI-specific antecedents: Anthropomorphism, Trust, Privacy Risk and Personalization, which were found through conducting a literature review of AI- and chatbot adoption. This integration allowed us to develop a customized adoption model that provides an understanding of chatbot adoption from a consumer perspective.

The study collects data through a questionnaire-based survey (n=126). Through several multiple regression analyses, significant drivers across all the models are revealed. Subjective Norm and Behavioral Control (TPB), Usefulness (TAM), Habit (UTAUT2) and Trialability (DOI) were all found to have a significant positive effect on the Intention to Use AI-powered chatbots. The Customized Model, created through stepwise estimation, includes Usefulness (TAM), Trialability (DOI), Habit (UTAUT2), and Anthropomorphism (Model Extensions). These four factors collectively explain 46.6% of the variance in consumers' Intention to Use AI-powered chatbots. In terms of explaining the adoption of AI-powered chatbots, the Customized Model outperforms traditional models by explaining the most variance while utilizing the fewest variables. This enhanced fit may make it a more effective tool for understanding how consumers adopt AI-powered chatbot technology. The study contributes to businesses’ understanding of the constructs influencing chatbot adoption and implementing effective strategies to enhance customer experiences.

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Chapter 1: Introduction

1.1 Background and Motivation

Advancements in Artificial Intelligence (AI) are revolutionizing the business landscape and transforming marketing and customer service as we know it (Davenport et al., 2020). AI technology offers advantages to both consumers and businesses (Winkler & Söllner, 2018), which has resulted in an exponential adoption growth in the past five years. The overall financial and social impacts of the technology are increasing at a significant pace (McKinsey, 2022), and with recent advancements in Machine Learning, businesses are able to predict consumer behavior in new ways (Yarkoni & Westfall, 2017). Consumers are now increasingly looking for automated solutions and AI-powered chatbots have become a prominent technology in various related fields (Deloitte, 2022). As chatbots provide various benefits, including cost reduction, enhanced user satisfaction, proactive information delivery, and improved efficiency (Winkler & Söllner, 2018), the global chatbot market is expected to reach a compound annual growth rate of over 29% between 2021 and 2025 (Technavio, 2021).

The adoption and use of chatbots by consumers has witnessed significant shifts in usage patterns. Most consumers primarily engage with chatbots for customer service or shopping-related tasks, but the scope of interactions is expanding (Ubisend, 2022). While chatbots were previously utilized for small-scale activities such as making reservations or small purchases, they are now increasingly used for more intricate purposes, including receiving medical or financial advice (CDP, 2022). The widespread usage and integration of the technology is supported by Drift's AI report (2021), which revealed that 73% of consumers have interacted with a brand using a chatbot in the past year.

As AI-powered chatbots continue to gain prominence as a compelling solution in various business domains, it is important to acknowledge the challenges associated with their adoption. To remain competitive, businesses may profit from understanding the key drivers behind chatbot adoption (Deloitte, 2022). Traditional theories of technology adoption have been instrumental in identifying key drivers and barriers that influence the adoption of new technologies. Well-established models such as the Theory of Planned Behavior (TPB), the Technology Adoption Model (TAM), the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), and the Diffusion of Innovation Theory (DOI) have been widely accepted and employed to explain adoption patterns (Rad et al., 2018).

Although the traditional adoption models remain valuable tools in understanding technology adoption, it is important to recognize that relying solely on traditional models may not fully capture the unique factors associated with the adoption of newer technologies (Venkatesh et al., 2012). As highlighted by Fichman (1999), there may be a need for customized models that specifically address the intricacies of adopting a particular technology. A customized model may provide a more accurate understanding of adoption process of AI-powered chatbots.

Businesses have recognized the importance of understanding how people adopt and use technologies (Deloitte, 2022), but it seems that little research has been conducted on chatbot adoption from a consumer perspective (Rafiq et al., 2022). The purpose of this exploratory study is to investigate constructs from traditional adoption models that drive or prevent consumers from adopting AI-powered chatbot technology. The traditional adoption models will be complemented with chatbot-specific antecedents found through a literature review to create a comprehensive model that will shed light on the critical factors that impact consumers' adoption of AI-powered chatbots.

1.2 Research Questions

While the literature on AI chatbot adoption is growing exponentially (Appendix M), it is primarily concentrated on organizational or business contexts, such as the healthcare industry, financial services, and retailing (Rafiq et al., 2022). While conducting a review of the literature (Appendix A), we discovered that there was a significant gap in research on the adoption of AI-powered chatbots from a consumer perspective. Hence, businesses' assumptions about consumers' preferences seem to be generally created from speculation, which may result in misconceptions regarding the priorities of the consumer. Therefore, it is important to gain insights into what factors drive consumer adoption of AI-powered chatbots. Filling this gap in knowledge may be vital in developing more comprehensive theories and business strategies to encourage the adoption of AI-powered chatbots. Consequently, our research question is:

Rq 1: *What constructs drive the adoption of AI-powered chatbots from a consumer perspective?*

In the field of technology adoption, various theoretical adoption models have been developed to understand the factors that drive the adoption of new technologies. However, there is a lack of a general chatbot-specific adoption model that incorporates custom constructs. In this paper, we conduct a systematic comparison of the four most used technology adoption models (Rad et al., 2018), including TPB (Ajzen, 1985), TAM (Davis, 1989), UTAUT2 (Venkatesh et al., 2012), and DOI (Rogers, 1983). We then combine constructs from the traditional adoption models with AI-specific antecedents which we uncover through our literature review (Appendix A). We aim to create a customized adoption model for chatbots that explains as much variance as possible with a minimal number of variables (Hair et al., 2014).

Rq 2: *Can we explain chatbot adoption better through a customized adoption model?*

1.3 Contributions to Theory and Managers

Theoretical Contributions

In recent years, AI-powered chatbots have witnessed significant advancements, attracting substantial research attention (Appendix M). As the prominence of AI-powered chatbots grows, an increasing number of corporations, consulting firms, and academic journals have begun to explore the practical application and utilization of this technology (Deloitte, 2022; Rafiq et al., 2022). However, the majority of existing studies primarily relate to the technology itself rather than the adoption of the technology. Interestingly, studies predominantly focus on highlighting the potential positive impacts of chatbots, with limited attention given to the factors influencing their adoption (Liveperson, 2023).

Extensive research has been conducted on technology adoption, with traditional adoption models such as TAM, TPB, UTAUT2, and DOI being widely credited and referenced across various technology domains (Rad et al., 2018). However, the body of literature specifically addressing the adoption of AI-powered chatbots remains relatively scarce. This study seeks to contribute to the theoretical field by bridging this gap and integrating renowned technology adoption models with new antecedents. Through the integration of different constructs, we aim to develop and validate both the traditional adoption models, and a customized adoption model capable of effectively explaining the adoption of AI-powered chatbots. By doing so, this study may enrich existing theoretical frameworks surrounding technology adoption and offer insights into the unique adoption dynamics of AI-powered chatbots.
Another contribution is our literature review which has the potential to enhance theoretical understanding by addressing existing gaps in knowledge and contribute to the theoretical

landscape of AI-powered chatbot adoption. By offering an overview of the current research in the field, we aim to summarize important findings that can inform future studies and provide valuable insights into the adoption process of chatbots. This review may contribute to the development of theoretical frameworks and chatbot-specific models, as well as refine and adapt existing technology adoption theories. Furthermore, the detailed description of our literature review process, including the gathering and search methodology, can serve as a reference for replication in this rapidly evolving theoretical field. It can also provide a solid starting point for further exploration of chatbot adoption studies, utilizing established theories, constructs, and measurement approaches presented in prior research (Appendix A).

Managerial Contributions

The rapid advancements in AI technology in marketing present promising opportunities for businesses seeking to improve customer engagement and gain a competitive advantage (Mariani et al., 2022). Businesses can leverage AI to make more informed marketing decisions across their organizations to effectively harvest its benefits, create competitive advantages, and enhance performance (Venkatesh et al., 2022). Consumers have increasingly adopted chatbots as a means of interacting with businesses, recognizing the benefits of the technology's efficiency and its potential to reduce customer service costs (Drift, 2021; Winkler & Söllner, 2018). As a result, managers have realized the significance of understanding how consumers adopt and utilize technologies (Deloitte, 2022). This study could provide valuable support to managers as the importance of understanding the drivers of chatbot adoption increases.

In this study, we retrieve constructs from several traditional technology adoption models and supplement them with model extensions. By understanding the influence of these extending constructs, managers may be able to implement chatbots in a way that maximizes their benefits for both their business and customers. Ultimately, understanding the factors that drive chatbot adoption may lead to improvements in customer satisfaction, cost reduction, and sales growth (Winkler & Söllner, 2018).

This study further develops a customized chatbot adoption model that incorporates drivers from existing technology adoption models and AI-specific antecedents. Leveraging this customized chatbot adoption model can contribute to businesses' development of effective strategies. This can potentially enable them to enhance the functionality and design of their own chatbot services, better meeting customer needs and expectations. If consumers ultimately adopt their chatbot, businesses may collect valuable data on consumer behavior and preferences, which may lead to improved marketing strategies, product offerings and better customer satisfaction (Davenport et al., 2020).

1.4 Outline

Chapter 2 introduces AI, AI-powered chatbots and various connected literature. Chapter 3 introduces TPB, TAM, UTAUT2 and DOI, followed by an introduction of constructs and findings from previous studies on these models and additional antecedents identified through our literature review (Appendix A), which are used to develop our own hypotheses. Chapter 4 outlines the methodology used to test the hypotheses derived from the chosen research model. Chapter 5 presents data analyses that address and assure the quality of the statistical models. Chapter 6 presents the results of the multiple regression analysis and the significance of the measured factors, along with a Customized Model. Chapter 7 provides theoretical and managerial implications, limitations and future research directions, before ultimately concluding the study.

Chapter 2: Artificial Intelligence and Chatbots

Chapter 2 serves as an introduction to the core concepts of AI and AI-powered chatbots, contextualizing their significance within the broader theoretical framework of the thesis. It provides a foundation for understanding AI technology and its construction. By establishing this groundwork, the chapter paves the way for further discussions and investigations in the subsequent chapters of the thesis.

2.1 What is AI?

There are numerous definitions of Artificial Intelligence, and as it is a complex and developing field, new definitions seem to be emerging regularly. The founding father of AI, John McCarthy, coined the term and first defined it as: "*AI is the science and engineering of making intelligent machines, especially intelligent computer programs*" (McCarthy, 2007, p. 2). Despite the challenge of precisely and comprehensively defining AI, newer definitions may give us a better understanding of the concept. An independent expert group formed by the European Commission on AI presents the definition: "*AI are systems that perform actions, physical or digital, based on the interpretation and processing of structured or unstructured data, with the intention of achieving a given goal. Some AI systems can also adapt by analyzing and taking into account how previous actions have affected the environment*" (AI HLEG, 2018, p. 7). Despite the numerous definitions, most agree that AI differs from other types of information technology, as it has the possibility to learn, connect and adapt. The level of the capabilities varies and depends on the AI type (Huang & Rust, 2021).

Another way to explain Artificial Intelligence is as human intelligence exercised by machines. These machines are constantly gaining characteristics that are more human-like, such as the ability to listen, write, read, talk, feel and possess consciousness (Ren & Bao, 2020). Huang and Rust (2021) propose that there are three different types of AI: mechanical, thinking and feeling. Firstly, Mechanical AI is designed for automating repetitive and routine tasks. Secondly, Thinking AI is designed for processing data so that it arrives at new conclusions or decisions. Thirdly, Feeling AI is designed for two-way interactions involving humans and for analyzing human feelings and emotions. The intelligence stems from advanced algorithms which can be defined as a series of steps that a machine follows to be able to perform specific tasks (Castelo et al., 2019). These algorithms would be less effective without utilizing the emerging Big Data to generate marketing insights (Wedel & Kannan, 2016).

2.1.1 Big Data

AI and Machine Learning algorithms rely heavily on Big Data to generate optimal predictions and decisions and it is described as a fundamental pillar for the success of AI technology (Castelo et al., 2019). According to De Mauro et al. (2015, p. 103), Big Data has become a ubiquitous term in both academic and business circles. To provide a clear understanding of this concept, they developed a comprehensive definition based on existing research and prior definitions: "*Big Data refers to information assets that possess such a high volume, velocity, and variety that they require specific technologies and analytical methods for their transformation into value*" (De Mauro et al., 2015, p.103).

The world of Big Data, with its increasing volume, velocity, and variety, presents lucrative opportunities for enhancing decision-making processes (Erevelles et al., 2016). The scale of Big Data is staggering, having expanded from mere megabytes to petabytes, which amount to several quadrillion bytes. To put this into perspective, more data crosses the internet every second than what the entire internet stored 20 years ago. Additionally, the velocity or speed at which Big Data is generated can provide businesses with greater flexibility to respond to changing market conditions. Finally, the diversity of data sources and types is also an important facet of Big Data, which allow companies to hold large streams of information from various locations, people, and activities (McAfee et al., 2012).

The use of Big Data has great potential for both businesses who were born digital and traditional businesses. By providing managers with vast amounts of information, Big Data enables them to improve their company's performance and decision-making capabilities (McAfee et al., 2012). However, Amado et al. (2018) emphasize that Big Data alone only holds value if utilized with the aim of gathering insightful knowledge. That is why marketing analytics has become a central trend in addressing many challenges. By harnessing Big Data, marketing analytics can help marketers identify customers (Moro et al., 2014) and unveil fascinating consumer trends (Lacoste, 2016). When applied effectively, Big Data provides an opportunity to uncover trends in consumer preferences and patterns in consumer behavior (Dekimpe, 2020). Ultimately, Big Data solutions may be regarded as the foundation for complex systems that make slow human analysis obsolete (Amado et al., 2018). Big Data and its constant flow of information have had a profound impact on Machine Learning, being regarded as the underlying foundation of its complexity (Regjeringen, 2020).

2.1.2 Machine Learning

Machine Learning is typically considered a subfield of AI (Goodfellow et al., 2016) where statistical methods are used to allow computers to find patterns in large amounts of data, which again gives them the ability to independently learn something new (Tidemann & Elster, 2022). Although there are many varieties of Machine Learning, it is often split into supervised, unsupervised and reinforcement learning. In supervised learning, the algorithm is trained using a given data set with both inputs and outputs (Regjeringen, 2020; Ubisend, 2022), with prediction being the primary focus. Applications of supervised learning can be seen in spam classifiers for emails, face recognizers, and text classifiers (De Mauro et al., 2022).

Huang and Rust (2021), elaborate on how unsupervised Machine Learning can be used in newer markets and for spotting outside opportunities where market structures and trends are unstable and unknown. Unlike supervised learning, where both inputs and outputs are defined, unsupervised learning involves undefined or unknown outputs. Its main goal is typically to extract information or find hidden patterns (Ma & Sun, 2020). Some applications of unsupervised learning are consumer and market segmentation, classification, and the detection of outliers (De Mauro et al., 2022).

Finally, reinforcement learning operates without any predetermined training data and is dependent on a learner who continuously informs the algorithm decision feedback. The algorithm is informed that a decision is either good or bad, which is fed into the system to help improve the model. In order to adapt to the ever-changing consumer preferences, recommender systems typically use reinforcement learning (De Mauro et al., 2022).

Neural Networks and Deep Learning

Neural Network technology is a subset of Machine Learning, that aims to replicate how the nerve cells in a brain are organized by encompassing various data structures and associated algorithms (Jones et al., 2018). Deep Learning, which is a more complex form of Machine Learning, has played a crucial role in numerous AI breakthroughs and tasks that demand human-like intelligence. It involves multiple layers of Neural Networks that can explore intricate non-linear patterns (Davenport & Kalakota, 2019). As Big Data continues to rapidly grow in terms of volume, velocity, and variety, the need for efficient interpretation has become increasingly crucial. Deep Learning technology has emerged as a powerful tool in addressing this challenge, with Unsupervised Machine Learning playing a significant role in its development (Bengio et al., 2013). Its significance is evident in recent marketing studies, where it has been widely employed for analyzing text and image data, as highlighted by Ma and Sun (2020).

The use of Neural Networks and Deep Learning has empowered the functionality of AI-powered chatbots. Recent advancements in Natural Language Processing (NLP) and machine translation have strengthened the capabilities of chatbots (Shah et al., 2016). The progress in conversational modeling suggests that the use of recurrent Neural Networks and sequence-to-sequence models will outperform the rule-based conversational modeling that has been prevalent in the past (Vinyals & Le, 2015). Vinyals and Le (2015) further state that Neural Networks play an important role in natural language understanding, as they can connect complicated structures together.

2.2 The state of AI

AI technology presents opportunities that are enabling the development of a new generation of products and services. In the business world, algorithms are being used to reduce costs, increase sales and improve customer service (European Parliament, 2020). AI is given a lot of attention and a report from McKinsey (2022) shows that both AI adoption and the average number of AI capabilities used by organizations have doubled in the last five years. The Norwegian government is planning to invest in research and development of AI, as their goal is to gain advanced expertise in the field. In doing so they expect to benefit from changes in technology development and become attractive partners for leading businesses and research environments (Regjeringen, 2020). AI is transforming many sectors, such as energy, transport, health, public administration and security. The European Union has proposed its first independent program for digitalization, which will run from 2021 to 2027. The program is set to have a budget of 9,2 billion euros, with AI making up 27% of it, indicating the increasing importance of AI in the future (European Parliament, 2020).

Davenport et al. (2020) argue that AI will have a transformative impact on business models, sales processes, consumer behavior and customer service. Business leaders from across the world seem to have the same perception, as 94% answered that AI will be critical to future success in a recent study by Deloitte (2022). The rapid development in the field of AI creates better competency and capabilities that go beyond basic cost reduction and revenue generation. AI-enabled systems are capable of personalizing customer experiences (Kumar et al., 2019) and help marketers use a wide variety of both solicited and unsolicited forms of customer engagement to improve marketing outcomes (Perez-Vega et al., 2021). The identification of target audiences and delivery of tailored content is becoming a dominant strategy (Deloitte, 2022), and companies that strategically scale AI investments report nearly three times the return compared to those who are hesitant (Accenture, 2022).

2.2.1 The state of AI in marketing

The marketing discipline has evolved due to rapid technological advancements, with AI being a frontrunner (Mariani et al., 2022). The potential benefits of AI for businesses and marketers are unprecedented, leading to a rush to invest in various business areas. Companies are seeking to deploy and leverage AI across their organizations to effectively harvest its benefits, create competitive advantages, and enhance performance (Venkatesh, 2022). AI has become increasingly applicable in various marketing areas, made possible by increased computing power, lower computing costs, accessible Big Data, and the technological progress of Machine Learning (Huang & Rust, 2021). According to McKinsey & Company's report "The State of AI in 2022", marketing and sales are among the areas that have seen the most significant revenue impact from AI (McKinsey, 2022).

AI and Machine Learning are impacting the field of marketing in an exceptional way (Siau & Yang, 2017), and businesses are leveraging these technologies to enhance their marketing capabilities. Due to Machine Learning, marketing activities have seen advancements in forecasting models, which simplifies decision-making (Cui et al., 2006). Systems in both e-commerce websites, social media and other content platforms are powered by Machine Learning algorithms. These algorithms have been effective in processing large-scale and unstructured data in real-time, which can generate accurate predictions to assist marketing decisions (Ma & Sun, 2020).

Traditionally, economic models have been used to explain marketing and consumer choice. However, there has been a recent shift towards psychological theories as the core of consumer behavior and marketing research (Mariani et al., 2022). This shift has allowed for a deeper understanding of the thinking, desires, and experiences of individuals through the embrace of psychology and other social sciences (Malter et al., 2020). AI and Machine Learning can be used to understand these cognitive processes and to predict future choices by integrating principles from computer science. While the field of psychology has traditionally emphasized explaining the causes of behavior, Yarkoni and Westfall (2017) advocate for the utilization of Machine Learning to predict these causes, leveraging the capabilities of AI and Machine Learning.

2.3 Possible Challenges with AI

According to the Norwegian government's "National Strategy for Artificial Intelligence", AI technology should build on ethical principles, digital security, and respect for privacy (Regjeringen, 2020). While AI presents numerous advantages for both consumers and businesses, it may also create challenges and raise difficult questions. Compared to traditional technological products, the ethical challenges of AI technologies seem to require more urgent attention due to their rapid growth and increasing capabilities.

2.3.1 AI Biases

As AI products have superior computing power and an autonomous nature, individual decision-making is increasingly being mediated by technology. Consumer decisions, such as applying for a loan, choosing insurance, or selecting a movie, are often influenced by AI through highlighted postings and recommendations. A common misconception is that the technology is more objective and less prone to biases than humans. However, bias has been shown to be a big weakness of AI, directly affecting the quality of AI-enabled products and user satisfaction (Du & Xie, 2021). As products and services enabled by AI are typically built on Machine Learning, they use large training data sets to develop algorithms (Torralba & Efros, 2011). Unbalanced and biased training data is a major driver of AI bias and stems from imbalances regarding variables such as race, gender, geography, education and income (Du & Xie, 2021). The use of biased training data could result in algorithmic biases in the AI systems being used in financial services, healthcare, law and other industries. These biases often reflect deep imbalances in institutional infrastructures (Zou & Schiebinger, 2018).

2.3.2 Privacy Concerns

Privacy involves the right to control information about oneself (DesJardins, 2014). When personal data is collected or used without a person's informed and voluntary consent, that right is violated. There are multiple ways in which privacy can be violated, like unauthorized information collection and use or improper information access by third parties (Malhotra et al., 2004). Two perspectives may be addressed regarding privacy concerns in relation to AI. Firstly, from a consumer perspective, it may be challenging to ensure that individuals keep control of their own data to prevent misuse and abuse by data owners. Secondly, from the perspective of data owners and brokers, the challenge could be to ensure compliance with data regulations, while preserving data utility.

The ethical challenges related to privacy arise due to AI technologies` heavy reliance on Big Data. The use of AI products or services increases the amount of personal information collected, accessed, and utilized by businesses (Kaplan & Haenlein, 2019). Substantial retention of behavioral, demographic, financial, socioeconomic, and other transactional data by companies, presents privacy issues in almost every field where Big Data is being utilized (Ali, et al., 2016). The high interactivity of AI-enabled products further increases the volume and variety of consumer data collected, utilized, and transmitted, triggering new challenges for consumer privacy protection (Du & Xie, 2021).

2.3.3 Cyber Security

Cyber security is closely related to privacy concerns, and over the past few years, there has been a rising number of data breaches in various sectors. Different companies, such as banks, social media companies, software developers and retailers have been victims of various attacks or had system failures. Some examples are the US federal reserve Bank, Facebook, Google, Adobe and Target (Udo et al., 2018). These types of breaches can expose confidential and sensitive personal information about consumers to people who may use the data for illegal purposes. The risk of cyber-crime and data breaches substantially increases as the scale of consumer data collected via AI-enabled products grows (Du & Xie, 2021). As a result, companies need to take proactive measures to protect their data. Despite companies' best efforts, data breaches may still happen. To deal with the issue, they may benefit from having a response strategy to minimize the damage and rebuild consumer trust (Du & Xie, 2021).

2.4 AI-powered Chatbots

AI-powered chatbots are interactive, virtual agents that serve as natural language user interfaces for data and service providers (Dale, 2016). They engage in human conversation through either auditory, textual, or mixed methods (Hatwar et al., 2016), and facilitate automated conversation through natural language processing (NLP) (Brandtzaeg & Følstad, 2017). While early chatbots were made functional based on simple keyword-matching techniques, modern chatbots rely on advanced AI to serve a wide range of purposes (Shah et al., 2016; Følstad & Brandtzæg, 2017). Chatbot technology is designed for two-way interactions with humans and for processing data to arrive at new conclusions or decisions, which aligns with the thinking and feeling types of AI described by Huang & Rust (2021).

One of the first chatbots, ELIZA, was an early attempt in trying to simulate human conversation. By using both a substitution approach and pattern matching, the creators from MIT Artificial Intelligence Laboratory, beguiled users with an illusion of the chatbots' understanding and reciprocity (Weizenbaum, 1966). ELIZA's success was surprising since the chatbot was incapable of understanding and could not converse on a deep, semantic level. Since then, there have been several creations of chatbots with the goal of fooling users into believing that they were real humans (Aamonth, 2014; Curry & O`Shea, 2012). However, recently the goal of building chatbot systems has shifted from trying to mimic a human conversation, to interacting with and impacting users in a variety of settings, including education, entertainment, retail, and the helping professions, such as physical, mental health, and behavioral change (Følstad & Brandtzæg, 2017; Kamphorst, 2017; Xu et al., 2021).

2.4.1 Consumer Usage

The use of chatbots among consumers has grown in popularity, as shown by Drift's (2021) AI report which revealed that 73% of consumers have interacted with a brand using a chatbot in the past year. While the majority of consumers use chatbots for customer service or shopping-related tasks, the range of interactions is expanding to include general problem-solving. According to a Ubisend report (2022), 58% of consumers have used chatbots for general problem solving and this number is expected to increase as the technology improves. Consumers are now also increasingly interested in obtaining content, resources, ideas and inspiration from chatbots.

Consumers' willingness to use chatbots is expanding to cover a wider range of interactions. While they were once typically used for small tasks such as making reservations or small purchases, they are now being used for more complex tasks like receiving medical or financial advice (CDP, 2022). The overall utilization of chatbots is increasing with younger consumers being the fastest adopters. According to a recent report from LivePerson (2023), 83% of consumers aged 18 to 24 prefer to interact with a chatbot rather than a human to discover a product.

2.4.2 Consumer Expectations

As chatbots are gaining popularity, consumers' expectations are increasing, potentially creating a gap between consumers' preferences and what businesses can deliver. In a survey by CDP (2022), 34% of consumers globally rated their overall perception of chatbots as positive. The remaining 66%, expressed that they were "okay" to use but need improvement, or dislike them altogether.

Consumers are demanding round-the-clock assistance in areas ranging from health and wellness to banking and finance. They have expressed that the time it takes to receive an answer is now more important than it was a year ago (CDP, 2022), and when interacting with chatbots, the most important factors for consumers are its problem-solving capabilities and quick response times (Drift, 2021). Further, consumers expect chatbots to understand natural language and provide personalized responses when answering complex questions or giving recommendations (CDP, 2022). The importance of anthropomorphism is a topic that has yielded conflicting findings. Some find it more natural to talk to a human-like chatbot, but the demand for urgency and accuracy often trumps this wish (Ubisend, 2022).

2.4.3 Consumer Barriers

Although chatbot adoption is on the rise, there are still barriers that prevent consumers from using them. A dominating factor is poor user experiences, which implies that they are difficult to use or that they do not provide helpful responses to their inquiries (LivePerson, 2023). Consumers also have privacy concerns regarding how AI technology uses their data for recommendations, customer service and support. Trust may be an important factor in making the consumer feel safe about their data sharing as they want their information to be utilized in a responsible manner when companies are creating personalized experiences (CDP, 2022). Trust in chatbot performance is particularly important in sensitive fields such as healthcare or finance, where mistakes may lead to physical, financial, or psychological harm (Bickmore & Cassell, 2001).

2.4.4 Advantages

The emergence of chatbots has the potential to benefit both businesses and consumers. Winkler & Söllner (2018) summarizes four main advantages from various fields. Firstly, chatbots can reduce the costs associated with customer service by replacing personal assistants. Secondly, they can increase user satisfaction by providing real-time interactions twenty-four hours a day. Thirdly, chatbots can predict customer questions, and thus provide users with useful information proactively. Finally, conversations can be automatically recorded and analyzed, allowing for sophisticated analysis that can better tailor products and services to individual needs.

The rapid technological development and increasing utilization of AI-powered chatbots displayed in this chapter, indicate the importance of understanding the adoption of the technology. It is found that chatbots can bring advantages for both consumers and businesses and by gaining insight into user preferences, it will be easier to increase the satisfaction of consumers. At the same time, businesses may also use this insight to improve their utilization of chatbots.

