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Are innovative digital humans accepted by consumers in online shops?

A theoretical and empirical analysis of the factors influencing consumers' acceptance

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List of abbreviations

AI	Artificial intelligence
BI	Behavioral intention
B2B	Business-to-Business
B2C	Business-to-Customer
EE	Effort expectancy
EQ	Emotional intelligence
HM	Hedonic motivation
HT	Habit
PE	Performance expectancy
SI	Social influence
TAM	Technology Acceptance Model
TR	Trust
UTAUT	Unified theory of acceptance and use of technology
UTAUT2	Extended unified theory of acceptance and use of technology

List of symbols

α	Significance level
α_c	Cronbach's alpha
b	Unstandardized coefficient
β	Standardized coefficient
df	Degrees of freedom
ΔF	Change in degrees of freedom
ΔR^2	Change in coefficient of determination
F	F-Statistics
M	Mean
n	Number of participants
p	Statistical significance
r	Pearson correlation
r_{IS}	Minimum of corrected item-total correlation (discriminatory power)
R^2	Coefficient of determination
Adjusted R^2	Corrected coefficient of determination
SB	Spearman-Brown coefficient
SD	Standard deviation
T	Tolerance
VIF	Variance inflation factor

Abstract

Changing global economic and political landscapes, in combination with the customers' desire for more human interaction, have created the need for more comprehensive digital innovations for online retailers. Recently, first companies are experimenting to use the innovation of the digital human, which offers the advantages of natural language processing in combination with emotional intelligence. In this master thesis, different use cases for the sales phases lead management, deal management and retention management in online commerce were developed. Due to the lack of all-important empirical evidence on acceptance of digital humans in online stores, this research aims to quantitatively analyze consumer acceptance of digital humans to uncover insights to help online retailers in their future digital orientation. The study reveals interesting, and statistically significant findings which can be useful to online retailer in the development and use of digital human-based solutions. The results showed that performance expectancy and habit are significant contributors of behavioral intention to use digital humans in online stores. In addition, the findings contribute to current insights to the existing literature on consumer acceptance of digital humans, on which there is limited research.

1 Introduction

The introduction provides insights on the relevance and the current state of research. It presents the overall topic and states the respective problem. Subsequently, it identifies the research gap and depicts the research objectives, including the research questions. In this context, a brief outline of the research framework used for this paper is given. Lastly, an overview of the structure is given.

1.1 Relevance of the problem

Nowadays, the widespread use of artificial intelligence (AI) has established a global trend that hardly any company can escape. It is all around us, whether we know we are using it or not. Artificial intelligence revolutionizes the way people communicate, consume and live (DFKI/Bitkom e.V. 2017, p. 13). Particularly one industry is affected by the use of AI: e-commerce. There is a growing need for online retailers to address the application areas of Artificial Intelligence in their specific context and the opportunities and challenges that arise with it. At the same time, consumers' need for social interaction is increasing. Retailers face the challenge of closing the gap between online and stationary retail in terms of product advice, brand loyalty, and communication. To achieve this, online retailers must be able to create interactions with customers and provide a more natural and engaging customer experience (Denner 2021). New technologies such as artificial intelligence are tools that provide more interactive customer experiences, thereby creating increased customer satisfaction. Augmented reality, virtual reality, 3D modeling, and live-streaming are examples of the continuing social shopping trend (Denner 2021). These emerging trends provide a more immersive shopping experience that goes beyond laptops and smart screens (Algolia 2021). Furthermore, the need has increased to offer the customer an omnichannel experience that gives the digital channels a human touch. This evolved into the next digital revolution a few years ago: The voice commerce. Instead of processing orders by clicking an order button, customers are handed over to the voice assistant (Sana Commerce EMEA B.V. 2022). Speech is a technology that enlivens the customer experience. Voice bots create and support a natural conversation with natural language processing (NLP) as well as with a human-like voice, which go beyond classic chatbots and applications (Denner 2021). In the process, various voice assistants, like Alexa or Google Assistant, act as personalities with which consumers can interact. Voice commerce may be a part of the future. Sales channels of voice commerce offer exciting opportunities for companies. Nevertheless, the expected breakthrough of voice commerce in Germany has not yet taken place (Beyto GmbH 2021). Technology of is the ideal channel for simple things like soap or paper towels for German consumers. However, when it comes to more comprehensive purchase processes, there are some major hurdles.