Chapter 3: Theoretical Framework

3.1 Literature Review

To gain a broader understanding of our research topic, we first explored various literature sources, such as articles and reports focusing on AI adoption and AI-powered chatbots. Additionally, we conducted a literature review (Appendix A) specifically on the topic of AI and chatbot adoption. This review served two purposes: firstly, to confirm the influence of existing adoption models, and secondly to explore new constructs that have not been extensively studied or included in existing models. By taking this approach, we aimed to expand our knowledge and uncover insights that can contribute to the understanding of AI and chatbot adoption.

The articles in our literature review were found using the Google Scholar search engine, with the searches being completed in January and February of 2023. We used the words "AI adoption", "Chatbot adoption" and "Chatbot Acceptance" in our search and narrowed it down by demanding the presence of both words in the title of the articles. We then chose to remove the filters "include patents" and "include citations". This left us with 283 articles on "AI adoption", 28 articles on "chatbot adoption", and 29 articles on "chatbot acceptance". From there, we only included the articles which studied the technology adoption from a consumer perspective. Due to limited research with this perspective and some limitations regarding accessibility, we were left with only 8 suitable articles on "AI adoption", 5 articles on "chatbot adoption" and 3 articles on "chatbot acceptance". All articles were published after 2019, with the majority published in 2022, indicating a growing interest in this research topic.

3.2 Theoretical Models and Hypothesis Development

In their extensive literature review of 330 articles on technology adoption, Rad et al. (2018) found that a variety of dependent variables are applied when researchers measure the adoption of technologies (Rad et al., 2018). They discovered that the most frequent dependent variables were "Intention to Use" (58,8%), "Adoption" (16.1%), "Continuance of Use" (7%). And "Actual System Use" (2.1%). Considering the literature review by Rad et al. (2018) alongside our own research and literature review regarding AI adoption, it seems common to refer to "Intention of Use" as the actual usage. Based on this, we will henceforth refer to the actual use of the technology as Intention to Use. Furthermore, Rad et al. (2018) discovered that TAM was the most frequently used technology adoption model, followed by DOI, UTAUT and TPB, which were also commonly observed in our literature review (Appendix A). Consequently, we apply these models to explain some of the factors that drive chatbot adoption. We have noted that the article by Rad et al. (2018) reviews papers from 2006-2015, making it somewhat antiquated in this fast-moving research field. However, by combining our own literature review (Appendix A) with existing research, we have confidence that these models collectively provide a comprehensive understanding of technology adoption.

Throughout the chapter, the four technology adoption models (TPB, TAM, UTAUT2 and DOI) and our Model Extensions are sequentially presented. When introducing each traditional technology adoption model, we start by explaining their background and logic, as well as presenting the model's variables and how they influence each other. Under each model, there are several constructs that will be defined and clarified. These constructs are further explored in an AI- and chatbot-related setting which is followed by examples from previous studies to illustrate its influence on adoption. Based on this, we develop our own hypotheses regarding the effect of each construct on chatbot technology adoption.

3.2.1 TPB - Theory of Planned Behavior

The Theory of Planned Behavior is a traditional model developed by Ajzen (1985), that aims to explain technology adoption. The model is rooted in the Theory of Reasoned Action (TRA) and accounts for conditions where individuals do not have complete control over their own behavior. This is claimed to be a major cause for the link between Intention and behavior. The TPB is based in social psychology and aims to both understand and predict behavior. There is an abundance of literature regarding the use of TPB, and a meta-analysis of the models' use in a wide variety of domains confirms its efficacy in predicting behavior and intention (Notani, 1998). Many research papers have examined TPB, making it one of the most applied theories in social and behavioral sciences (Rad et al., 2018). There is an ongoing interest in using TPB to explain and predict behavior in several domains (Bosnjak et al., 2020). In contrast to other adoption models, TPB does not assume that beliefs that apply in one context, also apply in other contexts (Mathieson, 1991).

The Theory of Planned Behavior consists of three constructs: Attitude, Subjective Norm, and Perceived Behavioral Control (hereby often referred to as Behavioral Control). Both Attitude and Subjective Norm are typically modeled to influence Behavioral Intention, and thereby actual behavior. Although this also applies to Behavioral Control, it may be modeled to influence actual behavior directly (Ajzen, 2020). The greater control individuals think they have over their behavior, the stronger their intention is to perform it, which may explain the influence on Behavioral Intention. Furthermore, Behavioral Control may also affect individuals' behavior directly, since they will try harder and longer to succeed if they feel like they have a high level of control (Brookes, 2021).

Attitude

Attitude can be explained as individuals' thoughts toward performing an action (Ajzen, 1985). Attitude can also be used as an indicator of how much effort a user is willing to put into performing a certain task, or finding the degree to which an individual has a favorable or unfavorable evaluation of performing a specific task (Ajzen and Fishbein, 1980; Ajzen, 1991). The TPB includes Attitude as a positive predictor of Behavioral Intention.

According to Fishbein and Ajzen (1975), Attitude may exert a positive impact on an individual's behavior, as people tend to behave in ways that align with their attitudes. Therefore, if a consumer has a positive Attitude toward chatbots, they are more likely to adopt. Rad et al. (2018) conducted a literature review on technology adoption and found that Attitude was the third most frequently used independent variable for explaining adoption. Weigel et al. (2014) found in their meta-analysis of 58 articles on innovation and consumer adoption, that Attitude generally had a strong, positive effect on adoption.

Attitude has been found to have a significant impact on the Intention to Use in recent studies, such as AI-driven digital news platforms (Lim & Zhang, 2022), service robots (Park et al., 2021), and AI fitness services (Chin et al., 2022). Furthermore, Brachten et al. (2021) conducted a study on the acceptance of chatbots in an enterprise context and found that Attitude had the strongest positive effect on Intention to Use. De Cosmo et al. (2021) found in their study on mobile advertising and chatbots that the intent to purchase was positively influenced by a positive Attitude toward chatbots. In their study on Mobile network chatbots, Poonpanich and Buranasiri (2022) identified a positive influence on Behavioral Intention. Similarly, Huang and Lee (2022) examined the continuous Intention to Use Fintech chatbots and established a significant positive effect of Attitude. Considering these studies and previous descriptions of

Attitude in the technology adoption field, we hypothesize that Attitude positively influences consumers' Intention to Use chatbots.

H1: *Attitude has a positive influence on Intention to Use chatbots.*

Subjective Norm

Subjective Norm can be explained as a person's perceptions and the perceived social pressure to perform or not perform an action (Ajzen, 1985). Fishbein & Ajzen (1975) explain it as a person's perception that the majority of those close to him think he should or should not perform a specific behavior. The impact of Subjective Norm, which functions as guiding boundaries for users in making decisions, varies depending on the specific technology and setting in which they are employed (Pookulangara et al., 2011).

Subjective Norm reflects individuals' perception of the environment and is believed to play a prominent role in decision-making processes (Morris & Venkatesh, 2000). It is believed that an individual's likelihood to adopt a technology may increase if the people he associates with are also using it and if it is socially acceptable. Even if an individual initially lacks a positive Intention to Use a new technology, this is likely to change as they often seek to comply with others (Morris & Venkatesh, 2000). Research has found Subjective Norm to have a positive influence on Intention to Use (Ajzen, 2015; Farah, 2017). A meta-analysis by Weigel et al. (2014) shows that Subjective Norm has a strong positive effect on adoption.

According to an AI study conducted by Kaye et al. (2020) on automated cars, Subjective Norm has a significant impact on behavioral intention. Similarly, Subjective Norm was found to be an important factor in the formation of behavioral intentions in both a study on robotic restaurants (Choe et al., 2022) and a study on AI in medical school (Li et al., 2022). In the case of AI-powered chatbots in an enterprise context, Brachten et al. (2021) found a significant positive effect on the Intention to Use. Based on these findings, we hypothesize a positive influence of Subjective Norm on the Intention to Use chatbots.

H2: *Subjective Norm has a positive influence on Intention to Use chatbots.*

Perceived Behavioral Control

Perceived Behavior Control is connected to a person's ability to execute a specific behavior and can be described as behaviors over which people have incomplete volitional control (Ajzen, 1991). The concept, as described by Taylor & Todd (1995), contains both external and internal factors that may limit someone's control over performing a behavior. This applies regardless of whether they are constraints that prevent certain actions or conditions that enable them.

The adoption of new technology is affected by the ability in which consumers think they are able to use it. This ability is determined by both internal and external factors that shape the consumers' perception of the availability or lack of resources required to complete the behavior (Ajzen, 1991). Mathieson (1991) discovered a significant relationship between Perceived Behavioral Control and the Intention to Use. Both the meta-analysis from Notani (1998) and Weigel et al (2014) identified Perceived Behavioral Control as a strong predictor of Behavioral Intention.

Behavioral Control has been shown to influence Behavioral Intention in recent AI studies. This applies to the context of robotic restaurants (Choe et al., 2022) and highly automated cars (Kaye et al., 2020). In the context of chatbots in enterprises, a study by Brachten et al. (2021) shows that Perceived Behavioral Control has a positive influence on Intention to Use. Based on these previous findings, we wish to investigate the relationship between Perceived Behavioral Control and Intention to Use, and we hypothesize a positive influence on Intention to Use chatbots.

H3: *Perceived Behavioral Control has a positive influence on Intention to Use chatbots.*

3.2.2 TAM – Technology Acceptance Model

TAM is according to Rad et al. (2018) the most used model to understand the acceptance of new technologies. The model is based on the principles of TRA, which is rooted in behavioral psychology (Fishbein & Ajzen, 1975), and is considered one of the most influential theories of human behavior (Venkatesh et al., 2003). TAM was initially developed to explain the adoption behavior of computer information technology in the workplace. It aimed to explain the determinants of acceptance in using IT and simplified the understanding of how interface characteristics and functionality relates to adoption (Davis et al., 1989). TAM has now become a widely recognized and influential theory in explaining individuals' acceptance of new technology and the meta-analysis conducted by King and He (2006) indicates that it is a powerful and robust predictive model. The model includes five elements: Perceived Ease of Use, Perceived Usefulness, Attitude towards Use, Intention to Use and Actual Use.

The model suggests that the two variables, Perceived Usefulness and Perceived Ease of Use (hereby often referred to as Usefulness and Ease of Use), influence the attitude towards the use of new technology. It also shows that a person's Attitude is the main determinant of Intention to Use, which ultimately leads to Actual Use. Usefulness is modeled to have a direct influence on the Intention to Use. In the original model, Ease of Use was thought to be fully mediated by Usefulness and Attitude (Davis, et al., 1989). However, later studies found that Ease of Use also has a direct influence on Intention to Use (Venkatesh & Davis, 1996).

Perceived Ease of Use

Perceived Ease of Use is a fundamental determinant in technology studies and Davis (1989) defines it as "*the degree to which a person believes that using a particular system would be free of effort"* (p.320). According to Mathieson (1991), Ease of Use can also be thought of as covering the match between the consumers' abilities and the skills required to make use of the technology.

Extensive research indicates that consumers have predefined assumptions considering how easy or difficult it will be to use a technology (Davis, 1989; Jan & Contreras, 2011). If a technology is perceived to be easy to use, consumers are more likely to use it. In their comprehensive literature review on technology adoption, Rad et al. (2018) found that Perceived Ease of Use was the most used independent variable in technology adoption literature. Furthermore, a meta-analysis by King & He (2016) identified the construct to be a strong predictor of technology adoption. Additionally, a meta-analysis on the acceptance of self-serving technology emphasized the importance of Ease of Use in explaining adoption (Blut et al., 2016).

In the context of chatbots, there are various factors that can alter a consumer's perception of it being easy to use. Systems that require plug-in installations, have complex settings, or a chaotic interface design, can all create barriers for the user (Müller et al., 2019). Müller et al. (2019) identified in their study on chatbot acceptance that the level of naturalness in the interaction with chatbots serves as a mediating variable for their acceptance. This suggests that a clear, simple, understandable and easy-to-learn chatbot could have a positive impact on users' Intention to Use it. Through the literature review, we found that Ease of Use has had a significant positive effect on AI-powered service agents (Ashfaq et al., 2020) and chatbots for hospitality and tourism (Pillai & Sivathanu, 2020). Ease of Use was further shown to affect the behavioral intention of banking chatbots (Richad et al., 2019) and was important in explaining baby boomers' acceptance of AI chatbot technology (Poonpanich & Buranasiri, 2022). Based on these findings, we propose the hypothesis:

H4: *Perceived Ease of Use has a positive influence on Intention to Use chatbots.*

Perceived Usefulness

Davis (1989) defines Perceived Usefulness as "*the degree to which a person believes that using a particular system would enhance his or her job performance*" (p.320). The Usefulness of a technology is proposed to positively influence intention through reasons of rewards or goal achievements (Davis et al., 1989).

The link between Usefulness and intention has been consistently demonstrated in the innovation adoption literature (Nysveen et al., 2005; Venkatesh & Davis, 2000). Usefulness reflects users' beliefs that there is a positive relationship between the use of a system and its performance, indicating that the more useful the technology is perceived to be, the more likely it is to be used (Davis, 1989). According to Rad et al. (2018), Perceived Usefulness is identified as the second most used independent variable in technology adoption studies. The meta-analysis by King & He (2016) also found Perceived Usefulness to be a robust predictor of technology adoption.

Problem-solving abilities of chatbots can determine the user's willingness to interact with them (Wuenderlich, 2017) and if the characteristics of a system can adequately support the user to accomplish a goal or task, it will be used more excessively (Pu et al., 2012). Several studies on chatbot adoption have shown that Usefulness significantly affects the Intention to Use and in two separate studies on banking chatbots, Usefulness was identified as an important driver of adoption (Alt et al., 2021; Richad et al., 2019). Similarly, it was found to be significant in the adoption of AI-powered teaching bots (Pillai et al., 2023), service robots (Park et al., 2021), and chatbots for hospitality and tourism (Pillai et al., 2020). Based on these findings, we predict a positive influence on the Intention to Use chatbots.

H5: *Usefulness has a positive influence on Intention to Use chatbots.*

3.2.3 UTAUT2 – Unified Theory of Acceptance and Use of Technology 2

The Unified Theory of Acceptance and Use of Technology (UTAUT) examines the adoption and acceptance of technology. It was developed by Venkatesh et al. (2003) through a comprehensive review of existing literature on user acceptance of technology. The review examines eight separate prior models which are compared and tested to provide a unified view of user acceptance of technology. UTAUT is distinguished from other technology adoption models, which may have limitations, as they explain behavior related to specific types of technology. Contrastingly, UTAUT is a comprehensive model that aims to provide a more generalized view of technology acceptance (Venkatesh et al., 2003).

The model integrates elements from different models and contains four main constructs: Performance Expectancy, Effort Expectancy, Facilitating Conditions, and Social Influence. These constructs are hypothesized to determine behavioral intention, which leads to behavior. Additionally, the model includes several moderating effects, such as gender, age, experience, and voluntariness of use, which influence the main constructs' effects on behavioral intention and perceived usefulness (Venkatesh et al., 2003). Although originally developed to explain technology adoption in organizational settings, UTAUT has been applied in various settings and has become a basis for research in technology acceptance (Dwivedi et al., 2011).

Following its increased utilization, the model faced criticism for its limited ability to predict consumer Intention to Use new technology in terms of performance expectancy measures, and the need to supplement it with hedonic performance expectancy was highlighted by researchers (Yang, 2010). In response, the authors developed UTAUT2, which included three additional constructs: Hedonic Motivation, Price Value, and Habit. The extensions made in UTAUT2 resulted in an improvement in the variance explained in behavioral intention and technology use (Venkatesh et al., 2012). Altogether there are seven main constructs in the UTAUT2: Performance Expectancy, Effort Expectancy, Facilitating Conditions, Social Influence, Hedonic Motivation, Price Value and Habit.

All factors in UTAUT2 are generally modeled to influence Behavioral Intention, except for Facilitating Conditions and Habit. In an organizational setting, many aspects of Facilitating Conditions will be freely available which is why it was originally modeled to directly influence use. However, in a consumer setting, the facilitation in the environment that is available to each consumer can vary significantly and be modeled as in the TPB, meaning it influences both behavioral intention and technology use directly (Ajzen, 1991; Venkatesh et al., 2012). Habit is also hypothesized to have both a direct and indirect effect on Actual Use through Intention. However, both paths depend on the extent to which people rely on routinized behavior when accepting technology (Venkatesh et al., 2012).

Performance Expectancy

Performance Expectancy can be defined as the degree to which a person believes that the usage of the system will help enhance the performance. The concept relates to Perceived Usefulness from TAM and Relative Advantage from DOI (Venkatesh et al., 2003).

Performance Expectancy was proven by Venkatesh et al. (2003) to be a strong predictor of behavioral intention and has been shown to have a significant influence on technology adoption. A study by Sun & Zhang (2006), confirms that the most important factor influencing technology acceptance is Performance Expectancy. In a meta-analysis of UTAUT by Dwivedi et al. (2011), which examines whether the theory performs consistently across various technology studies, Performance Expectancy displays the greatest number of significant relations with Behavioral Intention.

Gursoy et al. (2019) found a significant relationship between AI technology adoption and Performance Expectancy. Similarly, Kuberkar & Singhal (2020) found that Performance Expectancy directly affects the adoption of chatbots for public transport services, while Laumer et al. (2019) observed the same effect in the adoption of conversational chatbots for disease diagnosis. Furthermore, it was explained as a direct determinant of Intention to Use both coaching chatbots (Terblache & Kidd), and environmental information chatbots (Rukhiran et al., 2022). Given the consistent findings on the importance of Performance Expectancy, we hypothesize that it positively influences Intention to Use chatbots.

H6: *Performance Expectancy has a positive influence on Intention to Use chatbots.*

Effort Expectancy

Effort Expectancy can be defined as the degree of ease associated with the use of a technology. The construct shares characteristics with Perceived Ease of Use from TAM (Venkatesh et al., 2003), and it also appears to be related to Complexity (DOI) as they both reflect the user's perception of the ease or difficulty of using technology.

Effort Expectancy captures the effort of performing a task and can explain the adoption intention of a technology based on the notion that users normally dislike complex or difficult solutions. Effort Expectancy has been found to have a significant effect in several studies (Venkatesh et al., 2012), like in a study by Zhou et al., (2010) on mobile banking adoption, where it was found as a predictor of user intention. Dwivedi et al. (2011), also found the construct of Effort Expectancy to be a significant determinant of adoption in their meta-analysis.

Meyer-Waarden & Cloerec (2022) found a positive relationship between the Behavioral Intention to use AI-powered autonomous vehicles and Effort Expectancy. However, studies on Effort Expectancy in chatbot adoption studies have yielded various results. While one study on chatbots in tourism found an insignificant relationship between Effort Expectancy and Intention to Use (Melián-González et al., 2021), another study on chatbots in higher education found a significant effect (Almahri et al., 2020). However, positive effects seem most common as they were observed in studies on environmental chatbots (Rukhiran et al., 2022), coaching chatbots (Terblanche & Kidd, 2022), chatbots for public transport services (Kuberkar & Singhal, 2020), and conversational chatbots (Laumer et al., 2019). Examining the overall effects, we propose that Effort Expectancy has a positive influence on Intention to Use chatbots.

H7: *Effort Expectancy has a positive influence on Intention to Use chatbots.*

Social Influence

Social Influence, which is represented as Subjective Norm in TPB, refers to the extent to which a person perceives that other important individuals believe they should adopt a new technology. Despite having different labels, both constructs contain the notion that individuals' behavior is influenced by the way others view them (Venkatesh et al., 2003).

Social Influence has been found as significant regarding consumers' Intention to Use in studies on information technology innovations (Moore & Benbasat, 1991) and personal computing (Thompson et al., 1991). In their UTAUT meta-analysis, Dwivedi et al. (2011) found that social influence demonstrates the second highest number of significant relations with behavioral intention.

A study on chatbots in tourism found a significant relationship between Social Influence and Intention to Use (Melián-González et al., 2021), while the study on chatbots in higher education did not (Almahri et al., 2020). Furthermore, studies on environmental chatbots (Rukhiran et al., 2022), coaching chatbots (Terblanche & Kidd, 2022), chatbots for public transport services (Kuberkar & Singhal, 2020), and conversational chatbots (Laumer et al., 2019) have all reported positive effects on adoption regarding Social Influence. As most studies that have been examined have reported a positive influence, we propose the hypothesis:

H8: *Social Influence has a positive influence on Intention to Use chatbots.*

Facilitating Conditions

Facilitating Conditions can be defined as the degree to which an individual believes that the organizational and technical infrastructure exists to support the use of the system (Chang, 2012). This definition also captures the concept of Perceived Behavioral Control from TPB, and the variables are both operationalized to include aspects of the technological and organizational environment that remove consumers' barriers to use (Venkatesh et al., 2003).

Previous studies in the field of technology adoption have indicated that the construct of Facilitating Conditions has been found to have a positive impact on adoption. Specifically, the studies conducted by Foon and Fah (2011) on internet banking adoption and Madigan et al. (2016) on acceptance of automated road transport systems demonstrated a positive relationship between Facilitating Conditions and Behavioral Intention. Furthermore, the UTAUT meta-analysis conducted by Dwivedi et al. (2011) also supports the significant relationship between Facilitating Conditions and Intention to Use.

Several studies on different types of chatbots, including environmental chatbots (Rukhiran et al., 2022), coaching chatbots (Terblanche & Kidd, 2022), chatbots for public transport services (Kuberkar & Singhal, 2020), and conversational chatbots (Laumer et al., 2019) have shown that Facilitating Conditions have a positive effect on adoption. Given these findings, we hypothesize that Facilitating Conditions has a positive influence on Intention to Use chatbots.

H9: *Facilitating Conditions has a positive influence on Intention to Use chatbots.*

Hedonic Motivation

Hedonic Motivation refers to the fun or pleasure derived from using a technology and it has been shown to play a vital role in determining technology acceptance and use (Venkatesh et al., 2012). It seems that studies use Perceived Enjoyment as a close alternative to Hedonic motivation which according to Nysveen et al. (2005) refers to the pleasure and inherent satisfaction derived from a specific activity.

Hedonic Motivation was included in UTAUT2 to enhance its consumer focus and is a significant predictor of consumers' technology usage intentions (Venkatesh et al., 2012). Hedonic Motivation is clearly associated with technologies like video games (Xu, 2014) or social media (Herrero et al., 2017) which relates to enjoyment. However, Hedonic Motivation has been found relevant in studies that do not have a clear connection to pleasure or fun. A study by Nysveen et al. (2005) shows a relatively strong impact of perceived enjoyment, on intention to use mobile services. Melián-González et al. (2021) suggested that a hedonic perspective should be considered in the adoption of chatbots in the travel and tourism industry, and Morosan and DeFranco (2016) found Hedonic Motivation to have some effect on the adoption of NFC mobile payments.

While there are limited studies that have demonstrated a direct link between Hedonic Motivation and Intention to Use chatbots, research on other technologies has shown that Hedonic Motivation can have a positive effect on Intention to Use. Therefore, we find it reasonable to hypothesize that Hedonic Motivation has a positive influence on Intention to Use chatbots.

H10: *Hedonic Motivation has a positive influence on Intention to Use chatbots.*

Habit

Habit refers to the extent to which people tend to perform behaviors automatically because of learning. It can be described as a perceptual construct that reflects the results of prior experiences (Venkatesh et al., 2012). Habits reflect prior experiences (Ajzen & Fishbein, 2005), and can be measured as the extent to which an individual believes the behavior to be automatic (Venkatesh et al., 2012).

According to Ajzen and Fishbein (2005), Habit is hypothesized to have both a direct and indirect effect on actual use through intention. The stronger an individual's Habit of using a technology, the greater the likelihood of their Intention to Use it again. Only after a relatively long period of extensive practice can a Habit be stored in our long-term memory and override existing behavior patterns (Lustig et al. 2004). Kim et al. (2005) found that Habit and prior technology use strongly predict future technology use. However, the effect of Habit may vary depending on the consumer's sensitivity to change (Verplanken & Wood, 2006). In a stable context, Habit may lead to routinized behavior that is performed automatically with minimal conscious control (Ajzen, 2002). In today's rapidly changing consumer technology market, consumers may be more sensitive to change, and the impact of established Habits on their behavior may vary (Venkatesh et al., 2012).

Rahim et al. (2022) investigated the adoption of customer service chatbots for students in higher education and discovered that Malaysian students' use of chatbots was significantly determined by Habit. This implies that frequent use increases the likelihood of students using chatbots in the given context. In a similar study conducted in the United Kingdom, Almahri et al. (2020) identified Habit as one of the main predictors of students' behavioral Intention to Use chatbots. Additionally, Laumer et al. (2019) confirmed the relevance of Habit in explaining the adoption of conversational chatbots. Given the consistent findings across several studies, we predict that Habit will have a positive influence on Intention to Use chatbots.

H11: *Habit has a positive influence on Intention to Use chatbots.*

Price Value

Price Value can be defined as "*consumers' cognitive tradeoff between the perceived benefits of the applications and the monetary cost for using them*" (Venkatesh et al. 2012, p. 161).

Research by Venkatesh et al. (2012) shows that Price Value is a predictor of Intention to Use a technology. They further found that the likelihood of consumers' technology adoption is greater when the perceived value of benefits derived from using the technology outweighs the monetary costs associated with acquiring it (Venkatesh et al., 2012). A literature review by Tamilmani et al. (2018) revealed that 47 out of 79 UTAUT2 empirical studies failed to operationalize the concept of Price Value. It is important to note that most of the studies focused on technologies that did not require monetary costs from users.

The literature review (Appendix A) revealed that Laumer et al. (2019) were the only researchers who investigated the influence of Price Value on chatbot adoption. Their study revealed that Price Value had no significant effect on chatbot acceptance in healthcare. Because the chatbot studies included in our literature review are typically free, they exclude Price Value as a factor. Despite limited evidence regarding the specific impact of Price Value on chatbot adoption, it has been included due to UTAUT2 being a recognized model for explaining technology adoption.

H12: *Price Value has a positive influence on Intention to Use chatbots.*

3.2.4 DOI – Diffusion of Innovations

Rogers' diffusion of innovation theory aims to explain how innovations spread over time through a social system between actors. Consumers' probability of adopting an innovation is affected by their communication and influence on each other. Individual members of a system or entire social systems can adopt or reject innovations through collective or authority decisions (Rogers, 1983). Five characteristics have been identified in innovation research that are linked to diffusion: Relative Advantage, Compatibility, Complexity, Trialability, and Observability.

All constructs have a direct influence on Intention. The theory hypothesizes that adoption increases if Relative Advantage, Compatibility, Trialability and Observability increase. However, Complexity has been shown to have a negative influence on adoption (Lundblad, 2003). Despite the importance of DOI in technology adoption, our research found very few studies that directly connected the framework to AI and AI-powered chatbots. This may be due to the substitution of constructs from other technology adoption models, which are similar.

Relative Advantage

Relative Advantage is defined as "*the degree to which an innovation is perceived as being better than the idea it supersedes*" (Rogers, 1983, p.213).

If an innovation has a clear, unambiguous advantage in either effectiveness or cost-effectiveness it may be more easily adopted and implemented by consumers (Greenhalgh et al., 2004). With the goal of developing an updated meta-analysis, based on Tornatzky and Klein's meta-analysis from 1982, Weigel et al (2014) studied fifty-eight articles on innovation and consumer adoption. Both these meta-analyses found that all studies that examined the effect of the construct indicated a positive relationship between Relative Advantage and adoption. In addition, Agarwal and Prasad's (1998) research on the relationship between Relative Advantage and personal innovativeness in the IT domain claims that Relative Advantage is very important to user acceptance.

Zhu and Sun (2012) found that Relative Advantage had the strongest influence on Intention among several variables in their study on AI adoption in healthcare. Although we have not discovered substantial evidence of Relative Advantage influencing chatbot adoption in other studies due to the lack of DOI application, we found it to influence adoption in the beforementioned studies. Thus, we propose that it will have a positive influence on Intention to Use.

H13: *Relative Advantage has a positive influence on Intention to Use chatbots.*

Compatibility

Compatibility is defined as "*the degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters*" (Rogers, 1983, p.223).

Greenhalgh et al. (2004) propose that innovations that are compatible with the values, norms, and perceived needs of intended adopters are more likely to be adopted. Agarwal & Prasad (1998) suggest that individuals are more likely to adopt IT innovations that are perceived to be compatible with their existing values, experiences, and needs. Their study also revealed that perceptions of compatibility were the most important predictor of current usage. In addition, meta-analyses by both Weigel et al. (2014) and Tornatzky & Klein (1982) found that Compatibility consistently provided significant positive associations with innovation adoption.

In our literature review we did not find any evidence that suggests that Compatibility has a positive influence on Intention to Use chatbots. However, we have discovered studies indicating that compatibility has a positive effect on the intention to use other technologies. Therefore, we hypothesize that Compatibility has a positive influence on the Intention to Use chatbots.

H14: *Compatibility has a positive influence on Intention to Use chatbots.*

Complexity

Complexity is defined as "*the degree to which an innovation is perceived as relatively difficult to understand and use"* (Rogers, 1983, p. 223). In contrast to the other characteristics, Complexity negatively correlates with the rate of adoption. Complexity parallels "Perceived Ease of Use" from TAM quite closely (Davis, 1989), meaning they have very similar characteristics.

Complexity builds on the assumption that innovations which are perceived by consumers as simple to use are more easily adopted (Greenhalgh et al., 2004), which implies that innovations that are perceived as complex to use are less easily adopted. Both Weigel et al. (2014) and Tornatzky & Klein (1982) found complexity to be a significant construct. Research confirms that Complexity is a significant negative predictor of adoption (Venkatesh et al., 2003; Agarwal & Prasad, 1998).

Despite the lack of evidence on the influence of Complexity on chatbot adoption, the construct has been shown to have a significant impact on the adoption of innovations in general. Therefore, we hypothesize that Complexity has a negative influence on the Intention to Use chatbots.

H15: *Complexity has a negative influence on Intention to Use chatbots.*

Trialability

Trialability is defined as "*the degree to which an innovation may be experimented with on a limited basis*" (Rogers, 1983, p.231).

Trialability as a construct predicts that the more a consumer can experiment with the innovation on a limited basis, the more easily they are adopted and assimilated (Greenhalgh et al., 2004). Agarwal & Prasad (1989) also suggest that adopters are more likely to use and be motivated to adopt new technology during early stages if they feel they can experiment and explore it personally. In their meta-analysis, Weigel et al. (2014) found that Trialability is positively related to adoption.

As with the previous drivers of DOI, there is a lack of research specifically examining the relationship between Trialability and chatbot adoption, but previous technology studies have shown that trialability has a positive impact on the adoption. Therefore, we hypothesize that Trialability has a positive effect on Intention to Use chatbots.

H16: *Trialability has a positive influence on Intention to Use chatbots.*

Observability

Observability is defined as "*the degree to which the results of an innovation are visible to others*" (Rogers, 1983, p. 232). To better understand the characteristics of Observability, it can be separated into Result Demonstrability and Visibility. Result Demonstrability refers to the tangibility of the results of using an innovation, and Visibility is the extent to which potential adopters see the innovation as being visible in the adoption context (Moore & Benbasat, 1991).

The logic behind Observability is that the technology will be more easily adopted if the benefits of the innovation are visible to the consumer (Greenhalgh et al., 2004) and that being highly observable will increase the spread of the innovation (Rogers, 1983). The meta-analysis by Weigel et al. (2014) discovered that observability has a positive influence on adoption.

Although the specific influence of Observability on chatbot adoption has limited evidence, it has been included in the model due to its recognized significance and strength in explaining the adoption of innovations. We hypothesize that Observability has a positive influence on Intention to Use chatbots.

H17: *Observability has a positive influence on Intention to Use Chatbots.*

3.2.5 Model Extensions

From our literature review (Appendix A), we have gathered the most frequent and interesting constructs on consumer adoption of AI-powered chatbots. Anthropomorphism, Trust, Privacy Risk and Personalization have all emerged as antecedents complementing the constructs included in the traditional adoption models in the studies on consumer adoption of AI and chatbots. Hence, we find it interesting to test these chatbot-specific antecedents.

Anthropomorphism

According to Bartneck et al. (2009), Anthropomorphism refers to *"the attribution of a human form, human characteristics, or human behavior to nonhuman things such as robots, computers, and animals"*. Although there is some inconsistency in the conceptualization of Anthropomorphism in the literature, most agree that it is "the tendency" to attribute human characteristics to nonhumans (Li & Suh, 2021). According to Waytz et al. (2014), the process of Anthropomorphizing goes far beyond just attributing superficial human characteristics, but mainly an essential one: a humanlike mind.

Studies have confirmed the importance of Anthropomorphism in AI, particularly in its ability to influence users' perceptions and intentions in conversations between humans and chatbots (Castelo et al., 2019; Sheehan et al., 2020). However, due to a lack of agreement among researchers on how to conceptualize and operationalize Anthropomorphism in AI-enabled technology, Li & Suh (2021) conducted a literature review on the topic. They found that many researchers argue that the humanlike characteristics of AI-enabled technology are unique technological features that can influence consumers' adoption, perception and continued use of this technology. Out of the 35 relevant papers they found that 80% were published between 2019 and 2020, indicating that it is a growing research topic (Li & Suh, 2021).

Cheng et al. (2022) discovered that several anthropomorphic qualities in chatbots have a positive impact on consumers' perceived trust in chatbots. Waytz et al. (2014) claim that because of the attribution of competence, anthropomorphized technology is trusted more than mindless technology, resulting in a significant increase in trust and cooperation performance. It was further found by Kuberkar & Singhal (2020) that Anthropomorphism is important to the adoption of chatbot systems for public transport commuters. Moreover, studies on customer service chatbots (Sheehan et al., 2020), chatbots and mind perception (Lee et al., 2020), and chatbots in travel and tourism (Melián-González et al., 2021) have also found that Anthropomorphism has a positive impact on adoption. Based on the previous findings, we hypothesize that Anthropomorphism will have a positive influence on Intention to Use chatbots.

H18*: Anthropomorphism has a positive influence on Intention to Use chatbots.*

Trust

Trust has been the subject of extensive research across a variety of disciplines, from psychology and sociology to technology studies (Corritore et al., 2003). Hence, the definition of Trust varies. Mayer et al. (1995) suggest the definition: «*The willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other part»* (p.712). The concept is continuously being applied to newer situations and problems as technology rapidly evolves. In the area of AI, Madsen and Gregor (2000) proposed the definition of Trust as "*The extent to which a user is confident in, and willing to act on the basis of the recommendations, actions, and decisions of an artificially intelligent decision aid*" (p.1).

It has been demonstrated that Trust can be validly attributed to human relationships with complex technologies such as Machine Learning based trackers (Taddeo, 2010). McKnight et al. (2011) explain how Trust in information technology plays a role in shaping IT-related beliefs and behavior, as users with positive trusting views are more likely to assume that the technology has positive and desirable attributes. As autonomous technologies gain traction, research is addressing Trust in technology at an accelerating pace. Trust has been extensively studied in the context of human-robot interaction (Hancock et al., 2011) and automated systems (Jian et al., 2000). Furthermore, research has examined its implication in the context of technology adoption in e-commerce (Pavlou, 2003) and e-services (Gefen & Straub, 2003). A meta-analysis on mobile banking acceptance research found that initial Trust was one of the best predictors of the Intention to Use (Baptista & Oliveira, 2016).

Trust may be considered during the implementation of chatbots for several reasons. In environments such as healthcare, financial care and other fields demanding sensitive data, users may be exposed to financial, physical, or psychological harm (Bickmore & Cassell, 2001). The humanlike qualities of chatbots, such as their natural language abilities, may make Trust particularly important (Holtgraves et al., 2007). Recent studies on chatbots have found a significant positive relationship between Trust and Intention to Use. In their study on AI-powered chatbots for hospitality and tourism, Pillai and Sivathanu (2020) found Trust to have a strong positive effect on adoption. Similarly, Kasilingam (2020) found Trust to have a direct positive effect on Intention to Use in his study on smart phone chatbots for shopping. Given the previous findings, we hypothesize that Trust positively influences consumers' Intention to Use chatbots.

H19: *Trust has a positive influence on Intention to Use chatbots.*

Privacy Risk

Privacy can be defined as "*the ability of individuals to construct, regulate, and apply the norms for managing their information and interaction with others*." (Bélanger & James, 2020, p.510). In the literature, the term "privacy" is used in slightly different ways, such as "Privacy Concern" and "Privacy Risk" among other things. However, our literature review indicates that these concepts are related. Therefore, in our study, we will measure "Privacy Risk," but when forming our hypothesis, we will consider studies that use similar terms related to privacy.

If the consumers believe there is a Privacy Risk in using a product, they will be less likely to use it (Zhao & Zhou, 2018). A study by Park, Tung, and Lee (2021) on AI-powered service robots in cafés and hospitals, found that Privacy Concerns have a significant impact on Attitude towards these robots. In a study on mobile payment services, Johnson et al. (2018) found that Perceived Privacy Risk negatively impacts Perceived Security, which again negatively affects Intention to Use.

Prior research has established the importance of Privacy Risk in explaining chatbot adoption. Kwangsawad & Jattamart (2022) found that Privacy Risk influences Intention to Use customer service chatbots. In a study by Laumer et al. (2019) on the adoption of conversational chatbots in healthcare, it was discovered that Privacy Risk expectancy plays a fundamental role in the adoption decision. Similarly, Privacy Risk has played an important role in adoption studies on AI in-home voice assistants (McLean & Osei-Frimpong, 2019), corporate chatbot services (Cheng & Jiang, 2020) and retail chatbot interactions (Rese et al, 2020). Generally, it seems that many studies on AI and AI-powered chatbots have found Privacy Risk to act as a barrier with a negative influence on adoption. Based on these collective findings, we propose the following hypothesis:

H20*: Privacy Risk has a negative influence on Intention to Use chatbots.*

Personalization

From a technology perspective, Personalization can be defined as the extent to which the technology understands or represents the consumer's personal needs (Komiak & Benbasat, 2006). Srinivasan et al. (2002) explained that Personalization can create benefits for consumers, as it minimizes the time needed to search for precise information. Ho (2012) went further to say that personalized IT services can offer the right content in the right form to the right user at the right time and location.

Recent reports on customer service emphasize the importance of Personalization. According to a report by Deloitte (2022), customers have an increasingly strong desire for personalized services. Studies focusing on consumer attitudes toward chatbots further indicate a growing expectation for Personalization (Drift, 2021). Specifically, customers want recommendations tailored to their individual needs, preferences, and past interactions with a brand (CDP, 2022).

Prior research has shown that personalized products or services are more likely to be adopted by consumers. Komiak and Benbasat (2006) found that consumers' Perceived Personalization significantly influenced their adoption intention of recommendation agents. Similarly, Guo et al. (2016) examined consumer acceptance of mobile health services and found that perceived Personalization is positively associated with behavioral intention. Liu & Tao (2022) found that Personalization directly determined behavioral Intention to Use AI-powered smart healthcare services. Hence, we propose the hypothesis:

H21: *Personalization has a positive influence on Intention to Use Chatbots*

Chapter 4: Methodology

4.1 Research Design

According to Saunders et al. (2016), the nature of the research questions determines the design, which outlines the general approach to addressing the research questions. We have chosen a quantitative research design for our study and gathered data through a survey based on technology adoption literature. The selection of an exploratory, descriptive, or explanatory research design typically depends on the study's purpose and the extent of existing research on the subject (Saunders et al., 2016). As we wish to gain a thorough understanding of chatbot adoption, we decided that a descriptive research design would be the best fit. By implementing this research design, we aim to provide a detailed description and interpretation of the phenomenon of interest (Saunders et al., 2016). Additionally, our research is exploratory in nature as our overall goal is to explore and understand the adoption of chatbots from a consumer perspective.

4.2 Research Strategy

In this study, we have chosen a survey research strategy using a questionnaire as our method of data collection, which is common in quantitative research (Saunders et al., 2016). As we have relied on previous research to help us to develop hypotheses and analyze the collected data, we are following a deductive method (Saunders et al., 2016). We chose this strategy because it allowed us to gather standardized data cost-effectively, and easily compare and analyze the data. Moreover, surveys are widely perceived as trustworthy, which enhances the credibility of our study results. The simplicity of administering and comprehending surveys also made it an attractive option. The use of a survey strategy provides a reliable and efficient means of data collection, contributing to the overall quality of the research findings (Saunders et al., 2016).

4.3 Sampling

Our chosen respondent group is all students attending a bachelor's or master's degree program at the Norwegian School of Economics (NHH). We found several advantages in selecting this target group. Firstly, students are easily accessible which makes recruiting more effective and could result in higher response rates. We obtained access to all students' e-mail addresses through a school representative, which made data collection easier. Secondly, young and educated business students are assumed to have a certain interest in technology and the necessary knowledge to effectively participate in a survey on chatbots. Students are also assumed to be mature and experienced with taking surveys. Thirdly, we believed we would receive diverse responses from people of both genders and cultural backgrounds since NHH is seemingly diverse in both these areas.

We designed the survey using Qualtrics (Appendix B), which is a web-based survey tool. The survey was sent out via e-mail three times to the chosen respondents (Appendix C). After the first e-mail (sent out 24.03.2023), we received 85 replies followed by 60 on the second (sent out 29.03.2023) and 51 on the third (sent out 31.03.2023). The same day as the last survey was sent out, we also asked fellow students in the hallways of the school to participate.

4.4 Sample Demographics

Our survey was distributed to approximately 3100 unique students attending NHH and we received 196 responses, where 126 were usable. The gender distribution was 61.9% male and 37.3% female. This distribution appears to be representative of NHH, as approximately 44% of the students who received an admission offer in 2022 were female (NHH, 2022). We further see that the majority of respondents fall within the age group of 18-25 years old, representing 73% of the total responses (Table 4.1). This finding seems to align with the age distribution of students at NHH and indicates that the sample is likely to be a representative subset of the NHH student population in this regard as well.

When comparing the respondents who reported having moderate to extensive experience with chatbots (rated 5-7 on the scale) to those who reported having no to minimal experience (rated 1-3 on the scale), the data shows a clear difference. While 54,7% rated their experience from 5-7, only 23,1% rated their experience from 1-3, indicating that a majority of the NHH students had some level of familiarity with chatbots. This could have an important implication for the interpretation of the study's findings (Table 4.1).

The vast majority of students (81%) were most familiar with search engine chatbots, followed by banking chatbots (9.5%). Other chatbots and travel and hospitality chatbots had the lowest familiarity of 3.2% and 4.8%. Additionally, a small percentage of respondents (1.6%) reported that they have not used a chatbot (Table 4.1).

Table 4.1: Sample demographics

Gender	
Male	61.9%
Female	37.3%
Prefer not to say	0.8%
Age	
18-15 years	73%
Above 25 years	27%
Experience	
1 - None	2.4%
2	4.8%
3	15.9%
4	22.2%
5	35.7%
6	12.7%
7- Extensive	6.3%
Most familiar chatbot type	
Banking chatbot	9.5%
Search engine chatbot	81%
Travel and Hospitality	4.8%
Other chatbot	3.2%
I have not used a chatbot	1.6%

4.5 Pilot Test

To test the face validity of our survey, which indicates whether the survey makes sense (Saunders et al., 2016), we conducted a small pilot test. Before distributing it to the target group we wanted to ensure that the survey was free of errors and easily comprehensible to the respondents. The pilot was distributed to three students who were thoroughly instructed to give us feedback and inform us whether there was anything they did not understand, or thought was incorrect. We also wanted to evaluate the user-friendliness of the survey's layout and verify the proper functioning of distribution mechanisms in Qualtrics. This approach effectively helped us to identify and correct some errors or misinterpretations that were found in the survey, thereby improving the quality of the collected data.

On the page where the respondent chooses which chatbot he/she is most familiar with (Appendix B), there were two misinterpretations. One test respondent thought it was unclear what a search engine chatbot was, which is why we ended up including an example. Another test respondent thought using “finance chatbot” was confusing, as he was using a search engine chatbot for financial questions. Due to this misunderstanding, we changed “finance chatbot” to “banking chatbot” to make it more clearly associated with chatbots used by banks. Furthermore, there was one test respondent who thought “dependable” and “reliable” were too much alike in the part of the survey concerning Trust. Although we considered removing one of the questions, we included both due to prior literature on chatbot trust. The pilot test also let us know the average duration of the survey, which was six minutes. Overall, the pilot test revealed a few misinterpretations among the respondents, which were addressed by providing clarifications and making necessary changes.

4.6 Initial Data Preparation

Prior to the data analyses, we performed initial preparation of the dataset by cleaning it to improve its quality. This involved removing incomplete responses and careless answers from insufficiently motivated respondents to ensure the integrity of the dataset. DeSimone et al. (2015) suggest that one can screen respondents who respond too quickly, and who respond the same way to several consecutive items. We chose to exclude respondents who spent less than three minutes on the survey or had more than 15 consecutive identical answers on the 7-point Likert scale.

In total, there were 196 responses. After removing the ones that were unfinished, 133 remained. Then after removing the respondents who used less than three minutes, there were 127 remaining. Finally, after removing a respondent who had more than 15 similar consecutive answers, we were left with 126 usable responses (Table 4.1).

Table 4.2: Initial Data Preparation

Total responses	196
- Unfinished responses	-63
- Respondents using less than 3 minutes	-6
- Too many consecutive answers	-1
Total responses after cleaning	126

4.7 Ethical Concerns

Throughout a research process, ethical concerns are likely to arise. Saunders et al. (2016) clarify that a range of principles exist to acknowledge these ethical concerns that may arise across various research approaches. The principles include being transparent and honest, preserving the privacy of participants, clarifying the voluntary nature of participation, securing informed consent, and ensuring confidentiality. Such principles must be carefully considered when conducting research (Saunders et al., 2016).

We took several ethical considerations into account when creating the survey. It was highlighted in the survey that participation was anonymous and voluntary, and that completion of the entire survey was required for responses to be included in the analysis. To make sure the survey was anonymous, we used a feature in Qualtrics called "anonymize responses", which ensures anonymity. On the first page of the survey, respondents were required to provide their consent to participate in the survey and acknowledge that their data would be used for research purposes, to be able to proceed. Additionally, respondents were informed that the survey should not be shared beyond the students of NHH, and we provided our contact information if any questions emerged. During our data collection process, the survey asked for gender and age range. These attributes were not implemented to personally identify the participants but as parameters for data description.

Furthermore, it is important to maintain objectivity during data collection. This means that one must collect the data accurately and fully, and avoid exercising subjective selectivity (Saunders et al., 2016). The information from the survey was directly extracted from Qualtrics and underwent no modifications or interference. Although we cleaned the data for unusable responses, no unethical tampering occurred on the data or results to conform to our hypotheses. This is important not to impede future research from pursuing the same course of action and hypotheses (Saunders et al., 2016).

4.8 Reliability

4.8.1 Internal Reliability

In a research context, reliability is an aspect that ensures the consistency and stability of the research findings. The concept is often subdivided into internal and external reliability, with internal reliability focusing on ensuring consistency within the research project (Saunders et al., 2016). To guarantee the internal reliability of our study, we implemented a clear and systematic research plan that followed a standardized research method. Furthermore, we prioritized effective communication and regular updates to ensure that both authors were informed of any changes that may affect the research process. Saunders et al. (2016) describe two threats to internal reliability, which are participant error and participant bias.

Participant error refers to any factor that impacts how a participant performs. For instance, rushing through a survey due to time constraints or misinterpreting survey questions can be considered participant errors (Saunders et al., 2016). In our study, we avoided distributing the survey at times when students were likely to rush through it. Additionally, we removed participants using less than three minutes to answer the questionnaire during data cleaning (Table 4.2). To address misinterpretation, we conducted the pilot test to ensure survey questions were understandable (Chapter 4.5).

Participant bias refers to any factors concerning false responses from participants (Saunders et al., 2012). Before distributing the survey, we thought some participants may answer in socially desirable manners, which we partially tried to counter by informing the participant of anonymity and by formulating a set of questions that have been validated by researchers. To further prevent participant bias, we used the term "chatbots" instead of "chatbot adoption" during the survey invitation and introduction. This was because using "chatbot adoption" could make certain students attending NHH suspect what the study is about which may affect their answers. This approach aimed to prevent students who may be familiar with technology adoption theory from overthinking the purpose of the survey and from responding in a way that they believe is expected of them.

4.8.2 External Reliability

External reliability relates to the consistency and replicability of research findings. If data collection techniques and analytic procedures are repeated by the same or different researchers, they should be used consistently across the studies (Saunders et al., 2016). Saunders et al. (2016) describe two threats to external reliability which are researcher error and researcher bias.

Researcher error and researcher bias is any factor that alters the researcher's interpretation or induces bias in the researcher’s recording of responses (Saunders et al., 2016). To prevent research errors, we have double-checked all work and leveraged SPSS and Qualtrics which have helped reduce error by automating many processes. Despite having our own hypotheses, we have focused on staying neutral and open to various results throughout the research process. Confirmation bias is a particular concern, as it may lead researchers to test only those cases that are most likely to confirm their existing beliefs (Klayman & Ha, 1987). To counter this issue, we have made sure to import data directly from Qualtrics to SPSS and use the same standard tests for every model and construct without altering any variables. This approach may help to eliminate any potential bias from the analysis process.

4.9 Validity

4.9.1 Internal Validity

In addition to reliability, validity is an equally vital characteristic in ensuring good-quality data. Internal validity is established when an intervention can be statistically proven to lead to a particular result. In the case of a questionnaire-based survey, internal validity is established when a set of questions can be statistically associated with an analytical factor or outcome. It is important to note that research producing invalid results and conclusions will significantly impact its reliability since it is unlikely that an upcoming study will show the same false results and statistical relationships (Saunders et al., 2016).

Saunders et al. (2016) describe how past or recent events may change participants’ perceptions. Throughout the course of our research, several news articles have surfaced regarding chatbots, often with a negative undertone. One such example involves ChatGPT being used to cheat on exams (Lindland, 2023), while another instance involves Snapchat's new chatbot misinforming children with inappropriate information (Vik, 2023). The abundance of negative news articles may have had an impact on the likelihood of students choosing to participate in our survey. Those with a negative perception of chatbots may be less motivated to take part in the survey, resulting in a biased sample towards those who have a more positive or neutral outlook.

Additionally, the news coverage may also affect participants' experiences and opinions of the statements presented in the survey. When designing the survey, experience was included as a control variable to help account for potential effects of prior exposure to chatbots on the participants' responses. Students who have used chatbots before may have a different perception compared to those who have never used them. Controlling for experience may help to determine the true effect of the independent variables on the dependent variable, without the interference of confounding variables (Hair et al., 2014). This may overall improve the internal validity of the study.

Mortality is the impact of participants withdrawing from the study (Saunders et al., 2016). To avoid this threat, we took measures to sustain respondent motivation throughout the survey. Two encouraging messages were strategically placed within the 16-page survey. One was placed in the middle (page 8) and another towards the end (page 12). These messages emphasized the importance of the respondent's participation and provided reassurance that they were in the final stages of completing the survey (Appendix B). The survey was however relatively time-consuming and did not offer an incentive, so the mortality rate was rather high (Table 4.2).

Additionally, we address the construct validity in the study, which is whether the utilized items actually measure the presence of the construct we intended them to measure (Saunders et al., 2016). In this study, the majority of respondents (81%) indicated that they had the most experience with search engine chatbots (Table 4.1). However, the items used in the survey were not gathered from studies specifically focused on search engine chatbots. As a result, these items may not accurately capture the constructs related to this specific type of chatbot, potentially impacting the overall construct validity of the study.

4.9.2 External Validity

External validity relates to the ability of a study's research findings to be applied to other relevant settings or groups, rather than being limited to the specific context in which the study was conducted (Saunders et al., 2016). The sample size in our study was relatively small, as we collected usable data from only 126 out of approximately 3100 bachelor and master students. It is important to acknowledge the potential limitations of our sample size and the impact this may have on the generalizability of our findings. Additionally, since the study participants were exclusively NHH students, the applicability of the results to other populations may be limited. The high proportion of respondents with experience primarily limited to search engine chatbots (Table 4.1) may also impact the generalizability of the findings.

By providing a detailed account of the research process, including research questions, design, context, and findings, we have aimed to enhance the transferability of our findings to similar contexts. Providing evidence that the research can be applied in similar contexts establishes a level of transferability. Consistently providing this information, may empower others to make informed judgments about the applicability of our results, considering the specific characteristics and dynamics of their own setting (Saunders et al., 2016).

4.10 Common Method Bias

Measurement error is a threat to the validity of conclusions about the relationships between measures and can be both random and systematic in nature. Systematic measurement error is particularly problematic as it can provide an alternate explanation for observed relationships between measures. Common method bias is a type of systematic measurement error that is prevalent in research (Podsakoff et al., 2003). In single-method research designs, Harman's single-factor test is widely used for detecting Common Method Variance (Malhotra et al., 2006). The items in a study undergo exploratory factor analysis, in which Common Method Variance is assumed to exist if either a single factor emerges from unrotated factor solutions or a first factor explains the majority of the variance (>0,5) (Malhotra et al., 2006).

4.11 Assumptions for Multivariate Regression

In order to perform a Multivariate Regression Analysis (MLR), several assumptions have to be met, including normality, multicollinearity and autocorrelation.

Normality refers to the shape of the data distribution and its correspondence to the normal distribution, which serves as the benchmark for statistical methods. If the deviation from the normal distribution is large enough, all resulting statistical tests become invalid, as normality is required to use the F and t statistics. The degree of nonnormality is determined by two factors: the shape of the distribution and the sample size. The shape of any distribution can be characterized by two parameters: kurtosis and skewness. The distinction between kurtosis and skewness is that kurtosis indicates how peaked or flat the distribution is compared to a normal distribution, whereas skewness describes how balanced the distribution is. In skewed distributions, a left shift is indicated by a positive skew while a right shift is indicated by a negative skew. If values of skewness fall outside the range of -2 to +2 it is a substantially skewed distribution (Byrne, 2010). For kurtosis values, a range of -1.96 to 1.96 can be used as a threshold (Rose et al., 2015).

Multicollinearity occurs when a single independent variable is highly correlated with two or more independent variables and can impose a threat to the validity of the Multiple Regression Analysis. To minimize correlations between factors, orthogonal rotation and regression factor score method can be employed. Additionally, the absence of multicollinearity can be demonstrated by utilizing the tolerance and variance inflation factor (VIF). Ideally, the tolerance should not be lower than 0,25 and the VIF should not exceed 4. If tolerance is below 0,1 and VIF higher than 10, it indicates serious multicollinearity problems (Hair et al., 2014).

Finally, positive autocorrelation is typical in regression problems, which may occur when successive error terms are similar in magnitude and the difference in residuals are small. The Durbin-Watson test is a statistical test that is used to check for the presence of positive autocorrelation in regression model errors. If positive autocorrelation is detected, it suggests that the model is not capturing all the relevant information, and further investigation is required (Montgomery et al., 2015). The output from the Durbin-Watson test varies from 1-4 and the ideal value is 2 (Hair et al., 2014).

Chapter 5: Data Description and Validation

In this chapter, we delve into the data description and validation process of our study on consumer adoption of AI-powered chatbots. We first briefly discuss the quality of the dependent variable, Intention to Use, before proceeding with a more extensive analysis of the independent Variables of TPB, TAM, UTAUT2 and DOI. For each of these models, we provide measures of the constructs, conduct a factor analysis, and report factor loadings, measurement reliability, measurement validity, and descriptive statistics. By conducting a thorough quality check of our data, we ensure the robustness of our findings and provide a solid foundation for drawing conclusions (Saunders et al., 2016).

In chapters 5.1 and 5.2, we provide explicit clarification on threshold values for the tests used in chapter 5. These threshold values are subsequently applied in a more implicit manner in the following subchapters (5.3-5.6).