Consumers have neither the satisfaction of visual verification nor the certainty or confidence, they receive through a regular ordering process (Wong 2020). Some companies are already embracing more encompassing and integral solutions that shift away from voice-only to assistive use of voice. Online retailer Asos was one of the first leading fashion retailers to integrate voice shopping into its AR-based styling app, creating a more comprehensive shopping experience. With Google Assistant integration, customers can order their outfits by voice. This is a step forward from voice-only shopping (Iribarren 2018). Multimodal interfaces can simplify voice-assisted shopping behavior. The convenience and simplicity of voice-activated interfaces can be leveraged profitably through the strength of the visual online shop. This adds an extra layer of security and certainty for the customer when purchasing the desired product (Wong 2020). And what if customers could have a personal touch and a convenient online experience at the same time? Digital humans can play a crucial role in the future. They can meet with customers online on their devices or in brick-and-mortar stores on displays and assist them accordingly. The growth of artificial intelligence in digital humans offers a new interaction as part of the modern shopping experience: with digital humans, consumers can be offered AI-driven personalized advice throughout the buying process. They can have real conversations, recommend products to customers, and even take payments - all with a focus on a human brand experience. In complex buying processes, they can be used to advantage along the sales processes of online stores in lead generation and qualification, deal management, and retention management. Especially in those application areas where a close imitation of human-human communication is required. Therefore, there is a great need for research on the future of digital humans and their applicability as well as their acceptance to provide retailers and manufacturers with concrete recommendations for their future sales strategies in this important sector.

1.2 State of the research and research gap

Over the years, changes in sales management due to technological developments have often been investigated. Research on the acceptance of innovative technologies such as smart speakers and voice assistants is based on the Technology Acceptance Model (TAM) by Davis, Bagozzi & Warshaw (1989) and the unified theory of acceptance and use of technology (UTAUT) and the extended unified theory of acceptance and the use of technology (UTAUT 2) models by Venkatesh, Thong & Xu (2012). Quantitative studies in the field of voice commerce in Germany are mainly limited to the use of smart speakers only, such as those by Zaharia & Würfel (2021) or Grötsch (2019). In an empirical study from 2020 for the use of voice assistants across all hardware components, the acceptance and identification of acceptance factors regarding voice commerce in Germany were determined. The major obstacles to the acceptance of voice commerce are, among other things, the preferred use of devices with screens. The importance of more comprehensive and integral solutions is also shown here once again by Hoffmann (2020). There is limited research on AI-based digital humans as of now. In a quantitative survey, the willingness of consumers to interact with digital humans for fashion companies was investigated. The results showed that interaction between humans and digital humans must be as realistic as possible to be accepted. In this context, interaction via speech is preferred (Silva/Bonetti 2021). In another paper by Mills & Liu (2020), a technology trust theory was developed, which examines the roles of social presence, anthropomorphism, and privacy to understand trust and people's readiness to engage with digital humans. But as the possibility of creating digital humans is only now becoming technically feasible, research in this area is still sparse. For online retailers, it is also important to know whether there is consumer acceptance to interact with digital humans before investing in such expensive technologies.

1.3 Objectives and research question

Looking at the state of research, it can be noted that previous studies have not considered the acceptance of digital humans in online shops. According to the research gap, this master thesis aims to investigate the acceptance of artificially intelligent digital humans in the consumer context and to identify influencing factors of acceptance. In the first part of the thesis, possible applications of digital humans in online stores are elaborated based on the literature of chat- and voice bots. Within the framework of an empirical study, consumer acceptance of artificially intelligent digital humans will be investigated based on the established technology acceptance model of the extended unified theory of acceptance and the use of technology (UTAUT 2). This will provide important insights into what concerns exist among potential consumers regarding AI-based digital humans. In the process of the study, the following questions will be answered:

1) *What are the use cases of digital humans in the sales processes of online retailers?*
2) *Which factors influence the acceptance of innovative AI-based digital humans?*

1.4 Procedure and research design

To answer the research questions, the master thesis is structured as follows. The thesis is split into two parts. At the beginning of the paper, the theoretical background is covered. This part deals with the terminology and explanation of artificially intelligent digital humans, as well as their delimitation. Once various existing areas of application of digital humans are briefly presented, an expert interview follows that amplifies the relevance of innovative digital humans in practice. Subsequently, fields of application of digital humans along the sales processes are elaborated. This results in use cases of possible application scenarios for online retailers. Based on this, the basic features of the framework-based theory model of the extended unified theory of acceptance and the use of technology (UTAUT2) are presented and explained. Answering research question two regarding factors influencing consumer acceptance of AI-powered digital humans, the research model, and the hypotheses are developed on basis of the UTAUT2. For this purpose, five out of seven original UTAUT2 constructs, and one extended variable were subsequently adapted to the context of AI-based digital humans. In the main part of the thesis, the research model is tested within the framework of an empirical study. First, the descriptive results are presented and directed towards the testing of the hypotheses. Based on the analysis, the results are shown and finally, a general conclusion is drawn. Furthermore, the limitations of the master thesis, as well as further research, are addressed.

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2 Conversational commerce

The following chapter lays the theoretical foundation for this master's thesis. First, chapter 2.1 discusses the motivation and development of conversational commerce. Chapter 2.2 describes common conversational interfaces and their technology and serves as an introduction to chapter 2.3. In chapter 2.3, digital humans are explained in terms of their technology and their current areas of application. The chapter also includes an expert interview.

2.1 Motivation and development

Due to the acceleration of digital transformation in response to the COVID-19 pandemic, online commerce has profoundly emerged as the new normal of shopping among customers, which is poised to continue in the post-pandemic era (Lim 2021, p. 103). Traditionally, in stationary retail, salespeople play a central role by assisting customers in decision-making and thus encouraging them to make purchases. However, in the age of online shopping, the conversation has become secondary. The reason for this is that real-time and individual consultation is no more feasible with numerous customers. As a result, customers have to search, evaluate and decide on product selection and purchase themselves. Buying online is therefore increasingly referred to as one-way communication. Nowadays, direct communication to companies is dominantly associated with forms of contact or call hotlines with often long queues (Gentsch 2018, p. 86). However, compared to the classic sales conversation, this type of communication often is time-consuming, annoying, and one-sided for the customer (Gentsch 2018, p. 84).

In recent years, however, a change has developed. One driver of this is the informed and networked consumer with an increased desire for service, advice, and proximity to brands, who want competence and communication from companies in real-time. The second main driver is the advancing technologies in e-commerce. The technological development of messaging systems, artificial intelligence (AI), big data, and bots are driving the digital transformation towards a greater degree of maturity in terms of automated business (Gentsch 2018, p. 84).

Thus, the question of e-commerce is no longer whether it has to transform, but how it must establish itself for the future. The term ‘conversational commerce’ is currently being used to discuss these two lines of development.

Conversational commerce enables the optimization of customer interaction through intelligent automation. Messina (2016), a former Uber developer and social technology expert defines conversational commerce as *"[...] to utilizing chat, messaging, or other natural language interfaces (i.e., voice) to interact with people, brands, or services and bots that heretofore have had no real place in the bidirectional, asynchronous messaging context.*"

In other words, conversational commerce refers to transactions, including inquiries, purchases, and aftersales that are increasingly conducted and completed via messaging apps and voice assistants. It aims to provide consumers with "*[...] convenience, personalization, and decision support while people are on the go, with only partial attention to spare*" (Messina 2015).

A personalized, bidirectional, and real-time conversation can be established with the consumer without an unrealistic number of human resources. This conversation can take place via various tools such as chatbots, which are integrated as standalone tools on the company's landing page, or via platforms such as Facebook Messenger (Gentsch 2018, p. 86).