5.1 Testing Intention to Use

The dependent variable for all the following models is the Intention to Use chatbots (Rad et al., 2018). To measure the Intention to Use chatbots we use two items. The items are both adopted from a study on mobile services by Nysveen et al. (2005) and used in the same format (Appendix K). As expected, by conducting a factor analysis with a maximum likelihood extraction method, we end up with one factor (Appendix D1).

A Cronbach's Alpha test was conducted to determine whether the scale is consistent, and if the factor is stable enough to be used as scale. The factor has a score of 0,890 (Appendix D2), which is higher than the lower generally agreed upon limit of 0,7, suggested by Hair et al. (2014). The Average Variance Extracted (AVE), which measures the amount of variance in the indicators that is explained by the latent construct, is 0,425, and therefore falls short of the recommended value of being above 0,5 (Hair et al., 2014). Construct Reliability (CR) is a measure for internal consistency of the measured variables which is representing a latent construct. The factor also falls short of the CR measure, as 0,597 is lower than the limit of 0,7 (Hair et al., 2014). Skewness measures the symmetry of the distribution in comparison to a normal distribution. If values of Skewness fall outside the range of -2 to +2 it is considered to be a skewed distribution (Byrne, 2010). In this case, we see that Intention to Use has an acceptable value of -1, 270. The Kurtosis value is also acceptable, being within the range of -1.96 to 1.96 (Rose et al., 2015) (Table 5.4). Despite the shortcomings of some of these values, we keep the dependent variable as it is due to extensive prior research supporting its usage (Rad et al., 2018).

5.2 Testing TPB - Theory of Planned Behavior

5.2.1 TPB - Measurements

Throughout the study we use three different items to measure each independent variable. The items are formed through inspiration from previous studies using the same constructs, and further altered to fit our survey. To measure the constructs in TPB, we adopted the items from Nysveen et al. (2005). The questions are asked in the same manner, only switching the word "service" for "chatbots" (Table 5.2). In the study of Nysveen et al. (2005), the authors used four items to measure Attitude. As we chose to use three items for each construct in this study, we included the three items we believed would be most easily understood by the respondents (Appendix K).

5.2.2 TPB - Factor Analysis

The purpose of a factor analysis is to define the underlying structure among the variables in the analysis. It provides the tools needed for analyzing the structure of the relationships, by defining sets of variables that are highly interrelated, known as factors (Hair et al., 2014). As TPB has been comprehensively utilized with three constructs in the adoption literature (Weigel et al., 2014), a factor analysis was completed with the assumption that we would find three factors. Our assumption was confirmed (Table 5.1). We performed the factor analysis with an oblique rotation because the factors in the research model are expected to correlate. The oblique rotation takes this correlation into account (Hair et al., 2014), and the analysis was also conducted with a maximum likelihood extraction method.

Table 5.1: Total Variance Explained TPB

Initial Eigenvalues				Extraction Sums of Squared Loadings			
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
Attitude	3,377	37,522	37,522	2,912	32,357	32,357	2,390
Subjective Norm	1,737	19,297	56,820	1,332	14,799	47,156	2,156
Behavioral Control	1,342	14,912	71,731	1,032	11,467	58,623	1,763

KMO: 0,711, Bartlett: 425,877, < 001

The Kaiser Meier Olkin (KMO) measure is used to evaluate the degree to which the variables in the dataset are suitable for factor analysis. It measures the proportion of variance that could be caused by underlying factors, and a score of 0,6 or above, generally indicates that the dataset is suitable for factor analysis (Hair et al., 2014). The TPB model has a KMO of 0,711 (Appendix E1) and is therefore considered to be suitable for the analysis. To further ensure that the dataset is suitable, we conducted a Bartletts Test of Sphericity. The results show a significant p-value (<0,001) (Appendix E1) and indicates that sufficient correlations exist among the variables in the dataset (Hair et al., 2014).

The Eigenvalues presented in Table 5.1, indicate the rank in variance explained by each of the factors in the model. Factors are considered stable when the Eigenvalue is higher than 1, and the factors who do not meet this criterion should be excluded from the model (Hair et al., 2014). By keeping the factors with an Eigenvalue above 1,00, we end up with the three factors from the model.

Table 5.1 shows that the total model variance explained is 71,73%. According to Hair et al. (2014), you want to achieve a specified cumulative percentage of total variance by the retained factors. The model meets this criterion, as it explains over 60% of the variance. Further, we also see that none of the factors explain more than 50% of the variance. Attitude is the highest with 37,52%. Hence, the model satisfies the Harman test criterion for common method bias (Malhotra et al., 2006).

5.2.3 TPB - Factor Loadings

The Pattern Matrix (Appendix E3) shows the different measures and factor loadings on the three different factors for the items. Factor loadings with levels over 0,5 are considered to be goal values for a sample size of around 120 (Hair et al., 2014). Our sample size consists of 126 observations, and values of 0,5 and above indicate significant and well-defined measurements. Additionally, the main factor loading should not differ by less than 0,2 with regards to the next factor in loading value. Potential items which do not meet these criteria, should be removed from the measurement and the model (Hair et al., 2014).

The results in Table 5.2 show that all items have above significant factor loadings. We see that one item measuring Behavioral Control, also loads on Subjective Norm (Appendix E3). However, the main factor loading differs by 0,339, which is considerably higher than the lowest acceptable level of 0,2 (Hair et al., 2014). Therefore, we keep all the items in the model and additional factor analyses are unnecessary. The loadings are presented in Table 5.2.

Hair et al. 2014 introduces the Average Variance Extracted (AVE) as a measure of convergent validity. It measures the amount of variance in the indicators that is explained by the latent construct. Values above 0.5 are generally considered to indicate good convergent validity. All factors, except for Behavioral Control, meet this criterion (Table 5.2).

Table 5.2: Factor Analysis TPB

Dimension	Items	Loadings	α	CR	AVE
Attitude	*I believe that using chatbots is bad/good	0,721	0,829	0,829	0,632
	*I believe that using chatbot is foolish/wise	0,673			
	*I believe that using chatbots is negative/positive	0,947			
Subjective Norm	*People important to me think I should use chatbots	0,631	0,813	0,811	0,593
	*It is expected that people like me use chatbots	0,784			
	*People I look up to expect me to use chatbots	0,876			
Behavioral Control	*I have the necessary means and resources to use chatbots	0,623	0,666	0,685	0,426
	*I feel free to use the kind of chatbots I like to	0,774			
	*Using chatbots is entirely within my control	0,529			

5.2.4 TPB - Measurement Reliability

To further explore the quality of the model we tested the reliability of the measures. The first reliability measure is presented in Table 5.2 and was found using The Cronbach's Alpha test. By analyzing the alpha-values, we determine whether the scale is consistent, and if the factors are stable enough to be used as scales. A lower generally agreed upon limit suggested by Hair et al. (2014) is 0,7 and results from our test show that the factors Attitude and Subjective Norm fulfill this criterion. Behavioral Control, on the other hand, is marginally below the limit. This could possibly be explained by one item loading on both Subjective Norm and Behavioral Control (Appendix E3). As the breach is marginal and the model is extensively used in the literature, we decide to keep the measurement. We consider the model stable enough to be utilized as a scale.

Measures of Construct Reliability (CR) are also presented in Table 5.2. CR is a measure for internal consistency of the measured variables which is representing a latent construct (Hair et al., 2014). The critical value of CR has the same critical value as α (CR > 0.7). Hence, Behavioral Control, again falls short of the suggested limit. We decide to keep the factor based on the same argumentation for α above.

5.2.5 TPB - Measurement Validity

Construct Validity refers to what extent a set of items actually measure the intended constructs (Saunders et al., 2016). To measure the Construct Validity, we conducted a correlation analysis between each of the constructs. We also included Intention to Use, as it is the dependent variable in the model. The analysis shows whether the constructs differ from the other constructs measured. It also reveals if they share significant coefficients, as they are part of the same model (Hair et al., 2014). A value of 0,8 has been used as a cut-off for construct correlations (Berry & Feldman, 1985). None of the constructs exceed this value (Table 5.3), thereby indicating acceptable discriminance between the factors.

Discriminant Validity refers to the degree to which constructs differ from one another and is established when all constructs share more variance with its own items than with other constructs (Hair et al., 2014). We test this by checking whether the square root of the AVE is higher for each construct than the correlation between these constructs (Fornell & Larcker, 1981). This is true for all the constructs in the model and discriminant validity is established. As seen in Table 5.3 below, the square root of AVE is presented on the diagonal furthest out.

Table 5.3: Correlation Matrix TPB

Construct	(1)	(2)	(3)	(4)
Intention (1)	**0,652**			
Attitude (2)	0,317**	**0,795**		
Subjective Norm (3)	0,410**	0,316**	**0,770**	
Behavioral Control (4)	0,350**	0,337**	0,199*	**0,653**

5.2.6 TPB - Descriptive Statistics

The sample consists of 126 observations, which meets the minimal criterion of having more observations than variables. The desired sample size suggested by Hair et al. (2014) is five observations per variable. We see that this is fulfilled when considering only one technology adoption model. However, across the whole study, it falls short of the recommendation.

Skewness measures the symmetry of the distribution in comparison to a normal distribution. None of the values of Skewness fall outside the range of -2 to +2, and it is therefore not considered to be a substantially skewed distribution (Byrne, 2010).

Kurtosis measures the "flatness" or "peakedness" of a distribution when it is compared to the normal distribution. A negative value indicates a relatively flat distribution, while a positive value indicates a relatively peaked distribution (Hair et al., 2014). A range of -1.96 to 1.96 can be used as a threshold for Kurtosis values (Rose et al., 2015). We can conclude that the data distribution for all the factors in our model is normally distributed when it comes to Kurtosis.

Table 5.4: Descriptive Statistics TPB

Construct	Min	Max	Mean	Std. Deviation	Skewness	Kurtosis
Intention	1,00	7,00	5,4643	1,82338	-1,270	,460
Attitude	2,00	7,00	5,3598	1,15054	-,482	,037
Subjective Norm	1,00	7,00	3,7989	1,41238	-,089	-,457
Behavioral Control	2,33	7,00	5,7222	1,15912	-,784	-,134
Valid N: 126						

5.3 Testing TAM - Technology Acceptance Model

5.3.1 TAM - Measurements

To measure the constructs in TAM, we adopted items from Nysveen et al. (2005), switching the word "service" for "chatbots". As we wanted three items for each construct, we removed one of the four drivers used by Nysveen et al. (2005) which we perceived as the least relevant (Appendix K).

5.3.2 TAM - Factor Analysis

TAM is the most frequently used model in technology adoption theory and consists of two independent factors (Rad et al., 2020). We therefore conducted a factor analysis, assuming we would find two factors. The factor analysis resulted in only one factor being extracted (Appendix F2). However, due to the weight of previous TAM studies (King & He, 2016), we forced the analysis to create two factors as seen in the table below (Table 5.5). The factor analysis was performed with an oblique rotation and was also done with a maximum likelihood extraction method.

Table 5.5: Total Variance Explained TAM

Initial Eigenvalues				Extraction Sums of Squared Loadings			
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
Usefulness	4,350	72,501	72,501	3,995	66,582	66,582	3,737
Ease of Use	,849	14,145	86,646	,845	14,081	80,663	3,531

KMO:0,822. Bartlett:720,424, < 001

The TAM model has a KMO of 0,822 (Appendix F1), generally indicating it as suitable for factor analysis. The results of the Bartletts Test of Sphericity showed a significant p-value (Appendix F1), indicating that sufficient correlations exist among the variables in the dataset (Hair et al., 2014).

The Eigenvalue of Ease of Use is lower than 1,00 (Table 5.5), which means it does not meet the criterion for being included (Hair et al., 2014). However, it is included due to it being close to 1,00 and because of the TAM models' strength.

The total model variance explained is 86,65% (Table 5.5), which meets the criteria of being above 60%. However, it is shown that Usefulness explains 72,50% of the variance. This exceeds the criterion of maximum 50% which shows that it may inherit some common method bias (Malhotra et al., 2006). However, as TAM highly tested and robust model (Rad et al., 2018; King & He, 2016), we decided to keep the construct as it is.

5.3.3 TAM - Factor Loadings

As seen in the table 5.6 below, all factor loadings have acceptable values, as they exceed 0,5. This indicates significant and well-defined measurements. All AVE values are above 0,5, indicating good convergent validity (Hair et al., 2014).

Table 5.6: Factor Analysis TAM

Dimension	Items	Loadings	α	CR	AVE
Ease of Use	*It is easy to make chatbots do what I want them to do	0,752	0,882	0,874	0,701
	*My interactions with chatbots are clear and understandable	0,978			
	*It is easy to use chatbots	0,762			
Usefulness	*Using chatbots makes me save time	0,978	0,956	0,940	0,842
	*Using chatbots improves my efficiency	1,004			
	*Chatbots are useful to me	0,749			

5.3.4 TAM - Measurement Reliability

Both factors had values above 0,7 using the Cronbach's Alpha test (Table 5.6) and are considered stable enough to be utilized as a scale (Hair et al., 2014). The CR values have the same critical value as Cronbach's Alpha of 0,7. The collected data is therefore reliable according to Hair et al. (2014).

5.3.5 TAM - Measurement Validity

To assess the construct validity, we performed a correlation analysis between each of the constructs. When using 0,8 as a cut-off value for construct correlations (Berry & Feldman, 1985), none of the constructs exceed this value and we find discriminance between the factors (Table 5.7).

We further test the discriminant validity by checking whether the square root of the AVE is higher for each construct than the correlation between these constructs (Fornell & Larcker, 1981). This is true for all the constructs in the model and discriminant validity is established (Table 5.7).

Table 5.7: Correlation Matrix TAM

Construct	(1)	(2)	(3)
Intention (1)	**0,652**		
Ease of Use (2)	0,408**	**0,837**	
Usefulness (3)	0,590**	0,675**	**0,918**

5.3.6 TAM - Descriptive Statistics

As seen in table 5.8, values of Skewness are acceptable (Byrne, 2010) and the Kurtosis values are considered satisfactory (Rose et al., 2015).

Table 5.8: Descriptives TAM

	N	Min	Max	Mean	Std. Deviation	Skewness	Kurtosis
Intention	126	1,00	7,00	5,4643	1,82338	-1,270	,460
Ease of Use	126	1,00	7,00	4,8889	1,27889	-,620	,391
Usefulness	126	1,00	7,00	5,4974	1,64154	-1,170	,626
Valid N	126						

5.4 Testing UTAUT2 - Unified Theory of Acceptance and Use of Technology 2

5.4.1 UTAUT2 - Measurements

UTAUT2 is a model based on earlier technology adoption models and there are clear similarities between the items of TAM and TPB and those of UTAUT2 (Venkatesh et al., 2003) (Appendix K). We replaced some of these factors, as they are expected to have a substantially similar effect and capture the same variance. Specifically, we replaced Performance Expectancy and Effort Expectancy with Usefulness and Ease of Use from TAM. Similarly, Social Influence and Facilitating Conditions were substituted with Subjective Norm and Behavioral Control from TPB. As earlier mentioned, the measurement items from TPB and TAM were adopted from Nysveen et al. (2005) (Table 5.10).

Among the models we examined, Hedonic Motivation and Habit are unique constructs to UTAUT2. The items for the constructs were adopted from a study on Mobile Internet by Venkatesh et al. (2012), with the substitution of "chatbots" for "mobile internet" as the only modification to the items. Finally, we removed the Price Value construct as chatbots are typically free and because we found no chatbot studies which found any effect of the construct (Appendix K).

5.4.2 UTAUT2 - Factor Analysis

According to Rad et al. (2018), UTAUT and its predecessor UTAUT2 are among the most commonly used technology adoption models. We conducted a factor analysis assuming that six factors would be found, since UTAUT2 and its replaced constructs have been extensively tested. However, we found that UTAUT2 loaded on only five factors (Appendix G2), and thus had to be forced to six factors (Appendix G3). The factor analysis was performed using an oblique rotation and a maximum likelihood extraction method.

Table 5.9: Total Variance Explained UTAUT2

Initial Eigenvalues				Extraction Sums of Squared Loadings			
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
Usefulness	7,393	41,070	41,070	6,940	38,554	38,554	5,603
Hedonic Motivation	2,104	11,689	52,759	1,339	7,438	45,991	4,709
Habit	1,868	10,377	63,136	1,692	9,402	55,393	2,996
Behavioral Control	1,397	7,760	70,897	1,123	6,236	61,630	2,828
Subjective Norm	1,201	6,674	77,571	1,495	8,306	69,935	2,690
Ease of Use	0,788	4,375	81,946	0,730	4,055	73,990	4,920

KMO: 0,843. Bartlett: 1766,261, <0,001

The UTAUT2 model is suitable for factor analysis, which is shown by a KMO value of 0,843. Additionally, the significant p-value of the Bartletts Test of Sphericity (Appendix G1) suggests sufficient correlations among variables in the dataset (Hair et al., 2014).

Although the Eigenvalue of Ease of Use is lower than 1,00 and does not meet the inclusion criterion (Hair et al., 2014), it is included in the model due to being close to the threshold and the model's established strength (Table 5.9).

The total variance explained by the model is 81,95%, which exceeds the criterion of 60%. Usefulness accounts for 41,07% (Table 5.9) of the variance. This is below the 50% maximum criterion of the Harman-test, indicating no common method bias (Malhotra et al., 2006).

5.4.3 UTAUT2 - Factor Loadings

Table 5.10 shows that all factor loadings, except for one item related to Behavioral Control, have acceptable values exceeding 0,5 (Hair et al., 2014). Despite loading on three separate factors (Appendix G5), the last item on Behavioral Control was included due to the difference being above 0,2 (Hair et al., 2014). Additionally, all AVE values are above 0,5 except for Behavioral Control, demonstrating an acceptable level of Convergent Validity (Hair et al., 2014). As the Behavioral Control item has been used previously when testing TPB and is derived from a well-tested model, it is included in our study.

Table 5.10: Factor Analysis UTAUT2

Dimension	Items	Loadings	α	CR	AVE
Ease of Use	*It is easy to make chatbots do what I want them to do	0,737	0,882	0,858	0,673
	*My interactions with chatbots are clear and understandable	0,950			
	*It is easy to use chatbots	0,750			
Usefulness	*Using chatbots makes me save time	0,950	0,956	0,900	0,757
	*Using chatbots improves my efficiency	0,975			
	*Chatbots are useful to me	0,645			
Subjective Norm	*People important to me think I should use chatbots	0,597	0,813	0,789	0,561
	*It is expected that people like me use chatbots	0,752			
	*People I look up to expect me to use chatbots	0,872			
Behavioral Control	*I have the necessary means and resources to use chatbots	0,515	0,666	0,664	0,439
	*I feel free to use the kind of chatbots I like to	0,966			
	*Using chatbots is entirely within my control	0,344			
Hedonic Motivation	*Using chatbots is fun	-0,916	0,843	0,909	0,769
	*Using chatbots is enjoyable	-0,834			
	*Using chatbots is very entertaining	-0,878			
Habit	*The use of chatbots has become a habit for me	0,615	0,945	0,863	0,684
	*I am addicted to using chatbots	0,917			
	*I must use chatbots	0,912			

5.4.4 UTAUT2 - Measurement Reliability

Concerns regarding Behavioral Control also arise when examining the reliability of the model. The Cronbach's Alpha test and CR indicated that all factors had values above 0,7, except for Behavioral Control (Table 5.10). The collected data, except from in Behavioral Control, is considered reliable in line with the criteria proposed by Hair et al. (2014).

5.4.5 UTAUT2 - Measurement Validity

To evaluate construct validity, we conducted a correlation analysis among the constructs. None of the constructs exceeded the cut-off value of 0,8 (Table 5.11), indicating that there is sufficient discriminance among the factors (Berry & Feldman, 1985).

To assess discriminant validity, we used the criterion of Fornell and Larcker (1981) by comparing the square root of the AVE for each construct to the correlation between the constructs. This criterion was met for all constructs, indicating that there is good discriminant validity (Table 5.11).

Table 5.11: Correlation Matrix UTAUT2

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intention (1)	**0,652**						
Ease of use (2)	,408**	**0,820**					
Usefulness (3)	,590**	,675**	**0,870**				
Subjective Norm (4)	,410**	,293**	,437**	**0,749**			
Behavioral Control (5)	,350**	,468**	,424**	,199*	**0,663**		
Hedonic Motivation (6)	,419**	,468**	,594**	,329**	,363**	**0,877**	
Habit (7)	,430**	,304**	,399**	,239**	,156	,414**	**0,827**

5.4.6 UTAUT2 - Descriptive Statistics

As seen in table 5.12, values of Skewness are acceptable (Byrne, 2010) and the Kurtosis values are considered satisfactory (Rose et al., 2015).

Table 5.12: Descriptive Statistics UTAUT2

Construct	Min	Max	Mean	Std. Deviation	Skewness	Kurtosis
Intention	1,00	7,00	5,4643	1,82338	-1,270	,460
Ease of Use	1,00	7,00	4,8889	1,27889	-,620	,391
Usefulness	1,00	7,00	5,4974	1,64154	-1,170	,626
Subjective Norm	1,00	7,00	3,7989	1,41238	-,089	-,457
Behavioral Control	2,33	7,00	5,7222	1,15912	-,784	-,134
Hedonic Motivation	1,00	7,00	4,7249	1,63304	-,555	-,194
Habit	1,00	6,33	2,4048	1,38667	1,113	,667
Valid N: 126						

5.5 Testing DOI - Diffusion of Innovations

5.5.1 DOI - Measurements

To measure the factors in DOI, we used items from (Curran & Meuter, 2005) which were originally adopted from Moore & Benbasat (1991). For Relative Advantage, Compatibility, Trialability and Observability, the items were all inspired by these sources (Appendix K). For Complexity, two items were inspired by Curran and Meuter (2005), while one was adopted from Thompson et al. (1991). All the Questions were rewritten to fit the survey (Table 5.14).

5.5.2 DOI - Factor Analysis

DOI is a frequently used model in technology adoption literature and consists of five independent constructs (Rad et al., 2020). We therefore conducted a factor analysis, assuming we would find five factors. From the first analysis we extracted only four factors (Appendix H2), hence another factor analysis was conducted. By forcing the model to five factors we encountered some issues (Appendix H4). Firstly, the items from Relative Advantage and Complexity load on multiple factors. Secondly, one item from Trialability loads lower than the acceptable limit of 0,5 (Hair et al., 2014). Finally, one item from Observability loads on two separate factors and they do not differ by less than 0,2 (Hair et al., 2014). Based on this we chose to replace Relative Advantage and Complexity, with Usefulness and Ease of use from TAM, as they are similar constructs expected to capture the same variance (Venkatesh et al., 2003). We further removed the problematic items in Trialability and Observability (Table 5.14). The factor analysis was performed with an oblique rotation and was also done with a maximum likelihood extraction method.

Table 5.13: Total Variance Explained DOI

Initial Eigenvalues				Extraction Sums of Squared Loadings			
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
Observability	6,573	50,565	50,565	2,436	18,742	18,742	2,461
Usefulness	1,836	14,123	64,688	5,187	39,904	58,646	5,109
Ease of Use	1,182	9,094	73,782	,968	7,449	66,095	4,626
Compatibility	,884	6,803	80,585	,748	5,753	71,848	4,713
Trialability	,628	4,829	85,414	,633	4,871	76,719	2,456

KMO:0,860, Bartlett: 1280,341, <,001

The DOI model has a KMO of 0,860 and a significant p-value from the Bartletts Test of Sphericity (Appendix H1), indicating that it suitable for factor analysis (Hair et al., 2014).

The Eigenvalues of both Compatibility and Trialability do not meet the criterion from Hair et al. (2014) of being above 1. They are still included as the constructs are well-established in the literature (Weigel et al., 2014).

The model explains 85% of the variance and is within the criterion of 60% (Hair et al., 2014). We also see that Observability exceeds the limit used in the Harman test of 50% (Malhotra et al., 2006). This shows us that there might be common method bias. However, it is important to note that the variance only slightly exceeds the established threshold (Table 5.13), leaving room for alternative interpretations.

5.5.3 DOI - Factor Loadings

All factor loadings have acceptable values, as they exceed the suggested limit by Hair et al. (2014) of 0,5 (Table 5.14). The AVE values for all factors except Trialability, are above 0,5, which indicates good Convergent Validity (Hair et al., 2014). As Trialability is only marginally under the suggested limit, it is included (Table 5.14).

Table 5.14: Factor Analysis DOI

Dimension	Items	Loadings	α	CR	AVE
Ease of Use	*It is easy to make chatbots do what I want them to do	0,803	0,882	0,847	0,651
	*My interactions with chatbots are clear and understandable	0,887			
	*It is easy to use chatbots	0,722			
Usefulness	*Using chatbots makes me save time	0,900	0,956	0,859	0,675
	*Using chatbots improves my efficiency	0,900			
	*Chatbots are useful to me	0,637			
Compatibility	*Using chatbots is compatible with my lifestyle	0,819	0,893	0,849	0,652
	*Using chatbots is completely compatible with my needs	0,849			
	*Chatbots for well with the way I like to get things done	0,751			
Trialability	*It is easy to try out chatbots without a big commitment	0,794	0,714	0,624	0,462
	*I have had opportunities to try out chatbots	0,542			
	*~~I can use chatbots on a trial basis to see what it can do~~				
Observability	*I have no difficulty telling others about the results of using chatbots	1,020	0,872	0,865	0,768
	*I can communicate to others the outcomes of using chatbots	0,704			
	*~~The results of using chatbots are apparent to me~~				

5.5.4 DOI - Measurement Reliability

All the constructs in the model are considered stable enough to be used as a scale, as their Alpha values are above 0,7 (Table 5.14). The critical value for the measurement of Construct Reliability is met by all factors, except Trialability, which is marginally under the limit of 0,7 (Table 5.14). As the breach is marginal and the model is extensively used in the literature, we decide to keep the measurement.

5.5.5 DOI - Measurement Validity

We performed a correlation analysis between each of the constructs to assess the construct validity. When using 0,8 as a cut-off value for construct correlations (Berry & Feldman, 1985), all constructs fall within the limit. Based on this, we can conclude that there is sufficient discriminance between the factors.

We further test the discriminant validity by checking whether the square root of the AVE is higher for each construct than the correlation between these constructs (Fornell & Larcker, 1981). This is true for all the constructs in the model (Table 5.15).

Table 5.15: Correlation Matrix DOI

	(1)	(2)	(3)	(4)	(5)	(6)
Intention (1)	**0,652**					
Ease of Use (2)	0,408**	**0,807**				
Usefulness (3)	0,590**	0,675**	**0,822**			
Compatibility (4)	0,484**	0,559**	0,730**	**0,807**		
Trialability (5)	0,501**	0,414**	0,412**	0,271**	**0,678**	
Observability (6)	0,319**	0,280**	0,276**	0,288**	0,447**	**0,876**

5.5.6 DOI - Descriptive Statistics

As seen in table 5.16, all constructs have acceptable values of Skewness (Byrne, 2010) and the Kurtosis values are considered satisfactory (Rose et al., 2015)

Table 5.16: Descriptive Statistics DOI

Construct	Min	Max	Mean	Std. Deviation	Skewness	Kurtosis
Intention	1,00	7,00	5,4643	1,82338	-1,270	,460
Ease of Use	1,00	7,00	4,8889	1,27889	-,620	,391
Usefulness	1,00	7,00	5,4974	1,64154	-1,170	,626
Compatibility	1,00	7,00	4,3333	1,46485	-,360	-,260
Trialability	1,00	7,00	5,9444	1,23810	-1,297	1,458
Observability	1,00	7,00	5,5675	1,31507	-,696	,051

5.6 Testing Model Extensions

5.6.1 Model Extensions - Measurements

To operationalize the constructs for the Model Extensions, we found items through our literature review (Appendix A), which were newer and therefore less tested compared to previously used items. Firstly, for Anthropomorphism and Trust, the items were collected from Kuberkar & Singhal's (2020) study on AI-powered chatbots for public transport services. Secondly, the items used to measure Privacy Risk were collected from a study on sustainable adoption of chatbot services by Kwangsawad & Jattamart (2022). Lastly, for Personalization, two items were collected from a study on Personalization and adoption of recommender agents by Komiak & Benbasat (2006). The last item on Personalization was collected from Liu &

Tao's (2022) study on acceptance of smart healthcare services (Appendix K). The items were rewritten to fit our study (Table 5.18).