Chat conversations can range from product advice to purchases, making the consumption experience easier and better for the customer. In this context, the use of conversational agents allows customers to interact with artificial intelligence and receive personalized recommendations in online commerce, like the way salespeople do in brick-and-mortar retail (Lim et al. 2022, p. 4). It bridges the human-computer in online commerce by creating a humanized ecosystem where customers and technology representatives can chat and complete purchases (Piyush/Choudhury/Kumar 2016, p. 323). This provides the customer with a better customer experience which leads them to spend more time on the retail platform. As the customer communicates and interacts with brands or companies via messaging platforms as they would with a friend, this is also referred to as the "brand as a friend" concept (Van Doorn/Duivestein 2016, p. 15). Therefore, companies benefit from bots that are natural and feel human to the user (Gentsch 2018, p. 86).

2.2 Conversational interfaces

Gartner(2018) identifies conversational commerce as one of the most relevant technology trends for the coming years, driven by the advancing hype of chatbots and voice assistants. The two conversational interfaces play a significant role in today's market. Chatbots are computer programs that allow humans to interact with and conduct personalized conversations (Artificial Solutions 2021). Argal et al. (2018) add that the main aim is to appear as natural as possible and thus to imitate a human conversation partner as closely as possible. Chatbots based on artificial intelligence, so-called AI chatbots, use the machine learning approach to answer questions. On the one hand, some chatbots are trained on a set of questions with possible answer options. Using artificial intelligence, the chatbot determines which of the available answers is the most relevant and returns it to the user as an answer.

Some chatbots have a trained range of possible responses. They can independently generate, and output new answers based on the user input (Shridhar 2017).

In contrast to chatbots, spoken language serves as the interface between voice assistants and users. This is a young technology that is still developing rapidly. Voice assistants like Siri or Alexa have received a strong boost with the increasing spread of smartphones. Through intelligent assistants, users can also receive information through spoken language, considering contextual variables (Kiseleva et al. 2016, p. 121).

Voice bots and chatbots answer questions by analyzing and processing the user's input with the help of machine learning. It enables them to ensure that the intention of a question is understood, regardless of how it is formulated. The applications in e-commerce are manifold. For example, they can be used to answer customer queries. In contrast to human employees, they can work around the clock. Long waiting times can be prevented even at peak times and questions can be answered in real-time at any time of the day or night. In addition, chatbots and voice bots can be used in a multichannel format, which enables several requests to be answered at the same time across multiple channels. If these tools are also given a personality, a brand can be brought to life. One example of this is Amazon's voice assistant Alexa (Herianto 2022, pp. 6-7).

Furthermore, real-time communication in the form of live chats has gained importance in the context of the digitalization of customer communication. This is available in many industries nowadays (Gentsch 2018, p. 191). The need for advisory services is particularly high in online shopping. For this purpose, many companies have set up service hotlines or live chats on their website (Herianto 2022, p. 11). The overall goal of using live chats is customer satisfaction through individual support and personal dialog with the consumer (Mühling/Dirnberger/Bernhard 2011). Conversations are conducted by human employees who understand the emotions of customers, regardless of the largest of the request. Live chats are also intended to save costs, as one customer advisor can advise up to three customers in parallel with the help of live chat software. However, a direct comparison shows that one chatbot, deploys 20 or more agents, adding up to potentially the entire support team for a small business (Freshworks 2022). To provide 24/7 support with live chats, human agents would have to work around the clock. In addition, using chatbots means there is no expense for infrastructure or salaries, both cost factors that would be incurred with live chat. Especially at peak times, customer service reaches its limits and customers have to wait on hold or only receive a chat answer hours later. In addition, consumers are now used to shopping internationally.

Here, the time difference and language barriers make good customer service difficult (Herianto 2022, p. 11). Live chats have, therefore, proven to be a more resource-intensive and costly solution (Freshworks 2022).

However, if you combine the advantages of live chats with the advantages of chat or voice bots, this could be the path into the future of e-commerce. The digital human, which could enable a completely different kind of online shopping in the future, is an innovative approach. Digital humans use the natural language processing of chatbots and add emotional intelligence (EQ). They use a tone of voice, body language, and facial expressions that transmit empathy and kindness. A digital human can bridge the digital divide by offering the best of both worlds. On the one hand, menial tasks can be automated, and on the other, EQ can provide customers with a more comprehensive consultation. Figure 1 uses a matrix to illustrate the advantages of the chatbot, human, and digital human. As seen in the figure, the advantage of chatbots is the speed with which they answer questions. The personnel can be profitably employed for the most valuable customer interactions. While on the other hand, a digital human can provide a convenient and engaging experience (UneeQ 2022d).

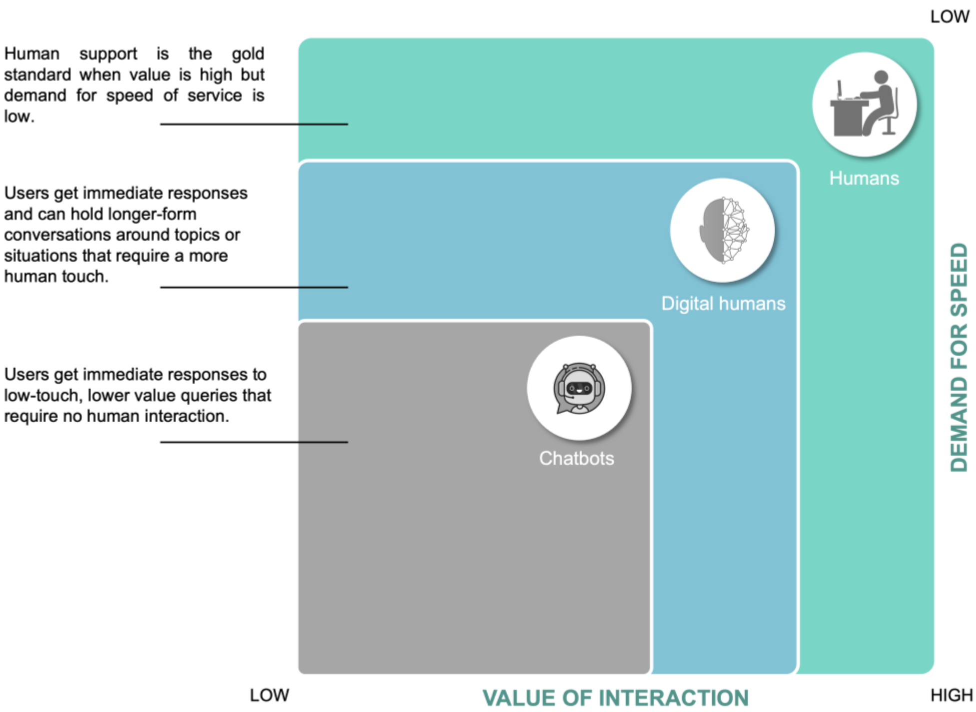

Figure 1 Matrix of chatbots, digital humans, and humans

Source: UneeQ (2020a)

2.3 Digital humans

2.3.1 Definition

A digital human can be defined as a digital avatar that can mimic a full range of human body language. Supported by AI, which can interpret the customer's input and return both the facts they need and the appropriate nonverbal response (Ward/Boom/Majenburg 2022). They can replicate real human conversations because we can see, hear, as well as understand these lifelike personas (UneeQ 2021b, p. 5; Ward/Boom/Majenburg 2022). Behind the digital human is an AI platform that determines behavior, emotional intelligence, and language in real-time (UneeQ 2021b, p. 5). This section of artificial intelligence is called conversational AI. It is a subfield of artificial intelligence which refers to the matters that enable technology to understand what we are saying and have a conversation with us. One of these is called natural language processing (NLP). This concerns how computers process and analyze the words we say or write. Conversational AI is also a type of machine learning. In other words, it's a technology that is constantly improving because it learns from every piece of information it receives (NTT DATA Business Solutions AG 2022). They learn once and they never forget. The terminology is assumed in the context of this master's thesis.