5.6.2 Model Extensions - Factor Analysis

The factor analysis loaded on four factors as we predicted. However, one item from Anthropomorphism had a factor loading below 0,5 (Appendix I3) (Hair et al., 2014), and was subsequently removed (Table 5.18).

Table 5.17: Factor Analysis Model Extensions

Initial Eigenvalues				Extraction Sums of Squared Loadings			
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
Personalization	3,777	34,334	34,334	3,143	28,575	28,575	2,598
Anthropomorphism	2,633	23,935	58,269	,885	8,046	36,620	2,354
Privacy Risk	1,407	12,790	71,059	2,364	21,487	58,108	2,395
Trust	1,039	9,448	80,507	1,513	13,754	71,861	2,621

KMO: 0,710. Bartlett: 820,387, <0,001,

The Model Extensions have a KMO of 0,710 (Appendix I1), which indicates it as suitable for factor analysis. When conducting a Bartletts Test of Sphericity we found a significant p-value (Appendix I1), which shows a sufficient correlation present among the variables in the dataset (Hair et al., 2014).

All Eigenvalues meet the criteria of being above 1,00 and are therefore included (Hair et al., 2014).

The model's total variance is 80,51%, which is also sufficient because it is above 60% (Hair et al., 2014). No factor has a lone variance of more than 50%, which indicates no common method bias (Malhotra et al., 2006).

5.6.3 Model Extensions - Factor Loadings

All factor loadings have acceptable values, as they exceed 0,5. Additionally, all AVE values exceed 0,5 which indicates good convergent validity (Hair et al., 2014).

Table 5.18: Factor Loadings Model Extensions

Dimension	Items	Loadings	α	CR	AVE
Anthropomorphism	* Interactions with chatbots are similar to interactions with humans	-0,933	0,828	0,797	0,668
	* Interactions with chatbots are natural	-0,682			
	* ~~Interactions with chatbots are interactive.~~				
Trust	*Chatbots are trustworthy	0,726	0,853	0,848	0,653
	* Chatbots are reliable	0,918			
	* Chatbots are dependable	0,767			
Privacy Risk	* Chatbots can cause personal information to be published	0,592	0,856	0,863	0,690
	* Disclosing personal information through chatbots is a risk	0,906			
	* Disclosing personal information through chatbots can be negative for me	0,984			
Personalization	* Chatbots provide personalized answers that are based on my information	0,527	0,816	0,843	0,656
	* Chatbots understand my needs	1,000			
	* Chatbots know what I want.	0,830			

5.6.4 Model Extensions - Measurement Reliability

All Cronbach's Alpha values are above 0,7, meaning the constructs are sufficiently stable. The CR values also exceed the critical value of 0,7, making the measurements reliable (Hair et al., 2014).

5.6.5 Model Extensions - Measurement Validity

To assess construct validity, a correlation analysis was performed between each construct. By using 0,8 as a cuf-off value for construct correlations (Berry & Feldman, 1985), no constructs exceeded this value (Table 5.19). Hence, sufficient discriminance was found between the factors.

Furthermore, as the root of the AVE values are higher for each construct (Table 5.19), we can establish discriminant validity (Fornell & Larcker, 1981).

Table 5.19: Correlation Matrix Model Extensions

	(1)	(2)	(3)	(4)	(5)
Intention (1)	**0,652**				
Anthropomorphism (2)	,247**	**0,817**			
Trust (3)	,106	,330**	**0,808**		
Privacy Risk (4)	,008	-,053	-,269**	**0,830**	
Personalization (5)	,189*	,486**	,245**	,101	**0,810**

5.6.6 Model Extensions - Descriptive Statistics

As seen in table 5.20, all constructs have acceptable values of Skewness (Byrne, 2010) and the Kurtosis values are considered satisfactory (Rose et al., 2015)

Table 5.20: Descriptive Statistics Model Extensions

Construct	Min	Max	Mean	Std. Deviation	Skewness	Kurtosis
Intention	1,00	7,00	5,4643	1,82338	-1,270	,460
Anthropomorphism	1,00	6,33	3,3995	1,30027	,219	-,528
Trust	1,00	7,00	3,5053	1,15141	,043	-,030
Privacy Risk	1,00	7,00	4,3704	1,45096	-,069	-,364
Personalization	1,00	6,33	3,9180	1,27240	-,319	-,642

Chapter 6: Results

This chapter sequentially presents the result outcomes of each traditional adoption model, starting with TPB, followed by TAM, UTAUT2, and DOI. We incorporate Attitude, Experience, and Chatbot Type Familiarity as control variables to consider their potential impact on chatbot adoption. For each model, Attitude is first integrated (Model 2), before Experience and Chatbot Type Familiarity are included (Model 3). The Customized Model is then created and presented along with its corresponding results. An evaluation of the assumptions required for conducting multivariate analysis is performed for each model.

6.1 TPB – Results

6.1.1 Assumptions for Multivariate Analysis

As seen in table 5.4, all constructs have acceptable values of Skewness (Byrne, 2010) and the Kurtosis values are considered satisfactory (Rose et al., 2015), assuring a normal distribution. In Table 6.1 we see that the criteria for Tolerance and VIF are met with good margin, as Tolerance is above 0,25 and VIF is under 4. Hence, there are no indications of multicollinearity problems. The model also passes The Durbin-Watson test for autocorrelation, as both models come close to the ideal value of 2 (Hair et al., 2014).

Table 6.1: Results TPB

	Model 1	Tolerance	VIF	Model 2	Tolerance	VIF
Attitude	0,135	0,822	1,217	0,046	0,766	1,305
Subjective Norm	0,319**	0,890	1,123	0,233**	0,827	1,210
Behavioral Control	0,241**	0,877	1,140	0,213**	0,814	1,229
Experience				0,297**	0,733	1,365
Chatbot Type				-0,117	0,920	1,087
Dur-Watson	2,077			2,070		
Adj. R-squared	0,240			0,322		
F-Value	14,128**			12,873**		

6.1.2 Results

In model 1, both Subjective Norm and Behavioral Control show a significant positive effect on the Intention to Use chatbots. In Model 2, when adding the Experience and Chatbot Type, we see that the significant drivers from Model 1 remain significant. However, their beta values decrease. Experience is significant in model 2 (Table 6.1).

The Adjusted R-squared value is 0,240 for Model 1 and 0,322 for Model 2. These numbers indicate what proportion of the variation in the dependent variable can be explained by the independent variables in the model (Hair et al., 2014).

6.2 TAM - Results

6.2.1 Assumptions for Multivariate Analysis

The data is considered to be normally distributed as the levels of Kurtosis and Skewness are within recommended thresholds (Table 5.8). In Table 6.2 we see that the criteria for Tolerance and VIF are met with good margin and there are no indications of multicollinearity problems. The model also passes The Durbin-Watson test, as all three models come close to the ideal value of 2.

Table 6.2: Results TAM

	Model 1	Tol.	VIF	Model 2	Tol.	VIF	Model 3	Tol.	VIF
Ease of Use	0,170	0,544	1,838	0,024	0,531	1,882	-0,007	0,524	1,909
Usefulness	0,579**	0,544	1,838	0,598**	0,460	2,172	0,529**	0,429	2,330
Attitude				-0,041	0,649	1,541	-0,107	0,624	1,602
Experience							0,313**	0,781	1,280
Chatbot Type							-0,002	0,921	1,085
Dur.Watson	2,168			2,156			2,208		
Adj. R square	0,338			0,334			0,404		
F-value	32,934**			21,883**			17,957**		

6.2.2 Results

Usefulness is shown to have a significant positive effect on the Intention to Use chatbots across all three models. Ease of Use was found to have an insignificant effect in all three models. Furthermore, Experience has a significant positive effect in model 3. The Adjusted R-squared value is 0,338 for model 1, 0,334 for model 2 and 0,404 for model 3.

6.3 UTAUT2 – Results

6.3.1 Assumptions for Multivariate Analysis

The data is normally distributed as values of Skewness are within the accepted range (Byrne, 2010). Kurtosis values are satisfactory (Table 5.12) (Rose et al., 2015). In Table 6.3 we see that the criteria for Tolerance and VIF are met and there are no indications of multicollinearity problems. All models satisfy the Durbin-Watson test, as their values are close to the ideal value of 2.

Table 6.3: Results UTAUT2

	Model 1	Tol.	VIF	Model 2	Tol.	VIF	Model 3	Tol.	VIF
Ease of Use	-0,042	0,500	2,001	-0,026	0,493	2,028	-0,043	0,490	2,039
Usefulness	0,396**	0,399	2,504	0.439**	0,368	2,714	0,356**	0,336	2,980
Hedonic.Mot	0,010	0,588	1,700	0,013	0,588	1,701	0,094	0,522	1,917
Habit	0,220**	0,786	1,273	0,236**	0,767	1,304	0,185*	0,575	1,740
Sub.Norm	0,167*	0,799	1,252	0,174*	0,794	1,259	0,124	0,745	1,342
Beh.Control	0,130	0,744	1,344	0,140	0,738	1,354	0,127	0,645	1,549
Attitude				-0,117	0,622	1,608	-0,149	0,611	1,636
Experience							0,218*	0,556	1,798
Chatbot Type							-0,940	0,749	1,334
Dur.Watson	2,195			2,180			2,169		
Adj. R square	0,401			0,405			0,443		
F-value	14,965**			13,164**			12,032**		

6.3.2 Results

Usefulness and Habit have significant positive effects on the Intention to Use chatbots across all three models. Subjective Norm has a significant effect in model 1 and 2, but not in model 3. In model 3, we observe a positive effect of Experience. The Adjusted R-squared value is 0,401 for model 1, 0,405 for model 2 and 0,443 for model 3.

6.4 DOI – Results

6.4.1 Assumptions for Multivariate Analysis

The data is considered to be normally distributed as the levels of Kurtosis and Skewness are within the recommended thresholds (Table 5.16). In Table 6.2 we see that the criteria for Tolerance and VIF are met with good margin and there are no indications of multicollinearity problems. The model also passes The Durbin-Watson test, as all three models come close to the ideal value of 2 (Hair et al., 2014).

Table 6.4: Results DOI

	Model 1	Tol.	VIF	Model 2	Tol.	VIF	Model 3	Tol.	VIF
Ease of Use	-0,086	0,510	1,960	-0,076	0,503	1,989	-0,073	0,499	2,002
Usefulness	0,408**	0,348	2,876	0,435**	0,326	3,063	0,433**	0,301	3,319
Compatibility	0,135	0,446	2,244	0,148	0,437	2,289	0,104	0,404	2,473
Trialability	0,307**	0,679	1,473	0,310**	0,678	1,475	0,223*	0,574	1,744
Observability	0,054	0,768	1,302	0,055	0,768	1,302	0,064	0,766	1,306
Attitude				-0,076	0,634	1,577	-0,112	0,617	1,622
Experience							0,221*	0,649	1,541
Chatbot Type							0,003	0,866	1,154
Dur.Watson	2,234			2,221			2,218		
Adj. R square	0,419			0,418			0,439		
F-value	19,044**			15,973**			13,243*		

6.4.2 Results

Usefulness and Trialability have significant positive effects across all three models. Experience is significant in Model 3. The Adjusted R-squared value is 0,419 for model 1, 0,418 for model 2 and 0,439 for model 3.

6.5 Model Extensions – Results

6.5.1 Assumptions for Multivariate Analysis

The data is considered to be normally distributed as the levels of Kurtosis and Skewness all fall within recommended thresholds (Table 5.16). As seen in Table 6.2, the criteria for Tolerance and VIF are met and there are no indications of multicollinearity problems. The model also passes The Durbin-Watson test, as all three models come close to the ideal value of 2. Model 1 has an insignificant F-value. As the Model Extensions consists of four distinct antecedents that have not been examined together in existing literature, we did not anticipate significant results from the model due to the lack of previous research on the combined effects of these factors.

Table 6.5: Results Model Extensions

	Model 1	Tol.	VIF	Model 2	Tol.	VIF	Model 3	Tol.	VIF
Anthropomorphism	0,061	0,751	1,332	-0,017	0,707	1,414	-0,060	0,700	1,428
Trust	0,054	0,813	1,230	-0,006	0,782	1,280	0,032	0,776	1,288
Privacy Risk	0,013	0,891	1,122	-0,045	0,856	1,169	0,022	0,837	1,195
Personalization	0,148	0,765	1,307	0,131	0,763	1,311	0,167	0,748	1,338
Attitude				0,298**	0,826	1,211	0,112	0,708	1,413
Experience							0,424**	0,800	1,250
Chatbot Type							-0,105	0,933	1,072
Dur.Watson	2,077			2,179			2,172		
Adj. R square	0,011			0,079			0,244		
F-value	1,339			3,143*			6,775**		

6.5.2 Results

Attitude has a significant effect in Model 2 and Experience is significant in Model 3. The Adjusted R-squared value is 0,011 for model 1, 0,079 for model 2 and 0,244 for model 3.

6.6 Customized Model – Results

6.6.1 Creating the Customized Model: Stepwise Estimation

To create the Customized Model, we performed a Stepwise Estimation, which is a method that selects variables for inclusion in the regression model. The best predictor of the dependent variable is selected first and additional independent variables are selected in terms of the incremental explanatory power they can add to the regression model. Independent variables can be added if their partial correlation coefficients are statistically significant, and they may also be dropped if their predictive power drops to a non-significant level when another independent variable is added (Hair et al. 2014). The stepwise estimation method resulted in four constructs: Usefulness, Trialability, Habit and Anthropomorphism (Table 6.6).

Table 6.6: Stepwise Estimation

Model	R	R^2	Adj. R^2	R^2 change	F change	Sig. F Change
1: Usefulness	0,590	0,349	0,343	0,349	66,360	<0,001
2: Usefulness, Trialability	0,654	0,428	0,419	0,080	17,161	<0,001
3: Usefulness, Trialability, Habit	0,683	0,466	0,453	0,037	8,561	0,004
4: Usefulness, Trialability, Habit, Anthropomorphism	0,695	0,483	0,466	0,017	4,043	0,047

As seen in Table 6.6, Usefulness is the strongest predictor of the independent variables as it explains 34,3% of the variance. Further, when Trialability is added to the model, the variance explained increases to 42,8%. Moving on, adding Habit increases the total variance explained to 45,3%. Finally, the inclusion of Anthropomorphism increases the model's total variance to 46,6%. The addition of Usefulness, Trialability, Habit and Anthropomorphism significantly contributed to the model fit, as indicated by the F-change values (Hair et al., 2014).

The stepwise estimation method revealed that Subjective Norm and Behavioral Control had a non-significant effect when added to the model, although they were significant in the traditional models (Appendix J15).

6.6.2 Assumptions for Multivariate Analysis

Usefulness, Trialability, Habit and Anthropomorphism have throughout chapter 6 been shown as normally distributed. In Table 6.7 we see that both the criterion for Tolerance and VIF are met and there are no indications of multicollinearity problems. The model also passes The Durbin-Watson test, as all three models come close to the ideal value of 2.

Table 6.7: Customized Model

	Model	Tolerance	VIF
Usefulness	0,416**	0,699	1,430
Trialability	0,290**	0,825	1,212
Habit	0,263**	0,741	1,349
Anthropomorphism	-0,148**	0,784	1,276
Dur.Watson	2,258		
Adj. R square	0,466		
F-value	28,274**		

6.6.3 Results

Usefulness, Trialability and Habit show a significant positive effect on Intention to Use chatbots. We hypothesized Anthropomorphism to have a positive influence on chatbot adoption. Interestingly, as observed in Table 6.7, the antecedent shows a significant negative effect on Intention to Use chatbots. The four constructs together, explain 46,6% of the variance.

Chapter 7: Discussion

7.1 Addressing the Research Questions

What constructs drive the adoption of AI-powered chatbots from a consumer perspective?

The initial research question in our study aimed to discover constructs that explain consumers' Intention to Use AI-powered chatbots. By extracting constructs from traditional adoption models, we tested their effect and significance through a multivariate regression analysis. Our findings revealed that Subjective Norm and Behavioral Control (TPB), Usefulness (TAM), Habit (UTAUT2) and Trialability (DOI) had significant positive effects on consumers' Intention to Use AI-powered chatbots (Table 7.1).

To further discover constructs that could explain consumers' Intention to Use AI-powered chatbots, we added antecedents found through a review of the literature (Appendix A). Anthropomorphism, Trust, Privacy Risk and Personalization, were all found to be insignificant through the regression analysis of the Model Extensions model (Table 6.5). However, Anthropomorphism was shown to be significant in the Customized Model (Table 6.7). Experience, which was added as a control variable, had a positive significant effect through all the models.

Table 7.1: Independent Variables Significance

Model	Independent Variable	Significance
TPB	Attitude*	Not significant
	Subjective Norm	**Significant**
	Behavioral Control	**Significant**
TAM	Usefulness	**Significant**
	Ease of Use	Not significant
UTAUT2	Habit	**Significant**
	Hedonic Motivation	Not significant
DOI	Compatibility	Not significant
	Trialability	**Significant**
	Observability	Not significant
Model Extensions	Anthropomorphism**	Not significant
	Trust	Not significant
	Privacy Risk	Not significant
	Personalization	Not significant

**Attitude is significant in Model Extensions, Model 2*

***Anthropomorphism is significant in the Customized Model*

We had a total of 21 hypotheses explaining how different independent variables affect the Intention to Use Chatbots. Due to changes made to ensure that the constructs did not overlap and capture the same variance (explained in Chapter 5), the regression analysis only included the constructs presented in Table 7.1. Five of the hypotheses are supported and a full overview of the hypotheses can be found in Appendix L.

Can we explain chatbot adoption better through a customized adoption model?

The second research question aimed to discover whether a customized adoption model could better explain consumers' adoption of chatbots. In our study, we found that out of the traditional adoption models, Model 3 from UTAUT2 explained the highest variance (44,3%). This model consists of six of the original independent variables and three control variables explaining the Intention to Use chatbots (Table 6.3). The Customized Model, created through a stepwise estimation, explained 46,6% of the variance. Therefore, the best traditional adoption model and our Customized Model only differ by 2,3%. Due to the small difference, we have insufficient evidence to confidently state that either model is better (Table 7.2).

However, as the target is to explain as much variance with as few independent variables as possible (Hair et al., 2014), one could argue that the Customized Model is more effective. The Customized model, consisting of Usefulness, Trialability, Habit and Anthropomorphism, has the lowest number of variables out of any of the models when they include the control variables (Table 7.2).

Table 7.2: Models including Control Variables Variance Explained

Model	Independent Variables	Variance Explained
1: Customized Model	**4**	**46,6%**
2: UTAUT2	9	44,3%
3: DOI	8	43,9%
4: TAM	5	40,4%
5: TPB	5	32,2%
6: Model Extensions	7	24,4%

When looking at the traditional adoption models without control variables (Table 7.3), we see that DOI is the best-fitting model. DOI explains 41,9% of the variance, which increases the difference between the traditional models and the Customized Model to 4,7%.

Table 7.3: Models Variance Explained

Model	Independent variables	Variance Explained
1: Customized Model	**4**	**46,6%**
2: DOI	5	41,9%
3: UTAUT2	6	40,1%
4: TAM	2	33,8%
5: TPB	3	24,1%
6: Model Extensions	4	1,1%

With the Customized Model explaining the most variance with the fewest variables, one could argue that this is the best model to explain the adoption of AI-powered chatbots. It enhances the variance explained by an additional 4.7% while using one less variable (Table 7.3).

7.2 Theoretical Implications

One of the declared contributions of this study was to extend the established adoption models (TPB, TAM, UTAUT2 and DOI) with antecedents. Additional constructs were included based on the findings in the literature review (Appendix A) and on previous evidence of their effects on consumers' Intention to Use AI-based technology. In the Model Extensions model, our study did not confirm any effects of Anthropomorphism, Trust, Privacy Risk, and Personalization on consumers' Intention to Use AI-powered chatbots (Table 6.5). However, through the stepwise estimation, and the creation of a Customized Model, Anthropomorphism showed a significant effect (Table 6.7). The Customized Model, which integrates traditional adoption theories and a chatbot-specific antecedent, has the potential to add to the theory of technology adoption by providing a better understanding of chatbot adoption behavior. It extends existing adoption models and is validated through empirical research, potentially allowing for more robust findings. Furthermore, the insights gained from this model can serve as a guide for future research that focuses on understanding the adoption patterns of emerging chatbot technologies.

Moving on, our literature review may enhance theoretical understanding by offering an overview of the current landscape of research on AI-powered chatbot adoption. By summarizing key findings, future researchers can gain insight into the existing knowledge and develop new studies based on established theories, constructs, and measurement approaches presented (Appendix A). Additionally, our description of the literature review process, including the gathering and search methodology (Chapter 3.1), can facilitate replication in a rapidly evolving theoretical field. It may also serve as a starting point for further exploration of AI technology and AI-powered chatbot adoption studies.

The literature review has further uncovered a notable research gap, as no previous studies, to our knowledge, have applied as many different adoption models to investigate the adoption of both AI technology and AI-powered chatbots. Each adoption model possesses unique constructs and measurement approaches, and the utilization of multiple models enables a more comprehensive understanding of the various constructs influencing adoption. This approach may facilitate meaningful comparisons across different models, thereby contributing to a more holistic understanding of the phenomenon being studied. In our study, we have identified significant drivers of adoption across traditional technology adoption models, thereby indicating a level of validity and efficacy of this approach.

7.3 Managerial Implications

In this study, we created a Customized Model combining the constructs: Usefulness, Habit, Trialability and Anthropomorphism. This implies that businesses may benefit from prioritizing these four constructs when designing and developing chatbots. Firstly, businesses can increase the likelihood of technology adoption by ensuring that the technology is perceived as useful to consumers, which may be achieved by highlighting the benefits and demonstrating how the technology can enhance performance or solve specific problems. Secondly, businesses may try to facilitate habit formation by encouraging frequent use. Thirdly, businesses can motivate users to experiment with the chatbot before committing to full adoption. Finally, they may benefit from developing chatbots that clearly demonstrate their machine nature, as Anthropomorphism was shown to have a negative influence on Intention to Use. By leveraging these constructs, managers can develop effective strategies for chatbot implementation and improve the functionality and design of their chatbots to better meet consumers' needs and expectations.

The literature review conducted in this study served as a foundational step in developing hypotheses and identifying Model Extensions. Through the review, a wide range of articles regarding the adoption of different AI technologies and AI-powered chatbot types were identified. This literature review may offer managers a deeper understanding of the research landscape and shed light on specific constructs that are important in general, as well as those that hold particular significance in their respective industries. The literature review encompasses a diverse range of articles, covering various domains of chatbot adoption, like healthcare, coaching, and banking, among others (Laumer et al., 2019; Terblanche & Kidd, 2022; Alt et al., 2021). By familiarizing themselves with the broader research field, managers can derive meaningful benefits and make informed decisions.

Overall, this research sheds light on the factors influencing chatbot adoption among consumers and presents implications for businesses that utilize chatbots. By identifying the drivers of chatbot adoption, the study may offer managers the opportunity to implement chatbots more effectively and maximize their benefits for both the business and consumers. Although the findings may not be entirely generalizable, they may provide businesses with a better understanding of the drivers and barriers of adoption, which can inform their chatbot implementation strategies.

7.4 Limitations

A limitation of our study is the sample size. While the statistical analyses typically indicate acceptable levels of validity and significant findings, a larger sample size may enhance the external validity and generalizability of our results. With a greater sample, the findings could have been applied with increased confidence. Overall, it is important to acknowledge the constraints imposed by time and resources in this study. Conducting a more extensive study would enable a more thorough exploration of our research topic and lead to findings that can be more widely applied and generalized.

Another limitation of this study is the composition of our sample. The sample consists of students attending the Norwegian School of Economics (NHH) exclusively, which likely reduces the applicability of the results to other populations. Furthermore, we acknowledge that around 62% of the respondents were male (Table 4.1), which aligns with the gender distribution at NHH but may not accurately represent the gender diversity among students in the general population. This gender imbalance could potentially affect the generalizability of our findings beyond our specific sample.

The high proportion of respondents (81%) with experience limited to search engine chatbots (Table 4.1) could also raise concerns regarding the generalizability of the findings. The dominance of search engine chatbot experience in the sample may affect the ability to draw broad conclusions applicable to all types of chatbots. Although this familiarity was so high, the survey items were not specifically developed to focus on search engine chatbots. Consequently, this makes it difficult to accurately capture the nuances and unique aspects of this chatbot type and could potentially impacting the overall construct validity of the study (Saunders et al., 2016).

Lastly, we removed one item from Trialability and one item from Anthropomorphism due to issues regarding factor loadings. This may compromise the reliability and robustness of the remaining items, reducing the precision in measuring the two constructs. The removal of these items may have prevented us from capturing the full nature of Trialability and Anthropomorphism, affecting the construct validity (Saunders et al., 2016). As a result, there may be an incomplete or biased understanding of these constructs and their relationship with other variables in the study. Subsequently, this may have affected the reliability of our Customized Model, which includes both Trialability and Anthropomorphism.

7.5 Future research

While this study focused on a sample of students attending bachelor's or master's degrees at The Norwegian School of Economics (NHH), future researchers could benefit from studying different demographic groups. For instance, it may be interesting to explore how chatbot adoption varies across different age groups, genders, and ethnicities. Additionally, since the sample for this study was limited to a single business school, it would be valuable to expand the sample to include participants from other universities or individuals from different backgrounds.

Although our study's purpose is to understand the factors that drive AI-powered chatbot adoption, it is important to note that it is likely to evolve over time. To gain a deeper understanding of this phenomenon, future researchers could conduct longitudinal studies that track changes in chatbot adoption over time (Saunders et al., 2016). By collecting data at multiple points in time, researchers could gain insights into how the Intention to Use chatbots may change as the technology becomes more prevalent. This may be interesting as perceptions are likely to change due to the rapid growth and popularity of the technology (McKinsey, 2022).

Karahanna et al. (1999), emphasize the need to differentiate between individuals’ beliefs and attitudes before adopting a technology and their beliefs and attitudes after using it. To gain a broader understanding of the chatbot adoption process, it would be interesting to examine the effects the constructs have over time. The drivers that are important for the initial adoption of a technology may differ from the drivers that are important for its continued use. Rad et al. (2018) found that the variable "Continuance of Use" is utilized in only 7% of the technology adoption studies included in their meta-analysis, suggesting that it is an understudied aspect.

The majority of respondents (81%) in our study were most familiar with search engine chatbots. To overcome the limitation of limited variation in chatbot types (Table 4.1), future research can benefit from gathering a more diverse sample with experience across different chatbot types. By comparing experiences across different chatbot types, researchers can gain a more comprehensive understanding of how different chatbot designs and functionalities influence adoption behaviors and outcomes. Furthermore, with the growing prevalence of search engine chatbot technology (Deloitte, 2022), users may increasingly perceive chatbots as being more closely related to search engine chatbots rather than traditional customer service chatbots. In future research, the impact of exposure to search engine chatbots on the adoption of other chatbot types could be explored. Further research on the factors driving the adoption of search engine chatbots specifically may also provide insights into how they can be designed and marketed more effectively in various contexts.

With the recent emergence of chatbots, negative or biased media coverage surrounding chatbots is seemingly increasing. In recent statistical findings, it has been revealed that 4 out of 10 Norwegians express concerns regarding the advancements of AI (NIPSOS, 2023), which could be enhanced by negative or biased media coverage. Exposure to such content may potentially have an impact on users' intentions to use chatbots. Studying the impact of media exposure on individuals' Intention to Use chatbots may provide valuable insights for businesses and marketers on addressing negative perceptions and effectively promoting the benefits of chatbots.