The technology of digital humans is based on four platforms: Chat Layer, Visual Layer, Hosting Layer, and Integration Layer. These four layers are shown in Figure 2 and are explained in the following.

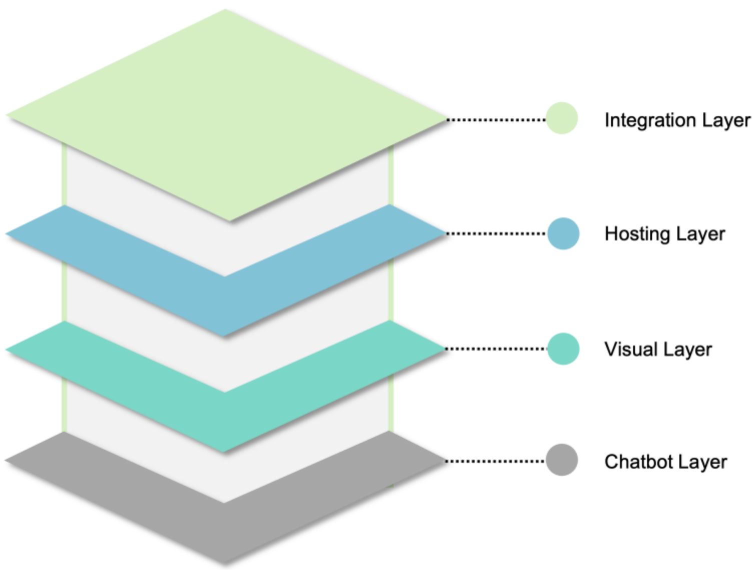

Figure 2 Four layers of digital humans

Source: Ward, Boom & Majenburg (2022)

The first level, the chatbot level, enables conversation with a digital human. At this level, the digital human is trained so that it can recognize the customer's questions and give the right answer. This can be done by a conversational AI platform, such as Google Dialogflow and IBM Watson (UneeQ 2022c). In the process, the chatbot's text is converted into speech. Reversely, the customer's spoken question is in turn transformed into text that the chatbot can process (Ward/Boom/Majenburg 2022).

A visual layer represents the actual digital human as well as the background. UneeQ, for example, is a company where those digital humans can be created. There is a choice of different characters and backgrounds so that the digital human is tailored to the brand in the best possible way. Digital humans can be online via a website or mobile app, or “physically” through a kiosk – or a mixture to create an omnichannel experience. Mimics and emotional presence are programmed to be expressed at the right place in the response of a digital human. This is done at the point between the chatbot layer and the visual layer.

The hosting layer is a cloud-based layer, for example, a Google Cloud project or any other cloud-based hosting setup. The integration layer includes the integration of all these layers. Deloitte is a well-known implementation partner for digital humans. They are project partners who create user interfaces based on customer requirements. They adapt the technology to the corresponding business processes and accompany clients during the implementation (Ward/Boom/Majenburg 2022).

2.3.2 Application areas of digital humans

Today digital humans are already working for some of the biggest brands in the world. They’re revolutionizing the digital experience in health care, financial services, retail, automotive, real estate, telecommunication, and technologies industries. Because today digital humans are the only solution that can bring a human-like, emotionally connected customer experience to the highly automated digital world. Some of the currently existing application areas of digital humans are explained briefly.

Health care

Accenture Analysis (2017) has already argued with artificial intelligence to counteract the shortage of healthcare workers in its publication "Artificial Intelligence: Healthcare’s New Nervous System". According to this, AI could save 20% on staff - and at the same time save 150 billion dollars per year in the entire industry. Chat- and voice bots have therefore become important in providing information quickly and conveniently over the past few years. Digital humans, on the other hand, can add friendliness and warmth to automated tasks when needed - for example, when explaining medication or dietary recommendations. One example is the

Cardiac Coach, which is currently still in the development phase. It was developed with the Centre for Digital Business to provide round-the-clock support for people with cardiac issues. Given the shortage of professionals around the world, Cardiac Coach was developed to take over some of the daily care, allowing more time for more urgent tasks. Patients are offered a natural conversation with the coach to answer questions about health, medication, and rehabilitation (UneeQ 2022a). Artificial intelligence plays a significant role in healthcare. Digital humans are leading the way in health support that gets to the heart of the problem at a human level.