AI has an increasing reliance on Big Data, which may result in an escalation of ethical challenges related to privacy. With the rising adoption of AI products and services, businesses collect, access, and utilize more personal information than ever (Kaplan & Haenlein, 2019). During the process of selecting our Model Extensions, Privacy Risk appeared repeatedly in the literature review. However, other constructs of Privacy, like Privacy Concern, could be explored further as they may yield different outcomes. Delving into the distinctions between different privacy-related constructs, may enhance our understanding of the role that privacy plays in the adoption of technology.

The surprising negative effect of Anthropomorphism on consumers' Intention to Use AI-powered chatbots found in this study emphasizes the importance of further research in this area. According to a report by Ubisend (2022), some people find it more natural to talk to a human-like chatbot, but the demand for urgency and accuracy often trumps this wish. It is possible that when consumers perceive chatbots as too human-like or having high levels of Anthropomorphism, they may have concerns or reservations about the chatbot's capabilities, reliability, or trustworthiness. Consumers may instead prefer chatbots that clearly demonstrate their machine nature, offering accurate and predictable responses. As a result, researchers can explore strategies to mitigate the negative effects of Anthropomorphism by providing transparent information about chatbot capabilities and limitations to manage users' expectations. Determining the ideal balance of human-like qualities and machine attributes may improve chatbot adoption.

Finally, future studies may also investigate the specific characteristics of Anthropomorphism that influence consumers' Intention to Use chatbots, in order to gain a better understanding of its influence. Given that our sample mainly uses search engine chatbots, it would be intriguing to examine whether consumers' preferred level of Anthropomorphism varies among different types of chatbots. Perhaps the demand for urgency and accuracy, rather than human-like chatbots (Ubisend, 2022), is more important when adopting search engine chatbots. An investigation of this could shed light on whether consumers have varying expectations and preferences regarding the human-like qualities of different chatbot categories. By exploring these distinctions, researchers can gain insights into the design and implementation of chatbots that align with consumers' preferences and contribute to enhanced adoption and acceptance of this technology.

7.6 Conclusions

The purpose of the study was to identify the constructs driving the adoption of AI-powered chatbots from a consumer perspective. Based on our findings we conclude that the most important adoption factors are Subjective Norm (TPB), Behavioral Control (TPB), Usefulness (TAM), Habit (UTAUT2), and Trialability (DOI), which significantly influenced consumers' Intention to Use AI-powered chatbots. The Customized Model, which consists of Usefulness, Trialability, Habit, and Anthropomorphism (Model Extensions), outperformed traditional adoption models in explaining consumer adoption, exhibiting a stronger explanatory power of 46.6% while using fewer constructs. Interestingly, Anthropomorphism showed a significant negative effect on Intention to Use chatbots. These findings highlight the potential of the Customized Model to be a foundation for future investigations into chatbot adoption. While we acknowledge the significance of the findings in this study, we also emphasize the limitations and exercise caution in drawing concrete generalizable conclusions.

The contributions found in this study may help researchers and managers better understand chatbot adoption and develop effective strategies for its implementation. The study highlights the importance of businesses understanding the constructs driving adoption of AI-powered chatbots. By leveraging the significant constructs and the Customized Model, businesses may improve the functionality and design of their chatbots to better meet consumers' needs and expectations. Our study also emphasizes the necessity for further research into the adoption of chatbots in diverse contexts and through various approaches.

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Appendix A: Literature Review

AI adoption

Title, Author(s) and Year	**Purpose**	**Method**	**AI Tech**	**Independent, mediating and moderating variables**	**Main results**
Adoption of AI-based chatbots for hospitality and tourism Pillai, Rajasshrie, & Brijesh Sivathanu 2020	Investigate customers' behavioral intention and actual usage of chatbots for hospitality and tourism in India.	Quantitative Survey	Chatbot for hospitality and tourism	Dependent variable: Adoption Variables used: Perceived Ease of Use, Perceived Usefulness, Technological Anxiety, perceived trust, Anthropomorphism, Perceived Intelligence, Stickiness to Traditional Travel Agents/ Planners, Adoption Intention	Perceived Ease of Use, Perceived Usefulness, Perceived Trust, Perceived Intelligence and Anthropomorphism significantly influence chatbot adoption, while Technological Anxiety does not. Stickiness to traditional human travel agents negatively moderates the relation of adoption intention and the actual usage of chatbots in tourism.
The adoption of AI service robots: A comparison between credence and experience service settings Park, S. S., Tung, C. D., & Lee, H. 2021	Find out if consumers experience the same psychological processes when adopting AI service robots in different service areas.	Quantitative Survey	Service Robot	Dependent variable: Adoption Intention Variables used: Privacy Concern, Trust, Perceived Ease of use, Perceived Usefulness, Attitude	Usefulness has a significant effect on consumers' attitudes toward adopting in a setting with a credence attribute (hospital), and not in a setting with an experience attribute (café). Privacy Concerns and Trust are shown to be significant antecedents in both cases.
Baby, you can drive my car: Psychological antecedents that drive consumers' adoption of AI-powered autonomous vehicles. Meyer-Waarden, L., & Cloarec, J. 2022	Analyze user acceptance of AI-powered autonomous vehicles by extending UTAUT.	Quantitative Survey	Autonomous vehicles	Dependent variable: Adoption Intention Variables used: Effort Expectancy, Social Recognition, Hedonism, Technology Security and Privacy Concerns, Performance Expectancy, User Well-being, Technology Trust, User Innovativeness	There is a positive relationship between performance-/effort expectancy, social recognition, well-being, hedonism, technology trust and security on the Adoption Intention of AI-powered AVs Privacy Concerns negatively influence technology trust.
Adoption of AI-driven personalization in digital news platforms: An integrative model of technology acceptance and perceived contingency Lim, J. S., & Zhang, J. 2022	Predict users` adoption of AI-driven personalization in digital news platforms.	Quantitative Survey	Digital news platforms	Dependent variable: Adoption Variables used: Perceived Ease of Use, Perceived Usefulness, Attitude, Contingency	Contingency plays a crucial role in predicting the adoption of AI-powered news platforms, showing a significant direct effect and an indirect effect on Adoption TAM variables are still important in predicting adoption behavior.

Students' adoption of AI-based teacher-bots (T-bots) for learning in higher education. Pillai, R., Sivathanu, B., Metri, B., & Kaushik, N. 2023	Investigate students' adoption intention and actual usage of artificial intelligence-based teacher bots by extending TAM.	Qualitative Survey	Teacher-bots	Dependent variable: Adoption Variables used: Perceived Ease of Use, Perceived Usefulness, Personalization, Interactivity, Perceived Trust, Anthropomorphism, Perceived Intelligence, Stickiness to Human Teachers, Intention to Use	Perceived Ease of Use, Perceived Usefulness, Personalization, Interactivity, Perceived Trust, Anthropomorphism and Perceived Intelligence all influence Intention Intention influences the actual use of T-bots, and its relationship is negatively moderated by stickiness to learn from human teachers in the classroom.
Exploring Patients' AI Adoption Intention in the Context of Healthcare. Zhu, Y., & Sun, S. 2021	Explain the adoption of AI in the context of healthcare using TAM and TPB.	Qualitative Survey	AI in healthcare	Dependent variable: Adoption Intention Variables used: Relative Advantage, Trust, Perceived Ease of Use, Perceived Risk, Fear of Technological Advance	Relative Advantage, Perceived Risk, and Trust directly affect AI Adoption Intention. Perceived Ease of Use affect intention through Trust and Relative Advantage. Relative Advantage had the biggest effect on Intention.
How to Increase Sport Facility Users' Intention to Use AI Fitness Services: Based on the Technology Adoption Model. Chin, J. H., Do, C., & Kim, M. 2022	Investigate relationships among drivers that can affect intention to use AI fitness services.	Qualitative Survey	AI fitness services	Dependent variable: Adoption Intention Variables used: Perceived Usefulness, Perceived Ease of Use, Importance of Exercise, Attitude	Perceived Usefulness, Perceived Ease of Use, and Importance of Exercise positively influence Attitude. Attitude positively influenced the Intention to use AI services. Usefulness had the biggest effect.
How Perceived Intelligence Affects Consumer Adoption of AI-Based Voice Assistants: An Affordance Perspective Bawack, R. E. 2021	Look at how perceived intelligence affects consumer adoption of voice assistant by dividing the concept in four dimensions.	Qualitative Survey	Voice assistants	Dependent variable: Adoption Intention Variables used: Perception, Comprehension, Action and Learning	Perception, Action and Learning significantly affect consumer Adoption of voice assistants.

Chatbot adoption

Title, Author(s) and year	Purpose	Method	AI Tech	Dependent variable Independent, mediating and moderating variables	Main results
Chatbot acceptance in Healthcare: Explaining user adoption of conversational agents for disease diagnosis. Laumer, Maier & Gubler 2019	Develope a research model explaining adoption of conversational agents for disease diagnosis.	Qualitative Semi-structured interviews	Conversational chatbot	Dependent variable: Intention Variables used: Performance Expectancy, Effort Expectancy, Facilitating Conditions, Social Influence, Price Value, Habit, Privacy Risk Expectancy, Trust in Provider and System, Compatibility, Experience in E-diagnosis, Access to Health System, Hedonic Motivation, Attitude	All UTAUT2 factors except Hedonic Motivation were relevant to explain adoption. Trust in providers and the system along with the other factors added by the researchers, were relevant and influenced Performance Expectancy the most. Privacy Risk Expectancy influences adoption.
Overcoming customer innovation resistance to the sustainable adoption of chatbot services: A community-enterprise perspective in Thailand. Kwangsawad & Jattamart 2022	Examine factors influencing consumers' intentions to continue using chatbot services in community enterprise.	Quantitative Survey	Chatbot customer service	Dependent variable: Intention of Continued Use Variables used: Perceived Usefulness, Perceived Ease of Use, Perceived Convenience, Perceived Information Quality, Perceived Time Risk, Perceived Privacy Risk, Technological Anxiety, Openness to Experience	Perceived Time and Privacy Risk directly influence attitudes and intentions to use. Technological Anxiety is a barrier that affects attitude, while Perceived Information Quality indirectly influences users to continue using chatbots. They found no correlation between Openness to Experience and attitudes toward the continued use, which shows that experienced users are affected by privacy and time constraints.
Factors Influencing Adoption Intention of AI Powered Chatbot for Public Transport Services within a Smart City. Kuberkar & Singhal 2020	To study adoption intention of AI - powered chatbots in smart cities.	Quantitative survey	Chatbot for public transport services	Dependent variable: Adoption Intention Variables used: Performance Expectancy, Effort Expectancy, Facilitating Conditions, Anthropomorphism, Trust	Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Anthropomorphism and Trust directly influence the Adoption Intention.
Adoption Factors and Moderating Effects of Age and Gender That Influence the Intention to Use a Non-Directive Reflective Coaching Chatbot Terblanche & Kidd 2022	Investigate what factors and moderating effects age and gender have on the adoption of a chatbot for goal-attainment coaching.	Quantitative survey	Chatbot for coaching	Dependent variable: Behavioral Intention Variables used: Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Perceived Risk. Gender, Age	Performance Expectancy, Social Influence, and Facilitating Conditions were significant as direct determinants of Behavioral Intention. Performance Expectancy was moderated by Gender, and Effort Expectancy was moderated by Age.
Adoption of Environmental Information Chatbot Services	Apply an integration of a framework for smart schools	Quantitative	Environmental information chatbot	Dependent variable: Use behavior Variables used:	Innovativeness, Performance Expectancy, Effort Expectancy, Facilitating Conditions, and Social

Based on the Internet of Educational Things in Smart Schools: Structural Equation Modeling Approach Rukhiran, Phaokla & Netinant 2022	developing a chatbot service and users' behavioral intentions toward the chatbot system.			Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Health and Safety, Innovativeness	Influence have a direct impact on behavioral intention of chatbot usage. The Health and Safety factor plays a major role in establishing and correlating behavior intent. Lastly, innovation through the internet of things and behavioral intent directly influence usage patterns.

Chatbot Acceptance

Title, Author(s) and year	**Purpose**	**Method**	**AI Tech**	**Independent, mediating and moderating variables**	**Main results**
Banking with a chatbot – a study on technology acceptance Alt, Vizeli,& Săplăcan 2021	Identify the factors that influence consumers' intention to use chatbot technology in the banking industry.	Quantitative . Survey	Banking chatbot	<u>Dependent variable:</u> Behavioral Intention to Use <u>Variables used:</u> Awareness of Service, Perceived Usefulness, Perceived Ease of Use, Perceived Compatibility, Perceived Privacy Risk	The study found Perceived Compatibility and Perceived Usefulness to be especially important in the adoption of chatbots. Awareness of the Service showed an effect on Perceived Ease of Use, Perceived Privacy Risk, and Indirectly affected Usage Intention of chatbots through Perceived Usefulness. Perceived Ease of Use and Perceived Privacy Risk show no effect on Usage Intention.
Analysis of factors influencing millennial's technology acceptance of chatbot in the banking industry in Indonesia Richad, Vivensius, Sfenrianto & Kaburuan 2019	Analyze factors that influence millennial's technology acceptance of chatbot in the banking industry in Indonesia.	Quantitative Survey	Banking chatbot	<u>Dependent variable:</u> Behavioral Intention <u>Variables used:</u> Innovativeness, Perceived Usefulness, Perceived Ease of Use, Attitude Towards Using	Innovativeness, Perceived Usefulness, Perceived Ease of Use and Attitude towards using the chatbot affected Behavioral Intention.
Factors Affecting Baby Boomers' Attitudes towards the Acceptance of Mobile Network Providers' AI Chatbot Poonpanich & Buranasiri 2022	Study the factors which affect "baby boomers'" attitudes towards the acceptance of mobile network providers' Chatbots in Thailand.	Quantitative Survey.	Mobile network chatbot	<u>Dependent variable:</u> Behavioral Intention to Use <u>Variables used:</u> Perceived Usefulness, Perceived Ease of Use, Compatibility, Privacy Concern, Attitude Toward Advertisement, Social Influence, Attitude Toward AI Chatbot	The results show the importance of Perceived Usefulness, Perceived Ease of Use, Compatibility, Privacy Concern, Attitude Toward Advertisement, and Social Influence on the acceptance of AI chatbot technology.

Appendix B: Complete Survey

Page 1 Consent

Dear fellow student!

This survey is a part of our master thesis at NHH and helps us to learn more about Chatbot services. The survey takes about 6-8 minutes, and we highly appreciate your contribution to our research.

The survey is anonymous and we will not be able to trace the response back to you. All information will be handled confidentially. Participation is voluntary, and you are free to withdraw from the survey at any time. Note, however, that you must complete the entire survey in order for your response to be used. Please do not distribute this survey to people outside NHH. If you have any questions or comments about the survey, please contact Thorgrim Bergene (Thorgrim.bergene@student.nhh.no) or Emil McCarthy Rød (Emil.rod@student.nhh.no).

I consent to take part in this survey and accept that data from it will be used for research purposes.

Yes

No

Page 2 Chatbot introduction

A short introduction of chatbots

AI-powered chatbots are computer programs designed to mimic human conversation using natural language processing algorithms (NLP). They have the ability to provide responses in real-time using pre-programmed or dynamically generated text. Chatbots can also be equipped with machine learning capabilities, which means they are able to learn and improve their responses over time based on the interactions they have with users.

Chatbots are becoming increasingly popular in various areas, including healthcare, finance, travel and search engines. They can be advantageous for both businesses and consumers as they provide efficient ways to interact with customers, enables support around the clock and improves personalized experiences. With that being said, they also have limitations when handling complex problems and understanding human emotion, among other things.

Page 3 Survey information

Survey information

On the following pages you will be introduced to several statements about chatbot services. You answer by indicating your opinion of the statements on a scale of 1-7. Feel free to use the entire scale when answering. There are no right or wrong answers. We want your opinion. You may experience that some statements appear similar. This is intentional, and we therefore ask you to consider each statement carefully.

On the next page the survey starts. Please answer the statements based on your knowledge about chatbot services. This knowledge can be based on the description of chatbot services on the prior page of this survey, prior information you have about chatbot services, or your own experience with chatbot services.

Page 4 Intention to use

On a scale of 1 to 7, how much do you agree or disagree with the following statements?

	Totally disagree 1	2	3	4	5	6	Totally agree 7
I intend to use a chatbot in the next six months	○	○	○	○	○	○	○
The next six months I intend to use chatbots frequently	○	○	○	○	○	○	○

Page 5 TPB: Attitude

On a scale from 1 – 7, please indicate your opinion of the statements below.

I believe that using chatbots is

Bad 1	2	3	4	5	6	Good 7
○	○	○	○	○	○	○

I believe that using chatbots is

Foolish 1	2	3	4	5	6	Wise 7
○	○	○	○	○	○	○

I believe that using chatbots is

Negative 1	2	3	4	5	6	Positive 7
○	○	○	○	○	○	○

Page 6 TPB: Subjective Norm and Behavioral Control

On a scale of 1 to 7, how much do you agree or disagree with the following statements?

	Totally disagree 1	2	3	4	5	6	Totally agree 7
People important to me think I should use chatbots.	O	O	O	O	O	O	O
It is expected that people like me use chatbots.	O	O	O	O	O	O	O
People I look up to expect me to use chatbots.	O	O	O	O	O	O	O
I have the necessary means and resources to use chatbots.	O	O	O	O	O	O	O
I feel free to use the kind of chatbots I like to.	O	O	O	O	O	O	O
Using chatbots is entirely within my control.	O	O	O	O	O	O	O

Page 7 TAM: Ease of Use and Usefulness

On a scale of 1 to 7, how much do you agree or disagree with the following statements?

	Totally disagree 1	2	3	4	5	6	Totally agree 7
It is easy to make chatbots do what I want them to do.	O	O	O	O	O	O	O
My interactions with chatbots are clear and understandable.	O	O	O	O	O	O	O
It is easy to use chatbots.	O	O	O	O	O	O	O
Using chatbots makes me save time.	O	O	O	O	O	O	O
Using chatbots improves my efficiency.	O	O	O	O	O	O	O
Chatbots are useful to me.	O	O	O	O	O	O	O

Page 8 UTAUT2: Hedonic Motivation and Habit

Thank you for making it this far, your response is very valuable to our thesis.

On a scale of 1 to 7, how much do you agree or disagree with the following statements?

	Totally disagree 1	2	3	4	5	6	Totally agree 7
Using chatbots is fun.	○	○	○	○	○	○	○
Using chatbots is enjoyable.	○	○	○	○	○	○	○
Using chatbots is very entertaining.	○	○	○	○	○	○	○
The use of chatbots has become a habit for me.	○	○	○	○	○	○	○
I am addicted to using chatbots.	○	○	○	○	○	○	○
I must use chatbots.	○	○	○	○	○	○	○

Page 9 DOI: Relative Advantage and Compatibility

On a scale of 1 to 7, how much do you agree or disagree with the following statements?

	Totally disagree 1	2	3	4	5	6	Totally agree 7
Using chatbots improves problem solving and information gathering.	○	○	○	○	○	○	○
Overall, using chatbots is advantageous.	○	○	○	○	○	○	○
Using chatbots is in general the best way to solve problems/receive information.	○	○	○	○	○	○	○
Using chatbots is compatible with my lifestyle.	○	○	○	○	○	○	○
Using chatbots is completely compatible with my needs.	○	○	○	○	○	○	○
Chatbots fit well with the way I like to get things done.	○	○	○	○	○	○	○

Page 10 DOI: Complexity and Trialability

On a scale of 1 to 7, how much do you agree or disagree with the following statements?

	Totally disagree 1	2	3	4	5	6	Totally agree 7
Chatbots are slow and complicated to use.	O	O	O	O	O	O	O
It is difficult to use chatbots.	O	O	O	O	O	O	O
It takes too long to learn how to use chatbots.	O	O	O	O	O	O	O
I can use chatbots on a trial basis to see what it can do.	O	O	O	O	O	O	O
It is easy to try out chatbots without a big commitment.	O	O	O	O	O	O	O
I have had opportunities to try out chatbots.	O	O	O	O	O	O	O

Page 11 DOI: Observability

On a scale of 1 to 7, how much do you agree or disagree with the following statements?

	Totally disagree 1	2	3	4	5	6	Totally agree 7
I have no difficulty telling others about the results of using chatbots.	O	O	O	O	O	O	O
I can communicate to others the outcomes of using chatbots.	O	O	O	O	O	O	O
The results of using chatbots are apparent to me.	O	O	O	O	O	O	O

Page 12 Model extensions: Anthropomorphism and Trust

You are soon done with the survey. Thank you again for taking the time. Your response is very valuable, so please keep going a little bit longer.

On a scale of 1 to 7, how much do you agree or disagree with the following statements?

	Totally disagree 1	2	3	4	5	6	Totally agree 7
Interactions with chatbots are similar to interactions with humans.	O	O	O	O	O	O	O
Interactions with chatbots are natural.	O	O	O	O	O	O	O
Interactions with chatbots are interactive.	O	O	O	O	O	O	O
Chatbots are trustworthy.	O	O	O	O	O	O	O
Chatbots are reliable.	O	O	O	O	O	O	O
Chatbots are dependable.	O	O	O	O	O	O	O

Page 13 Model Extensions: Privacy Risk and Personalization

On a scale of 1 to 7, how much do you agree or disagree with the following statements?

	Totally disagree 1	2	3	4	5	6	Totally agree 7
Chatbots can cause personal information to be published.	O	O	O	O	O	O	O
Disclosing personal information through chatbots is a risk.	O	O	O	O	O	O	O
Disclosing personal information through chatbots can be negative for me.	O	O	O	O	O	O	O
Chatbots provide personalized answers that are based on my information.	O	O	O	O	O	O	O
Chatbots understand my needs.	O	O	O	O	O	O	O
Chatbots know what i want.	O	O	O	O	O	O	O

Page 14 Chatbot experience and Chatbot type familiarity

How much experience do you have with chatbots?

None 1	2	3	4	5	6	Extensive 7

Which type of chatbot are you most familiar with?

- Banking chatbot
- Search engine chatbot (e.g., ChatGPT)
- Travel and hospitality
- Other chatbot
- I have not used a chatbot

Page 15 Gender and age

What is your gender?

- Male
- Female
- Prefer not to say

What is your age?

- 18 - 25
- Above 25

Page 16 Thank you for participating

Thank you for your participation. Your contribution to our research is highly valued and we appreciate you taking the time to respond.

By responding to this survey, you contributed to our master thesis on antecedents of chatbot adoption. More specifically, we aim to test the relevance of various established adoption models for adoption of chatbot services, and to develop an adoption model particularly relevant for chatbot services.

Thank you!

Best regards

Thorgrim Ekkeren Bergene og Emil McCarthy Rød

Appendix C: Survey invitations

E-mail 1

Subject: Invitation to Participate in Our Survey on Chatbots

Dear fellow students

As part of our research for our master's thesis at the Norwegian School of Economics (NHH), we are conducting a survey about chatbots, and we would like to invite you to participate.

Chatbots are becoming increasingly popular in various areas such as healthcare, finance, travel, and search engines. By participating in our survey, you will contribute to a better understanding of chatbots, which may benefit both companies and consumers.

Your participation is crucial to our research project, and as students, we are dependent on your responses. The survey will take approximately 6-8 minutes to complete. All data will be treated confidentially, and your participation is voluntary. Your response will be anonymous.

We understand that your time is valuable, but your participation will be greatly appreciated. Your contribution will help us in our research and will be a valuable addition to our master's thesis.

Survey Link: https://nhh.eu.qualtrics.com/jfe/form/SV_5pAT7plkiAeVgAS

Thank you for considering our invitation.

Best regards

Thorgrim Bergene/ thorgrim.bergene@student.nhh.no

Emil McCarthy Rød/ emil.rod@student.nhh.no

E-mail 2

Subject: Reminder to participate in our Chatbot Survey
Dear fellow students
I hope this e-mail finds you well. We would like to remind you about the survey we sent out earlier this week regarding chatbots. The survey aims to gather information about chatbots and their increasing popularity in various areas such as healthcare, finance, travel, and search engines.
We highly appreciate your participation in our survey, as your responses are crucial to our research project. Your contribution will help us in our research and will be a valuable addition to our master thesis.
Please note that all data will be treated confidentially, and your participation is voluntary. Your response will be anonymous, and the survey will take approximately 6-8 minutes to complete.
If you have not yet had the chance to take the survey, please consider doing so by clicking on the following link: https://nhh.eu.qualtrics.com/jfe/form/SV_5pAT7plkiAeVgAS
Thank you in advance for your participation.
Best regards,
Thorgrim Bergene/ thorgrim.bergene@student.nhh.no
Emil McCarthy Rød/ emil.rod@student.nhh.no

E-mail 3
Subject: Last reminder to participate in our Chatbot Survey
Dear fellow students
As your response is very valuable, we would like to remind you again about the survey we sent out earlier this week regarding chatbots. The survey aims to gather information about chatbots and their increasing popularity in various areas such as healthcare, finance, travel, and search engines.
We highly appreciate your participation in our survey, as your responses are crucial to our research project. Your contribution will help us in our research and will be a valuable addition to our master thesis.
Please note that all data will be treated confidentially, and your participation is voluntary. Your response will be anonymous, and the survey will take approximately 6-8 minutes to complete.

If you have not yet had the chance to take the survey, please consider doing so by clicking on the following link: https://nhh.eu.qualtrics.com/jfe/form/SV_5pAT7plkiAeVgAS

Thank you in advance for your participation.

Best regards,

Thorgrim Bergene/ thorgrim.bergene@student.nhh.no

Emil McCarthy Rød/ emil.rod@student.nhh.no

Appendix D: Testing Intention to Use

D1: Total variance explained (Intention to Use)

Total Variance Explained

	Initial Eigenvalues		
Factor	Total	% of Variance	Cumulative %
1	1,807	90,363	90,363
2	,193	9,637	100,000

Extraction Method: Maximum Likelihood.

D2: Cronbach's Alpha (Intention to Use)

Reliability Statistics

Cronbach's Alpha	N of Items
,890	2

D3: Communalities (Intention to Use)

Communalities

	Initial
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - I intend to use a chatbot in the next six months	,652
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - The next six months I intend to use chatbots frequently	,652

Extraction Method: Maximum Likelihood.

Appendix E: Testing TPB

E1: KMO and Bartlett's Test

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,711
Bartlett's Test of Sphericity	Approx. Chi-Square	425,877
	df	36
	Sig.	<,001

E2: Total variance explained (TPB)

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Loadings[a]
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	3,377	37,522	37,522	2,912	32,357	32,357	2,390
2	1,737	19,297	56,820	1,332	14,799	47,156	2,156
3	1,342	14,912	71,731	1,032	11,467	58,623	1,763
4	,692	7,693	79,425				
5	,513	5,699	85,123				
6	,460	5,113	90,236				
7	,366	4,063	94,299				
8	,307	3,412	97,711				
9	,206	2,289	100,000				

E3: Pattern Matrix (TPB)

Pattern Matrix[a]

	Factor 1	2	3
I believe that using chatbots is - 1	,721		
I believe that using chatbots is - 1	,673		
I believe that using chatbots is - 1	,947		
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - People important to me think I should use chatbots.		,631	
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - It is expected that people like me use chatbots.		,784	
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - People I look up to expect me to use chatbots.		,876	
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - I have the necessary means and resources to use chatbots.		,224	,623
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - I feel free to use the kind of chatbots I like to.			,774
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Using chatbots is entirely within my control.			,529

Extraction Method: Maximum Likelihood.
Rotation Method: Oblimin with Kaiser Normalization.
a. Rotation converged in 5 iterations.

E4: Cronbach’s Alpha (TPB)

Attitude:

Reliability Statistics

Cronbach's Alpha	N of Items
,829	3

Subjective norm:

Reliability Statistics

Cronbach's Alpha	N of Items
,813	3

Behavioral Control:

Reliability Statistics

Cronbach's Alpha	N of Items
,666	3

E5: Correlations (TPB)

Correlations

		Intention	attitude	SubNorm	BehControl
Intention	Pearson Correlation	1	,317**	,410**	,350**
	Sig. (2-tailed)		<,001	<,001	<,001
	N	126	126	126	126
attitude	Pearson Correlation	,317**	1	,316**	,337**
	Sig. (2-tailed)	<,001		<,001	<,001
	N	126	126	126	126
SubNorm	Pearson Correlation	,410**	,316**	1	,199*
	Sig. (2-tailed)	<,001	<,001		,025
	N	126	126	126	126
BehControl	Pearson Correlation	,350**	,337**	,199*	1
	Sig. (2-tailed)	<,001	<,001	,025	
	N	126	126	126	126

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

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

E6: Descriptive Statistics (TPB)

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Intention	126	1,00	7,00	5,4643	1,82338	-1,270	,216	,460	,428
attitude	126	2,00	7,00	5,3598	1,15054	-,482	,216	,037	,428

SubNorm	126	1,00	7,00	3,7989	1,41238	-,089	,216	-,457	,428
BehControl	126	2,33	7,00	5,7222	1,15912	-,784	,216	-,134	,428
Valid N (listwise)	126								

Appendix F: Testing TAM

F1: KMO and Bartlett's Test

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,822
Bartlett's Test of Sphericity	Approx. Chi-Square	720,424
	df	15
	Sig.	<,001

F2: Total variance explained (TAM)

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	4,350	72,501	72,501	3,832	63,873	63,873
2	,849	14,145	86,646			
3	,352	5,873	92,519			
4	,239	3,989	96,508			
5	,151	2,518	99,027			
6	,058	,973	100,000			

Extraction Method: Maximum Likelihood.

F3: Total variance explained (TAM) – Forced to 2 factors

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	4,350	72,501	72,501	3,995	66,582	66,582	3,737

2	,849	14,145	86,646	,845	14,081	80,663	3,531
3	,352	5,873	92,519				
4	,239	3,989	96,508				
5	,151	2,518	99,027				
6	,058	,973	100,000				

Extraction Method: Maximum Likelihood.

a. When factors are correlated, sums of squared loadings cannot be added to obtain a total variance.

F4: Pattern Matrix (TAM)

Pattern Matrix[a]

	Factor	
	1	2
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - It is easy to make chatbots do what I want them to do.		,752
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - My interactions with chatbots are clear and understandable.		,978
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - It is easy to use chatbots.		,762
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Using chatbots makes me save time.	,978	

On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Using chatbots improves my efficiency.	1,004	
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Chatbots are useful to me.	,749	

Extraction Method: Maximum Likelihood.
Rotation Method: Oblimin with Kaiser Normalization.
a. Rotation converged in 4 iterations.

F5: Cronbach's Alpha (TAM)

Ease of Use

Reliability Statistics

Cronbach's Alpha	N of Items
,882	3

Usefulness

Reliability Statistics

Cronbach's Alpha	N of Items
,956	3

F6: Correlations (TAM)

Correlations

		Intention	EaseOfUse	Usefulness
Intention	Pearson Correlation	1	,408**	,590**
	Sig. (2-tailed)		<,001	<,001
	N	126	126	126

EaseOfUse	Pearson Correlation	,408**	1	,675**
	Sig. (2-tailed)	<,001		<,001
	N	126	126	126
Usefulness	Pearson Correlation	,590**	,675**	1
	Sig. (2-tailed)	<,001	<,001	
	N	126	126	126

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

F7: Descriptive Statistics (TAM)

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Intention	126	1,00	7,00	5,4643	1,82338	-1,270	,216	,460	,428
EaseOfUse	126	1,00	7,00	4,8889	1,27889	-,620	,216	,391	,428
Usefulness	126	1,00	7,00	5,4974	1,64154	-1,170	,216	,626	,428
Valid N (listwise)	126								

Appendix G: Testing UTAUT2

G1: KMO and Bartlett's Test

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,843
Bartlett's Test of Sphericity	Approx. Chi-Square	1766,261
	df	153
	Sig.	<,001

G2: Total variance explained (UTAUT 2)

Total Variance Explained

Factor	Initial Eigenvalues Total	% of Variance	Cumulative %	Extraction Sums of Squared Loadings Total	% of Variance	Cumulative %	Rotation Sums of Squared Loadings[a] Total
1	7,393	41,070	41,070	6,856	38,088	38,088	5,650
2	2,104	11,689	52,759	1,286	7,142	45,230	4,516
3	1,868	10,377	63,136	1,665	9,249	54,479	2,908
4	1,397	7,760	70,897	1,497	8,316	62,795	2,801
5	1,201	6,674	77,571	1,020	5,666	68,461	4,918
6	,788	4,375	81,946				
7	,645	3,586	85,532				
8	,545	3,030	88,563				
9	,384	2,133	90,696				
10	,336	1,866	92,562				
11	,294	1,631	94,193				
12	,266	1,478	95,672				
13	,212	1,176	96,847				
14	,172	,953	97,800				
15	,147	,814	98,615				
16	,133	,739	99,354				
17	,064	,357	99,711				
18	,052	,289	100,000				

Extraction Method: Maximum Likelihood.

a. When factors are correlated, sums of squared loadings cannot be added to obtain a total variance.

G3: Total variance explained (UTAUT 2) - Forced to 6 factors

Total Variance Explained

Factor	Initial Eigenvalues Total	% of Variance	Cumulative %	Extraction Sums of Squared Loadings Total	% of Variance	Cumulative %	Rotation Sums of Squared Loadings[a] Total
1	7,393	41,070	41,070	6,940	38,554	38,554	5,603
2	2,104	11,689	52,759	1,339	7,438	45,991	4,709
3	1,868	10,377	63,136	1,692	9,402	55,393	2,996
4	1,397	7,760	70,897	1,123	6,236	61,630	2,828
5	1,201	6,674	77,571	1,495	8,306	69,935	2,690
6	,788	4,375	81,946	,730	4,055	73,990	4,920
7	,645	3,586	85,532				

8	,545	3,030	88,563				
9	,384	2,133	90,696				
10	,336	1,866	92,562				
11	,294	1,631	94,193				
12	,266	1,478	95,672				
13	,212	1,176	96,847				
14	,172	,953	97,800				
15	,147	,814	98,615				
16	,133	,739	99,354				
17	,064	,357	99,711				
18	,052	,289	100,000				

Extraction Method: Maximum Likelihood.

a. When factors are correlated, sums of squared loadings cannot be added to obtain a total variance.

G4: Pattern Matrix (UTAUT2)

Pattern Matrix

	Factor				
	1	2	3	4	5
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - It is easy to make chatbots do what I want them to do.					,750
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - My interactions with chatbots are clear and understandable.					,903
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - It is easy to use chatbots.					,766

On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Using chatbots makes me save time.	,945				
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Using chatbots improves my efficiency.	1,002				
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Chatbots are useful to me.	,656				,202
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - People important to me think I should use chatbots.				,606	
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - It is expected that people like me use chatbots.				,758	
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - People I look up to expect me to use chatbots.				,876	

On a scale of 1 to 7, how much do you agree or disagree with the following statements? - I have the necessary means and resources to use chatbots.					,336
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - I feel free to use the kind of chatbots I like to.					,373
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Using chatbots is entirely within my control.		-,224		-,200	,331
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Using chatbots is fun.		-,905			
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Using chatbots is enjoyable.		-,819			
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Using chatbots is very entertaining.		-,854			
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - The use of chatbots has become a habit for me.			,620		

On a scale of 1 to 7, how much do you agree or disagree with the following statements? - I am addicted to using chatbots.			,921		
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - I must use chatbots.			,900		

Extraction Method: Maximum Likelihood.
Rotation Method: Oblimin with Kaiser Normalization.
a. Rotation converged in 6 iterations.

G5: Pattern Matrix (UTAUT2) – Forced to 6 factors

Pattern Matrix[a]

	Factor					
	1	2	3	4	5	6
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - It is easy to make chatbots do what I want them to do.						,737
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - My interactions with chatbots are clear and understandable.						,955
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - It is easy to use chatbots.						,750

On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Using chatbots makes me save time.	,950					
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Using chatbots improves my efficiency.	,975					
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Chatbots are useful to me.	,645					
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - People important to me think I should use chatbots.					,597	
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - It is expected that people like me use chatbots.					,752	
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - People I look up to expect me to use chatbots.					,872	

On a scale of 1 to 7, how much do you agree or disagree with the following statements? - I have the necessary means and resources to use chatbots.				,515		
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - I feel free to use the kind of chatbots I like to.				,966		
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Using chatbots is entirely within my control.		-,201		,344	-,221	
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Using chatbots is fun.		-,916				
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Using chatbots is enjoyable.		-,834				
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Using chatbots is very entertaining.		-,878				
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - The use of chatbots has become a habit for me.			,615			

On a scale of 1 to 7, how much do you agree or disagree with the following statements? - I am addicted to using chatbots.			,917			
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - I must use chatbots.			,912			

Extraction Method: Maximum Likelihood.
Rotation Method: Oblimin with Kaiser Normalization.
a. Rotation converged in 6 iterations.

G6: Cronbach's Alpha (UTAUT2)

Ease of Use (Effort expectancy)

Reliability Statistics

Cronbach's Alpha	N of Items
,882	3

Usefulness (Performance expectancy)

Reliability Statistics

Cronbach's Alpha	N of Items
,956	3

Subjective norm (Social Influence):

Reliability Statistics

Cronbach's Alpha	N of Items
,813	3

Behavioral control (Facilitating Conditions):

Reliability Statistics

Cronbach's Alpha	N of Items
,666	3

Habit:

Reliability Statistics

Cronbach's Alpha	N of Items

,843	3

Hedonic:

Reliability Statistics

Cronbach's Alpha	N of Items
,945	3

G7: Correlations (UTAUT2)

Correlations

		Intention	EaseOfUse	Usefulness	SubNorm	BehControl	Hedonic	Habit
Intention	Pearson Correlation	1	,408**	,590**	,410**	,350**	,419**	,430**
	Sig. (2-tailed)		<,001	<,001	<,001	<,001	<,001	<,001
	N	126	126	126	126	126	126	126
EaseOfUse	Pearson Correlation	,408**	1	,675**	,293**	,468**	,468**	,304**
	Sig. (2-tailed)	<,001		<,001	<,001	<,001	<,001	<,001
	N	126	126	126	126	126	126	126
Usefulness	Pearson Correlation	,590**	,675**	1	,437**	,424**	,594**	,399**
	Sig. (2-tailed)	<,001	<,001		<,001	<,001	<,001	<,001
	N	126	126	126	126	126	126	126
SubNorm	Pearson Correlation	,410**	,293**	,437**	1	,199*	,329**	,239**
	Sig. (2-tailed)	<,001	<,001	<,001		,025	<,001	,007
	N	126	126	126	126	126	126	126
BehControl	Pearson Correlation	,350**	,468**	,424**	,199*	1	,363**	,156
	Sig. (2-tailed)	<,001	<,001	<,001	,025		<,001	,082
	N	126	126	126	126	126	126	126
Hedonic	Pearson Correlation	,419**	,468**	,594**	,329**	,363**	1	,414**
	Sig. (2-tailed)	<,001	<,001	<,001	<,001	<,001		<,001
	N	126	126	126	126	126	126	126

Habit	Pearson Correlation	,430**	,304**	,399**	,239**	,156	,414**	1
	Sig. (2-tailed)	<,001	<,001	<,001	,007	,082	<,001	
	N	126	126	126	126	126	126	126

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

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

G8: Descriptives (UTAUT2)

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Intention	126	1,00	7,00	5,4643	1,82338	-1,270	,216	,460	,428
EaseOfUse	126	1,00	7,00	4,8889	1,27889	-,620	,216	,391	,428
Usefulness	126	1,00	7,00	5,4974	1,64154	-1,170	,216	,626	,428
SubNorm	126	1,00	7,00	3,7989	1,41238	-,089	,216	-,457	,428
BehControl	126	2,33	7,00	5,7222	1,15912	-,784	,216	-,134	,428
Hedonic	126	1,00	7,00	4,7249	1,63304	-,555	,216	-,194	,428
Habit	126	1,00	6,33	2,4048	1,38667	1,113	,216	,667	,428
Valid N (listwise)	126								

Appendix H: Testing DOI

H1: KMO and Bartlett's Test

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,860
Bartlett's Test of Sphericity	Approx. Chi-Square	1280,341
	df	78
	Sig.	<,001

H2: Total variance explained (DOI)

Total Variance Explained

Factor	Initial Eigenvalues	Extraction Sums of Squared Loadings	Rotation Sums of Squared Loadings[a]

	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	6,006	40,042	40,042	5,611	37,406	37,406	4,423
2	2,291	15,271	55,313	1,899	12,660	50,066	2,858
3	1,465	9,766	65,079	1,083	7,221	57,287	2,713
4	1,059	7,062	72,141	,774	5,157	62,444	3,309
5	,704	4,696	76,837				
6	,603	4,023	80,860				
7	,532	3,550	84,410				
8	,445	2,969	87,378				
9	,421	2,804	90,182				
10	,353	2,355	92,537				
11	,301	2,004	94,541				
12	,267	1,781	96,321				
13	,212	1,413	97,734				
14	,198	1,319	99,053				
15	,142	,947	100,000				

Extraction Method: Maximum Likelihood.

a. When factors are correlated, sums of squared loadings cannot be added to obtain a total variance.

H3: Total variance explained (DOI) - Forced to five factors

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[a]
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	6,573	50,565	50,565	2,436	18,742	18,742	2,461
2	1,836	14,123	64,688	5,187	39,904	58,646	5,109
3	1,182	9,094	73,782	,968	7,449	66,095	4,626
4	,884	6,803	80,585	,748	5,753	71,848	4,713
5	,628	4,829	85,414	,633	4,871	76,719	2,456
6	,467	3,594	89,008				
7	,338	2,601	91,609				
8	,267	2,054	93,663				
9	,245	1,888	95,550				
10	,210	1,619	97,170				
11	,179	1,379	98,549				

12	,133	1,023	99,572				
13	,056	,428	100,000				

Extraction Method: Maximum Likelihood.

a. When factors are correlated, sums of squared loadings cannot be added to obtain a total variance.

H4: Pattern Matrix (DOI) – Using original DOI

Pattern Matrix[a]

	Factor			
	1	2	3	4
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Using chatbots improves problem solving and information gathering.	,601			,251
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Overall, using chatbots is advantageous.	,593			,336
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Using chatbots is in general the best way to solve problems/receive information.	,718			
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Using chatbots is compatible with my lifestyle.	,794			

On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Using chatbots is completely compatible with my needs.	,831			
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Chatbots fit well with the way I like to get things done.	,850			
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Chatbots are slow and complicated to use.	-,212		,647	
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - It is difficult to use chatbots.			,845	
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - It takes too long to learn how to use chatbots.			,560	-,414
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - I can use chatbots on a trial basis to see what it can do.	,201	-,206		,445

On a scale of 1 to 7, how much do you agree or disagree with the following statements? - It is easy to try out chatbots without a big commitment.				,787
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - I have had opportunities to try out chatbots.				,561
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - I have no difficulty telling others about the results of using chatbots.		-,837		
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - I can communicate to others the outcomes of using chatbots.		-,852		
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - The results of using chatbots are apparent to me.	,277	-,369		,346

Extraction Method: Maximum Likelihood.
Rotation Method: Oblimin with Kaiser Normalization.
a. Rotation converged in 7 iterations.

H5: Pattern Matrix (DOI) – Forced to 5 factors

Pattern Matrix[a]

	Factor				
	1	2	3	4	5

On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Using chatbots improves problem solving and information gathering.	,326		-,368		,265
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Overall, using chatbots is advantageous.			-,477		,359
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Using chatbots is in general the best way to solve problems/receive information.	,976				
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Using chatbots is compatible with my lifestyle.			-,851		
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Using chatbots is completely compatible with my needs.			-,765		
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Chatbots fit well with the way I like to get things done.			-,783		

On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Chatbots are slow and complicated to use.			,322	,625	
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - It is difficult to use chatbots.				,846	
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - It takes too long to learn how to use chatbots.				,538	-,431
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - I can use chatbots on a trial basis to see what it can do.					,444
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - It is easy to try out chatbots without a big commitment.					,783
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - I have had opportunities to try out chatbots.					,584
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - I have no difficulty telling others about the results of using chatbots.		,845			

On a scale of 1 to 7, how much do you agree or disagree with the following statements? - I can communicate to others the outcomes of using chatbots.		,877			
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - The results of using chatbots are apparent to me.		,400			,331

Extraction Method: Maximum Likelihood.
Rotation Method: Oblimin with Kaiser Normalization.
a. Rotation converged in 9 iterations.

H6: Pattern matrix (DOI) – Modified by replacing and removing items.

Pattern Matrix[a]

	Factor				
	1	2	3	4	5
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Using chatbots is compatible with my lifestyle.				,819	
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Using chatbots is completely compatible with my needs.				,849	

On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Chatbots fit well with the way I like to get things done.				,751	
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - It is easy to try out chatbots without a big commitment.					,794
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - I have had opportunities to try out chatbots.					,542
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - I have no difficulty telling others about the results of using chatbots.	1,020				
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - I can communicate to others the outcomes of using chatbots.	,704				
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Using chatbots makes me save time.		,900			

On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Using chatbots improves my efficiency.		,900			
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Chatbots are useful to me.		,637			,205
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - It is easy to make chatbots do what I want them to do.			,803		
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - My interactions with chatbots are clear and understandable.			,887		
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - It is easy to use chatbots.			,722		

Extraction Method: Maximum Likelihood.
Rotation Method: Oblimin with Kaiser Normalization.
a. Rotation converged in 6 iterations.

H7: Cronbach’s Alpha (DOI)

Compatibility

Reliability Statistics

Cronbach's Alpha	N of Items
,893	3

Trialability

Reliability Statistics

Cronbach's Alpha	N of Items
,714	2

Observability

Reliability Statistics

Cronbach's Alpha	N of Items
,872	2

Ease of Use (Complexity)

Reliability Statistics

Cronbach's Alpha	N of Items
,882	3

Usefulness (Relative advantage)

Reliability Statistics

Cronbach's Alpha	N of Items
,956	3

H8: Correlations (DOI)

Correlations

		Intention	EaseOfUse	Usefulness	Compatibilty	Trialability	Observability
Intention	Pearson Correlation	1	,408**	,590**	,484**	,501**	,319**
	Sig. (2-tailed)		<,001	<,001	<,001	<,001	<,001
	N	126	126	126	126	126	126
EaseOfUse	Pearson Correlation	,408**	1	,675**	,559**	,414**	,280**
	Sig. (2-tailed)	<,001		<,001	<,001	<,001	,002
	N	126	126	126	126	126	126
Usefulness	Pearson Correlation	,590**	,675**	1	,730**	,412**	,276**
	Sig. (2-tailed)	<,001	<,001		<,001	<,001	,002
	N	126	126	126	126	126	126
Compatibilty	Pearson Correlation	,484**	,559**	,730**	1	,271**	,288**

	Sig. (2-tailed)	<,001	<,001	<,001		,002	,001
	N	126	126	126	126	126	126
Trialability	Pearson Correlation	,501**	,414**	,412**	,271**	1	,447**
	Sig. (2-tailed)	<,001	<,001	<,001	,002		<,001
	N	126	126	126	126	126	126
Observability	Pearson Correlation	,319**	,280**	,276**	,288**	,447**	1
	Sig. (2-tailed)	<,001	,002	,002	,001	<,001	
	N	126	126	126	126	126	126

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

H9: Descriptive statistics (DOI)

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Intention	126	1,00	7,00	5,4643	1,82338	-1,270	,216	,460	,428
EaseOfUse	126	1,00	7,00	4,8889	1,27889	-,620	,216	,391	,428
Usefulness	126	1,00	7,00	5,4974	1,64154	-1,170	,216	,626	,428
Compatibilty	126	1,00	7,00	4,3333	1,46485	-,360	,216	-,260	,428
Trialability	126	1,00	7,00	5,9444	1,23810	-1,297	,216	1,458	,428
Observability	126	1,00	7,00	5,5675	1,31507	-,696	,216	,051	,428
Valid N (listwise)	126								

Appendix I: Testing Model Extensions

I1: KMO and Bartlett's Test

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,710
Bartlett's Test of Sphericity	Approx. Chi-Square	820,387

	df	55
	Sig.	<,001

I2: Total variance explained (Model Extensions)

Total Variance Explained

Factor	Initial Eigenvalues Total	% of Variance	Cumulative %	Extraction Sums of Squared Loadings Total	% of Variance	Cumulative %	Rotation Sums of Squared Loadings[a] Total
1	3,777	34,334	34,334	3,143	28,575	28,575	2,598
2	2,633	23,935	58,269	,885	8,046	36,620	2,354
3	1,407	12,790	71,059	2,364	21,487	58,108	2,395
4	1,039	9,448	80,507	1,513	13,754	71,861	2,621
5	,543	4,936	85,443				
6	,527	4,791	90,234				
7	,394	3,579	93,813				
8	,244	2,216	96,030				
9	,202	1,836	97,866				
10	,126	1,148	99,014				
11	,108	,986	100,000				

Extraction Method: Maximum Likelihood.

a. When factors are correlated, sums of squared loadings cannot be added to obtain a total variance.

I3: Pattern Matrix (Model Extensions)

Pattern Matrix[a]

	Factor 1	2	3	4
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Interactions with chatbots are similar to interactions with humans.		-1,013		
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Interactions with chatbots are natural.		-,694		

On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Interactions with chatbots are interactive.		-,252		
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Chatbots are trustworthy.				,725
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Chatbots are reliable.				,919
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Chatbots are dependable.				,767
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Chatbots can cause personal information to be published.			,586	
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Disclosing personal information through chatbots is a risk.			,905	
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Disclosing personal information through chatbots can be negative for me.			,987	

On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Chatbots provide personalized answers that are based on my information.	,530			
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Chatbots understand my needs.	1,011			
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Chatbots know what i want.	,837			

Extraction Method: Maximum Likelihood.
Rotation Method: Oblimin with Kaiser Normalization.
a. Rotation converged in 7 iterations.

I4: Pattern Matrix (Model Extensions) – Removed one item from Anthropomorphism

Pattern Matrix[a]

	Factor			
	1	2	3	4
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Interactions with chatbots are similar to interactions with humans.		-,993		
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Interactions with chatbots are natural.		-,682		

On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Chatbots are trustworthy.				,726
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Chatbots are reliable.				,918
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Chatbots are dependable.				,767
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Chatbots can cause personal information to be published.			,592	
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Disclosing personal information through chatbots is a risk.			,906	
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Disclosing personal information through chatbots can be negative for me.			,984	

On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Chatbots provide personalized answers that are based on my information.	,527			
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Chatbots understand my needs.	1,000			
On a scale of 1 to 7, how much do you agree or disagree with the following statements? - Chatbots know what i want.	,830			

Extraction Method: Maximum Likelihood.
Rotation Method: Oblimin with Kaiser Normalization.
a. Rotation converged in 6 iterations.

I5: Cronbach's Alpha (Model Extensions)

Anthropomorphism

Reliability Statistics

Cronbach's Alpha	N of Items
,828	2

Trust

Reliability Statistics

Cronbach's Alpha	N of Items
,853	3

Privacy Risk

Reliability Statistics

Cronbach's Alpha	N of Items
,856	3

Personalization

Reliability Statistics

Cronbach's Alpha	N of Items
,816	3

I6: Correlations (Model Extensions)

Correlations

		Intention	Anthropomorphism	Trust	PrivacyRisk	Personalization
Intention	Pearson Correlation	1	,247**	,106	,008	,189*
	Sig. (2-tailed)		,005	,235	,933	,034
	N	126	126	126	126	126
Anthropomorphism	Pearson Correlation	,247**	1	,330**	-,053	,486**
	Sig. (2-tailed)	,005		<,001	,558	<,001
	N	126	126	126	126	126
Trust	Pearson Correlation	,106	,330**	1	-,269**	,245**
	Sig. (2-tailed)	,235	<,001		,002	,006
	N	126	126	126	126	126
PrivacyRisk	Pearson Correlation	,008	-,053	-,269**	1	,101
	Sig. (2-tailed)	,933	,558	,002		,261
	N	126	126	126	126	126
Personalization	Pearson Correlation	,189*	,486**	,245**	,101	1
	Sig. (2-tailed)	,034	<,001	,006	,261	
	N	126	126	126	126	126

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

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

I7: Descriptive Statistics (Model Extensions)

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Intention	126	1,00	7,00	5,4643	1,82338	-1,270	,216	,460	,428

Anthropomorphism	126	1,00	6,33	3,3995	1,30027	,219	,216	-,528	,428
Trust	126	1,00	7,00	3,5053	1,15141	,043	,216	-,030	,428
PrivacyRisk	126	1,00	7,00	4,3704	1,45096	-,069	,216	-,364	,428
Personalization	126	1,00	6,33	3,9180	1,27240	-,319	,216	-,642	,428
Valid N (listwise)	126								

Appendix J: Results

J1: Results TPB

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,508[a]	,258	,240	1,59002	2,077

a. Predictors: (Constant), BehControl, SubNorm, attitude

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	107,152	3	35,717	14,128	<,001[b]
	Residual	308,437	122	2,528		
	Total	415,589	125			

a. Dependent Variable: Intention

b. Predictors: (Constant), BehControl, SubNorm, attitude

Coefficients

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Colli Tole
1	(Constant)	,585	,857		,682	,496	
	attitude	,214	,136	,135	1,568	,119	,822
	SubNorm	,412	,107	,319	3,862	<,001	,890
	BehControl	,379	,131	,241	2,891	,005	,877

a. Dependent Variable: Intention

J2: Results TPB - Including Experience and Chatbot type

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson

1	,591[a]	,349	,322	1,50140	2,070

a. Predictors: (Constant), Which type of chatbot are you most familiar with?, SubNorm, BehControl, attitude, How much experience do you have with chatbots?

b. Dependent Variable: Intention

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	145,087	5	29,017	12,873	<,001[b]
	Residual	270,503	120	2,254		
	Total	415,589	125			

a. Dependent Variable: Intention

b. Predictors: (Constant), Which type of chatbot are you most familiar with?, SubNorm, BehControl, attitude, How much experience do you have with chatbots?

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	,891	,939		,948	,345		
	attitude	,072	,133	,046	,543	,588	,766	1,305
	SubNorm	,301	,105	,233	2,878	,005	,827	1,210
	BehControl	,335	,128	,213	2,606	,010	,814	1,229
	How much experience do you have with chatbots?	,404	,117	,297	3,446	<,001	,733	1,365
	Which type of chatbot are you most familiar with?	-,331	,218	-,117	-1,519	,131	,920	1,087

a. Dependent Variable: Intention

J3: Results TAM

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,591[a]	,349	,338	1,48338	2,168

a. Predictors: (Constant), Usefulness, EaseOfUse

b. Dependent Variable: Intention

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	144,938	2	72,469	32,934	<,001[b]
	Residual	270,651	123	2,200		
	Total	415,589	125			

a. Dependent Variable: Intention

b. Predictors: (Constant), Usefulness, EaseOfUse

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	1,812	,542		3,343	,001		
	EaseOfUse	,024	,141	,017	,168	,867	,544	1,838
	Usefulness	,643	,110	,579	5,872	<,001	,544	1,838

a. Dependent Variable: Intention

J4: Results TAM - Including Attitude

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,591[a]	,350	,334	1,48819	2,156

a. Predictors: (Constant), attitude, EaseOfUse, Usefulness

b. Dependent Variable: Intention

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	145,393	3	48,464	21,883	<,001[b]
	Residual	270,196	122	2,215		
	Total	415,589	125			

a. Dependent Variable: Intention

b. Predictors: (Constant), attitude, EaseOfUse, Usefulness

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	VIF
1	(Constant)	1,996	,678		2,941	,004		
	EaseOfUse	,034	,143	,024	,235	,815	,531	1,882
	Usefulness	,665	,120	,598	5,562	<,001	,460	2,172
	attitude	-,065	,144	-,041	-,453	,651	,649	1,541

a. Dependent Variable: Intention

J5: Results TAM - Including Attitude, Experience and Chatbot Type

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,654[a]	,428	,404	1,40749	2,208

a. Predictors: (Constant), Which type of chatbot are you most familiar with?, EaseOfUse, How much experience do you have with chatbots?, attitude, Usefulness

b. Dependent Variable: Intention

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	177,865	5	35,573	17,957	<,001[b]
	Residual	237,725	120	1,981		
	Total	415,589	125			

a. Dependent Variable: Intention

b. Predictors: (Constant), Which type of chatbot are you most familiar with?, EaseOfUse, How much experience do you have with chatbots?, attitude, Usefulness

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	VIF
1	(Constant)	1,293	,840		1,539	,126		
	EaseOfUse	-,011	,136	-,007	-,078	,938	,524	1,909
	Usefulness	,587	,117	,529	5,017	<,001	,429	2,330

	attitude	-,169	,138	-,107	-1,221	,225	,624	1,602
	How much experience do you have with chatbots?	,427	,107	,313	4,011	<,001	,781	1,280
	Which type of chatbot are you most familiar with?	-,006	,204	-,002	-,028	,978	,921	1,085

a. Dependent Variable: Intention

J6: Results UTAUT2

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,656[a]	,430	,401	1,41084	2,195

a. Predictors: (Constant), BehControl, Habit, SubNorm, Hedonic, EaseOfUse, Usefulness

b. Dependent Variable: Intention

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	178,723	6	29,787	14,965	<,001[b]
	Residual	236,867	119	1,990		
	Total	415,589	125			

a. Dependent Variable: Intention

b. Predictors: (Constant), Habit, BehControl, SubNorm, Hedonic, EaseOfUse, Usefulness

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	,593	,696		,853	,395		
	EaseOfUse	-,059	,140	-,042	-,424	,672	,500	2,001
	Usefulness	,440	,122	,396	3,620	<,001	,399	2,504
	Hedonic	,011	,101	,010	,111	,912	,588	1,700
	Habit	,290	,103	,220	2,822	,006	,786	1,273
	SubNorm	,215	,100	,167	2,154	,033	,799	1,252
	BehControl	,205	,126	,130	1,623	,107	,744	1,344

a. Dependent Variable: Intention

J7: Results UTAUT2 - Including Attitude

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,662[a]	,438	,405	1,40626	2,180

a. Predictors: (Constant), attitude, SubNorm, BehControl, Habit, Hedonic, EaseOfUse, Usefulness

b. Dependent Variable: Intention

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	182,235	7	26,034	13,164	<,001[b]
	Residual	233,354	118	1,978		
	Total	415,589	125			

a. Dependent Variable: Intention

b. Predictors: (Constant), attitude, SubNorm, BehControl, Habit, Hedonic, EaseOfUse, Usefulness

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	1,035	,768		1,347	,181		
	EaseOfUse	-,038	,140	-,026	-,268	,789	,493	2,028
	Usefulness	,487	,126	,439	3,859	<,001	,368	2,714
	Hedonic	,014	,100	,013	,140	,889	,588	1,701
	Habit	,311	,104	,236	3,002	,003	,767	1,304
	SubNorm	,225	,100	,174	2,251	,026	,794	1,259
	BehControl	,220	,126	,140	1,739	,085	,738	1,354
	attitude	-,185	,139	-,117	-1,333	,185	,622	1,608

a. Dependent Variable: Intention

J8: Results UTAUT2 - Including Attitude, Experience and Chatbot Type

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,695[a]	,483	,443	1,36122	2,196

a. Predictors: (Constant), Which type of chatbot are you most familiar with?, Hedonic, How much experience do you have with chatbots?, SubNorm, BehControl, attitude, EaseOfUse, Habit, Usefulness

b. Dependent Variable: Intention

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	200,651	9	22,295	12,032	<,001[b]
	Residual	214,939	116	1,853		
	Total	415,589	125			

a. Dependent Variable: Intention

b. Predictors: (Constant), Which type of chatbot are you most familiar with?, Hedonic, How much experience do you have with chatbots?, SubNorm, BehControl, attitude, EaseOfUse, Habit, Usefulness

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	1,244	,885		1,406	,162		
	EaseOfUse	-,061	,136	-,043	-,447	,656	,490	2,039
	Usefulness	,396	,128	,356	3,089	,003	,336	2,980
	Hedonic	,105	,103	,094	1,014	,313	,522	1,917
	Habit	,243	,116	,185	2,099	,038	,575	1,740
	SubNorm	,160	,100	,124	1,605	,111	,745	1,342
	BehControl	,200	,131	,127	1,533	,128	,645	1,549
	attitude	-,236	,135	-,149	-1,743	,084	,611	1,636
	How much experience do you have with chatbots?	,298	,122	,218	2,437	,016	,556	1,798
	Which type of chatbot are you most familiar with?	-,271	,219	-,095	-1,236	,219	,749	1,334

a. Dependent Variable: Intention

J9: Results DOI

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,665[a]	,442	,419	1,38961	2,234

a. Predictors: (Constant), Observability, Usefulness, Trialability, EaseOfUse, Compatibilty

b. Dependent Variable: Intention

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	183,869	5	36,774	19,044	<,001[b]
	Residual	231,720	120	1,931		
	Total	415,589	125			

a. Dependent Variable: Intention

b. Predictors: (Constant), Observability, Usefulness, Trialability, EaseOfUse, Compatibilty

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	-,265	,712		-,373	,710		
	EaseOfUse	-,122	,136	-,086	-,899	,370	,510	1,960
	Usefulness	,454	,128	,408	3,532	<,001	,348	2,876
	Compatibilty	,168	,127	,135	1,323	,188	,446	2,244
	Trialability	,452	,122	,307	3,713	<,001	,679	1,473
	Observability	,075	,108	,054	,693	,489	,768	1,302

a. Dependent Variable: Intention

J10: Results DOI – Including Attitude

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,668[a]	,446	,418	1,39084	2,221

a. Predictors: (Constant), attitude, Observability, Trialability, Compatibilty, EaseOfUse, Usefulness

b. Dependent Variable: Intention

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.

1	Regression	185,392	6	30,899	15,973	<,001[b]
	Residual	230,197	119	1,934		
	Total	415,589	125			

a. Dependent Variable: Intention

b. Predictors: (Constant), attitude, Observability, Trialability, Compatibilty, EaseOfUse, Usefulness

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	VIF
1	(Constant)	,044	,793		,055	,956		
	EaseOfUse	-,108	,137	-,076	-,785	,434	,503	1,989
	Usefulness	,483	,133	,435	3,639	<,001	,326	3,063
	Compatibilty	,184	,128	,148	1,433	,155	,437	2,289
	Trialability	,457	,122	,310	3,745	<,001	,678	1,475
	Observability	,076	,108	,055	,707	,481	,768	1,302
	attitude	-,120	,136	-,076	-,887	,377	,634	1,577

a. Dependent Variable: Intention

J11: Results DOI- Including Attitude, Experience and Chatbot Type

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,689[a]	,475	,439	1,36531	2,218

a. Predictors: (Constant), Which type of chatbot are you most familiar with?, Compatibilty, Observability, How much experience do you have with chatbots?, attitude, Trialability, EaseOfUse, Usefulness

b. Dependent Variable: Intention

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	197,493	8	24,687	13,243	<,001[b]
	Residual	218,096	117	1,864		
	Total	415,589	125			

a. Dependent Variable: Intention

b. Predictors: (Constant), Which type of chatbot are you most familiar with?, Compatibilty, Observability, How much experience do you have with chatbots?, attitude, Trialability, EaseOfUse, Usefulness

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-,044	,954		-,046	,963		
	EaseOfUse	-,104	,135	-,073	-,768	,444	,499	2,002
	Usefulness	,481	,136	,433	3,551	<,001	,301	3,319
	Compatibilty	,130	,131	,104	,989	,325	,404	2,473
	Trialability	,329	,130	,223	2,524	,013	,574	1,744
	Observability	,089	,106	,064	,841	,402	,766	1,306
	attitude	-,177	,135	-,112	-1,310	,193	,617	1,622
	How much experience do you have with chatbots?	,287	,113	,211	2,535	,013	,649	1,541
	Which type of chatbot are you most familiar with?	,010	,204	,003	,047	,963	,866	1,154

a. Dependent Variable: Intention

J12: Results Model Extensions

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,206[a]	,042	,011	1,81356	2,077

a. Predictors: (Constant), Personalization, PrivacyRisk, Trust, Anthropomorphism

b. Dependent Variable: Intention

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	17,619	4	4,405	1,339	,259[b]
	Residual	397,971	121	3,289		
	Total	415,589	125			

a. Dependent Variable: Intention

b. Predictors: (Constant), Personalization, PrivacyRisk, Trust, Anthropomorphism

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	VIF
1	(Constant)	4,032	,879		4,588	<,001		
	Anthropomorphism	,039	,066	,061	,591	,555	,751	1,332
	Trust	,085	,156	,054	,547	,585	,813	1,230
	PrivacyRisk	,016	,118	,013	,139	,890	,891	1,122
	Personalization	,212	,146	,148	1,454	,149	,765	1,307

a. Dependent Variable: Intention

J13: Results Model Extensions – Including Attitude

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,340[a]	,116	,079	1,74992	2,179

a. Predictors: (Constant), attitude, PrivacyRisk, Personalization, Trust, Anthropomorphism

b. Dependent Variable: Intention

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	48,124	5	9,625	3,143	,011[b]
	Residual	367,465	120	3,062		
	Total	415,589	125			

a. Dependent Variable: Intention

b. Predictors: (Constant), attitude, PrivacyRisk, Personalization, Trust, Anthropomorphism

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	VIF
1	(Constant)	2,546	,970		2,625	,010		
	Anthropomorphism	-,011	,066	-,017	-,162	,872	,707	1,414
	Trust	-,010	,154	-,006	-,066	,948	,782	1,280

	PrivacyRisk	-,057	,117	-,045	-,488	,626	,856	1,169
	Personalization	,187	,141	,131	1,328	,187	,763	1,311
	Attitude	,472	,150	,298	3,156	,002	,826	1,211

a. Dependent Variable: Intention

J14: Results Model Extensions – Including Attitude, Experience and Chatbot Type

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,535[a]	,287	,244	1,58501	2,172

a. Predictors: (Constant), Which type of chatbot are you most familiar with?, Trust, How much experience do you have with chatbots?, PrivacyRisk, Personalization, attitude, Anthropomorphism

b. Dependent Variable: Intention

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	119,143	7	17,020	6,775	<,001[b]
	Residual	296,446	118	2,512		
	Total	415,589	125			

a. Dependent Variable: Intention

b. Predictors: (Constant), Which type of chatbot are you most familiar with?, Trust, How much experience do you have with chatbots?, PrivacyRisk, Personalization, attitude, Anthropomorphism

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	1,536	1,070		1,436	,154		
	Anthropomorphism	-,039	,060	-,060	-,648	,518	,700	1,428
	Trust	,051	,140	,032	,364	,717	,776	1,288
	PrivacyRisk	,027	,107	,022	,256	,798	,837	1,195
	Personalization	,239	,129	,167	1,853	,066	,748	1,338
	attitude	,178	,146	,112	1,216	,226	,708	1,413
	How much experience do you have with chatbots?	,578	,119	,424	4,876	<,001	,800	1,250

	Which type of chatbot are you most familiar with?	-,299	,229	-,105	-1,309	,193	,933	1,072

a. Dependent Variable: Intention

J15: Results Stepwise Estimation

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	Usefulness	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).
2	Trialability	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).
3	Habit	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).
4	Anthropomorphism	.	Stepwise (Criteria: Probability-of-F-to-enter <= ,050, Probability-of-F-to-remove >= ,100).

a. Dependent Variable: Intention

Model Summary[e]

					Change Statistics					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	,590[a]	,349	,343	1,47756	,349	66,360	1	124	<,001	
2	,654[b]	,428	,419	1,38976	,080	17,161	1	123	<,001	
3	,683[c]	,466	,453	1,34892	,037	8,561	1	122	,004	
4	,695[d]	,483	,466	1,33241	,017	4,043	1	121	,047	2,258

a. Predictors: (Constant), Usefulness

b. Predictors: (Constant), Usefulness, Trialability

c. Predictors: (Constant), Usefulness, Trialability, Habit

d. Predictors: (Constant), Usefulness, Trialability, Habit, Anthropomorphism

e. Dependent Variable: Intention

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	144,876	1	144,876	66,360	<,001[b]
	Residual	270,713	124	2,183		
	Total	415,589	125			
2	Regression	178,022	2	89,011	46,085	<,001[c]
	Residual	237,567	123	1,931		
	Total	415,589	125			
3	Regression	193,600	3	64,533	35,466	<,001[d]
	Residual	221,989	122	1,820		
	Total	415,589	125			
4	Regression	200,777	4	50,194	28,274	<,001[e]
	Residual	214,812	121	1,775		
	Total	415,589	125			

a. Dependent Variable: Intention

b. Predictors: (Constant), Usefulness

c. Predictors: (Constant), Usefulness, Trialability

d. Predictors: (Constant), Usefulness, Trialability, Habit

e. Predictors: (Constant), Usefulness, Trialability, Habit, Anthropomorphism

Coefficients[a]

		Unstandardized Coefficients		Standardized Coefficients			Correlations			Collinearity Statistics	
Model		B	Std. Error	Beta	t	Sig.	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	1,859	,462		4,026	<,001					
	Usefulness	,656	,081	,590	8,146	<,001	,590	,590	,590	1,000	1,000
2	(Constant)	-,075	,638		-,117	,907					
	Usefulness	,514	,083	,463	6,185	<,001	,590	,487	,422	,830	1,204
	Trialability	,456	,110	,310	4,143	<,001	,501	,350	,282	,830	1,204
3	(Constant)	-,139	,619		-,224	,823					
	Usefulness	,427	,086	,384	4,961	<,001	,590	,410	,328	,730	1,369
	Trialability	,435	,107	,296	4,062	<,001	,501	,345	,269	,827	1,210
	Habit	,278	,095	,212	2,926	,004	,430	,256	,194	,837	1,195

4	(Constant)	,116	,625		,185	,853					
	Usefulness	,463	,087	,416	5,328	<,001	,590	,436	,348	,699	1,430
	Trialability	,427	,106	,290	4,029	<,001	,501	,344	,263	,825	1,212
	Habit	,346	,100	,263	3,467	<,001	,430	,301	,227	,741	1,349
	Anthropomorphism	-,096	,048	-,148	-2,011	,047	,142	-,180	-,131	,784	1,276

a. Dependent Variable: Intention

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance	VIF	Minimum Tolerance
1	attitude	-,038[b]	-,424	,672	-,038	,664	1,505	,664
	SubNorm	,188[b]	2,370	,019	,209	,809	1,236	,809
	BehControl	,122[b]	1,527	,129	,136	,821	1,219	,821
	EaseOfUse	,017[b]	,168	,867	,015	,544	1,838	,544
	Hedonic	,106[b]	1,180	,240	,106	,647	1,545	,647
	Habit	,231[b]	3,021	,003	,263	,841	1,190	,841
	Compatibilty	,113[b]	1,068	,288	,096	,468	2,139	,468
	Trialability	,310[b]	4,143	<,001	,350	,830	1,204	,830
	Observability	,169[b]	2,275	,025	,201	,924	1,082	,924
	Trust	-,014[b]	-,185	,853	-,017	,959	1,043	,959
	PrivacyRisk	-,034[b]	-,467	,641	-,042	,995	1,005	,995
	Personalization	-,030[b]	-,387	,700	-,035	,867	1,153	,867
	Anthropomorphism	-,067[b]	-,862	,390	-,078	,884	1,131	,884
2	attitude	-,063[c]	-,746	,457	-,067	,661	1,513	,600
	SubNorm	,134[c]	1,754	,082	,157	,781	1,280	,729
	BehControl	,065[c]	,843	,401	,076	,791	1,264	,738
	EaseOfUse	-,063[c]	-,669	,505	-,060	,522	1,916	,522
	Hedonic	,107[c]	1,265	,208	,114	,647	1,545	,571
	Habit	,212[c]	2,926	,004	,256	,837	1,195	,730
	Compatibilty	,133[c]	1,340	,183	,120	,466	2,144	,418
	Observability	,067[c]	,867	,388	,078	,790	1,266	,710
	Trust	-,006[c]	-,085	,933	-,008	,958	1,044	,798
	PrivacyRisk	-,013[c]	-,186	,853	-,017	,989	1,011	,823
	Personalization	,009[c]	,124	,901	,011	,853	1,173	,709
	Anthropomorphism	-,062[c]	-,856	,394	-,077	,884	1,131	,746
3	attitude	-,105[d]	-1,280	,203	-,116	,642	1,556	,570
	SubNorm	,120[d]	1,610	,110	,145	,778	1,286	,659

	BehControl	,071[d]	,957	,341	,087	,790	1,265	,654
	EaseOfUse	-,074[d]	-,803	,424	-,073	,521	1,919	,487
	Hedonic	,052[d]	,613	,541	,056	,610	1,640	,554
	Compatibilty	,015[d]	,144	,886	,013	,382	2,618	,382
	Observability	,070[d]	,942	,348	,085	,790	1,266	,707
	Trust	-,052[d]	-,754	,453	-,068	,911	1,098	,721
	PrivacyRisk	-,007[d]	-,105	,917	-,010	,989	1,012	,723
	Personalization	-,073[d]	-,955	,341	-,087	,748	1,336	,676
	Anthropomorphism	-,148[d]	-2,011	,047	-,180	,784	1,276	,699
4	attitude	-,086[e]	-1,040	,300	-,095	,632	1,583	,561
	SubNorm	,111[e]	1,505	,135	,136	,775	1,291	,629
	BehControl	,064[e]	,872	,385	,079	,789	1,268	,625
	EaseOfUse	-,043[e]	-,465	,643	-,042	,505	1,980	,485
	Hedonic	,034[e]	,407	,684	,037	,603	1,659	,524
	Compatibilty	,082[e]	,743	,459	,068	,351	2,845	,351
	Observability	,070[e]	,952	,343	,087	,790	1,266	,691
	Trust	-,023[e]	-,322	,748	-,029	,866	1,155	,696
	PrivacyRisk	-,024[e]	-,367	,714	-,034	,972	1,029	,689
	Personalization	-,034[e]	-,431	,667	-,039	,692	1,445	,664

a. Dependent Variable: Intention

b. Predictors in the Model: (Constant), Usefulness

c. Predictors in the Model: (Constant), Usefulness, Trialability

d. Predictors in the Model: (Constant), Usefulness, Trialability, Habit

e. Predictors in the Model: (Constant), Usefulness, Trialability, Habit, Anthropomorphism

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions (Constant)	Usefulness	Trialability	Habit	Anthropomorphism
1	1	1,959	1,000	,02	,02			
	2	,041	6,870	,98	,98			
2	1	2,933	1,000	,00	,01	,00		
	2	,046	7,988	,18	,98	,09		
	3	,021	11,920	,82	,02	,91		
3	1	3,765	1,000	,00	,00	,00	,01	
	2	,171	4,694	,03	,01	,02	,92	
	3	,044	9,303	,16	,97	,07	,07	
	4	,021	13,504	,82	,01	,90	,00	
4	1	4,643	1,000	,00	,00	,00	,01	,01
	2	,175	5,152	,03	,01	,03	,64	,05

3	,118	6,260	,00	,01	,01	,30	,91
4	,043	10,351	,15	,95	,06	,05	,01
5	,020	15,159	,81	,02	,90	,00	,03

a. Dependent Variable: Intention

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	1,3140	7,9009	5,4643	1,26737	126
Residual	-5,28347	3,34592	,00000	1,31091	126
Std. Predicted Value	-3,275	1,923	,000	1,000	126
Std. Residual	-3,965	2,511	,000	,984	126

a. Dependent Variable: Intention

Appendix K: Operationalization of Constructs

Construct	**Items 1**	**Items 2**	**Reference(s)** **Item 1** **Item 2**
Intention to use	- I intend to use “service” the next six months. - The next six months I intend to use “service” frequently		(Nysveen et al., 2005)
Attitude to use	- Bad / Good - Foolish / Wise ~~- Unfavorable / Favorable~~ - Negative / Positive		(Nysveen et al., 2005)
Subjective norm	- People important to me think I should use “service”. - It is expected that people like me use “service”. - People I look up to expect me to use “service”		(Nysveen et al., 2005)
Behavioral control	- I feel free to use the kind of “service” I like to - Using “service” is entirely within my control. - I have the necessary means and resources to use “service”		(Nysveen et al., 2005)
Ease of use	- It is easy to make “service” do what I want it to - My interaction with “service” is clear and understandable. ~~- Learning to use “service” is easy to me.~~ - It is easy to use “service”		(Nysveen et al., 2005)
Usefulness	- Using “service” makes me save time.		(Nysveen et al., 2005)

	- Using "service" improves my efficiency. - "Service" is useful to me		
Performance expectancy	- ~~I find mobile internet useful in my daily life.~~ - ~~Using mobile internet helps me accomplish things more quickly.~~ - ~~Using mobile internet increases my productivity.~~		(Venkatesh et al., 2012)
Effort Expectancy	- ~~Learning how to use mobile internet is easy for me.~~ - ~~My interaction with mobile internet is clear and understandable.~~ - ~~I find mobile internet easy to use.~~ - ~~It is easy for me to become skillful at using mobile internet.~~		(Venkatesh et al., 2012)
Social influence	- ~~People who are important to me think that I should use mobile Internet.~~ - ~~People who influence my behavior think that I should use mobile internet.~~ - ~~People whose opinions I value prefer that I use mobile Internet.~~		(Venkatesh et al., 2012)
Facilitating conditions	- ~~I have the resources necessary to use mobile Internet.~~ - ~~I have the knowledge necessary to use mobile internet.~~ - ~~Mobile internet is compatible with other technologies I use.~~ - ~~I can get help from others when I have difficulties using mobile Internet.~~		(Venkatesh et al., 2012)
Hedonic Motivation	- Using mobile Internet is fun. - Using mobile Internet is enjoyable. - Using mobile Internet is very entertaining.		Venkatesh et al., 2012)
Habit	- The use of mobile internet has become a habit for me - I am addicted to using mobile internet - I must use mobile internet		Venkatesh et al., 2012)
Price value	- ~~Mobile internet is reasonably priced~~ - ~~Mobile internet is good value for the money~~		Venkatesh et al., 2012)

	- ~~At the current price, mobile internet provides a good value~~		
Relative advantage	~~- Using the system enables me to accomplish tasks more quickly~~ ~~- Using the system improves the quality of the work I do~~ ~~- Using the system makes it easier to do my job~~ ~~- Using the system enhances my effectiveness on the job~~ - ~~Using the system increases my productivity~~	- Using the SST improves the prescription refill process. - Overall, I believe using the SST is advantageous. - I believe the SST, in general, is the best way to order a prescription refill	(Moore & Benbasat, 1991) Curran & Meuter (2005)
Compatibility	~~- Using the system is compatible with all aspects of my work~~ ~~- I think using the system fits well with the way I like to work~~ ~~- Using the system fits in to my work style~~	- Using the SST is compatible with my lifestyle. - Using the SST is completely compatible with my needs. - The SST fits well with the way I like to get things done.	(Moore & Benbasat, 1991) (Curran & Meuter, 2005)
Complexity	~~- Using the system takes too much time of my normal duties.~~ ~~- Working with the system is so complicated, it is difficult to understand what is going on.~~ ~~- Using the system involves too much time doing mechanical operations (e.g., data input)~~ - It takes too long to learn how to use the system to make it worth the effort	- I believe that the SST is cumbersome (slow and complicated) to use. - It is difficult to use the SST. ~~- I believe that the SST is easy to use.~~	(Thompson et al., 1991) (Curran & Meuter, 2005)
Trialability	~~- Before deciding whether to use the system, I was able to properly try them out.~~ - ~~I was permitted to use the system on a trial basis long enough to see what it could do.~~	- I can use the SST on a trial basis to see what it can do. - It is easy to try out the SST without a big commitment - I've had opportunities to try out the SST	(Moore & Benbasat, 1991) (Curran & Meuter, 2005)
Observability	~~- I would have no difficulty telling others about the results of using the system~~ ~~- I believe I could communicate to others the consequences of using the system.~~ ~~- The results of using the system are apparent to me.~~ ~~- I would have difficulty explaining why using the system may or may not be beneficial.~~	- I would have no difficulty telling others about the results of using the SST. - I believe I could communicate to others the outcomes of using the SST - The results of using the SST are apparent to me.	(Moore & Benbasat, 1991) (Curran & Meuter, 2005)
Anthropomorphism	- I believe interactions with a Chatbot for public transport		(Kuberkar & Singhal, 2020)

	will be similar to interaction with the human operator. - I believe interactions with a Chatbot for public transport will be natural. - I believe interactions with a Chatbot for public transport will be interactive.		Adapted from (Bartneck et al., 2009)
Trust	- I will use a Chatbot for public transport if it is trustworthy - I will use a Chatbot for public transport if it is reliable - I will use a Chatbot for public transport if it is dependable		(Kuberkar & Singhal, 2020) Adapted from: (Zhang et al, 2019)
Privacy Risk	- I think chatbot conversations can cause personal information to be published. - I recognize that disclosing personal information through chatbots is a risk. - I recognize that disclosing personal information through chatbots can have a negative impact on me. - ~~Privacy risks are an essential part of my next chatbot decision.~~		(Kwangsawad & Jattamart, 2022) Adapted from: (Jattamart and Leelasantitham, 2020; Rese et al, 2020)
Personalization	- This RA (Recommendation Agents) understands my needs - This RA knows what I want - ~~This RA takes my needs as its own preferences~~	- Smart healthcare services provide personalized services that are based on my information. - ~~Smart healthcare services personalize my health management experience.~~ - ~~Smart healthcare services personalize my health management by acquiring my personal preferences.~~ - ~~Smart healthcare services personalize and deliver healthcare services to me according to my information.~~ - ~~Smart healthcare services deliver personalized healthcare services.~~	(Komiak & Benbasat, 2006) (Liu & Tao, 2022)

Appendix L: Support of Hypotheses

Hypothesis	Supported/Not supported/Not tested
H1: *Attitude has a positive influence on Intention to Use chatbots.*	Not supported
H2: *Subjective Norm has a positive influence on Intention to Use chatbots.*	**Supported**
H3: *Perceived Behavioral Control has a positive influence on Intention to Use chatbots.*	**Supported**
H4: *Perceived Ease of Use has a positive influence on Intention to Use chatbots.*	Not supported
H5: *Perceived Usefulness has a positive influence on Intention to Use chatbots.*	**Supported**
H6: *Performance Expectancy has a positive influence on Intention to Use chatbots*	Not Tested
H7: *Effort Expectancy has a positive influence on Intention to Use chatbots.*	Not Tested
H8: *Social influence has a positive influence on Intention to Use chatbots.*	Not Tested
H9: *Hedonic Motivation has a positive influence on Intention to Use chatbots.*	Not supported
H10: *Habit has a positive influence on Intention to Use chatbots.*	**Supported**
H11: *Price Value has a positive influence on Intention to Use chatbots.*	Not Tested
H12: *Relative Advantage has a positive influence on Intention to Use chatbots.*	Not Tested
H13: *Compatibility has a positive influence on Intention to Use chatbots.*	Not supported
H14: *Complexity has a negative influence on Intention to Use chatbots.*	Not supported
H15: *Trialability has a positive influence on Intention to Use chatbots.*	**Supported**
H16: *Observability has a positive influence on Intention to Use Chatbots.*	Not supported
H17: *Anthropomorphism has a positive influence on Intention to Use chatbots.*	**Supported**
H18: *Trust has a positive influence on Intention to Use chatbots.*	Not supported
H19: *Privacy Risk has a negative influence on Intention to Use chatbots.*	Not supported
H20: *Personalization has a positive influence on Intention to use Chatbots.*	Not supported

Appendix M: Literature on AI chatbot Adoption

Graph showing number of search results in Google Scholar on "AI Chatbot Adoption" from 2012 to 2022.