Education

Artificial intelligence has also made inroads into the education sector. This makes virtual tutoring, remote learning, and student support more than just autonomous and digital education. Through conversational AI, digital humans create a personalized learning experience on an emotional basis that makes a big difference. The Hebrew University of Jerusalem has launched Digital Einstein in 2021. This will allow younger generations to digitally interact with one of the most influential scientific figures in history. Users can talk to Digital Einstein about his life and his most important works. Visitors can learn new things about a topic of their choice or participate in daily quizzes (UneeQ 2021a).

Digital Einstein has shown impressive results already two weeks after its launch. Within two weeks, 60,000 conversations were conducted with Digital Einstein and more than 350,000 questions were answered by Digital Einstein. Figure 3 below also shows that 39% would rate the experience with digital Einstein with a 10 out of 10 and 42% would be willing to interact with digital Einstein again.

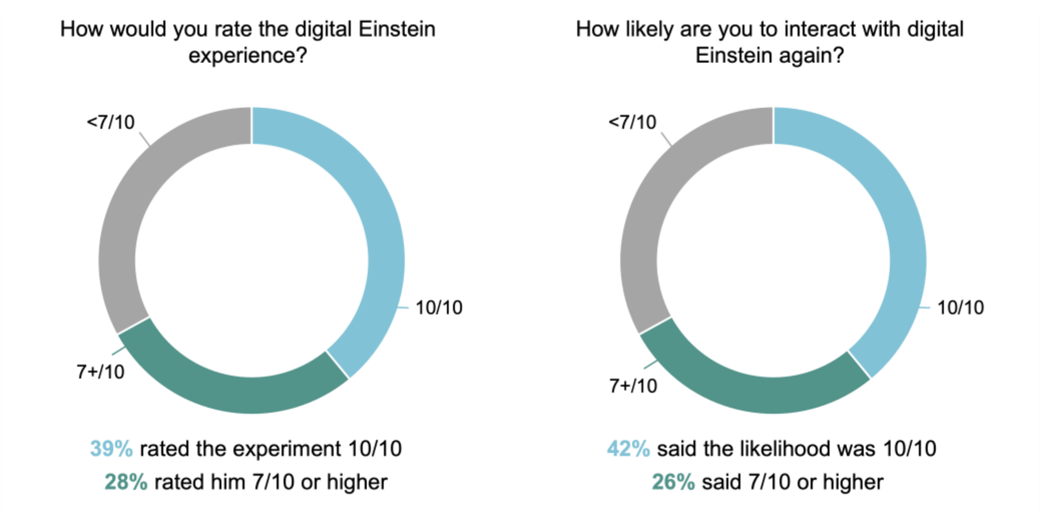

Figure 3 Experiment within two weeks of Digital Einstein

Source: UneeQ (2021a)

Retail

As described in Section 2.1, the advance of e-commerce has largely improved the retail experience, but this has resulted in a loss of the personal customer experience that used to be provided by humans. Through virtual assistants and other automated tools, people are trying to make contact and solve a wide variety of problems digitally. With conventional AI in digital humans, customers benefit from the personal touch associated with the convenient online shopping experience. With digital humans, real sales conversations can be conducted face-to-face in real-time and even payments can be made. All with a focus on a human brand experience (UneeQ 2022b).

An interesting example of this is Nola, a digital shopping assistant as a sales specialist, living in-store at Noel Leeming, part of New Zealand's largest single retail group. Nola serves as a concierge with a big virtual difference: she greets customers, helps customers find products, and answers product questions. The interaction takes place via a kiosk in the physical shop. The conversation is conducted via the screen to simplify the customer visit and make it more attractive. On request, she can also hand it off to one of her team, so shoppers get a personal experience from start to finish. Retail has changed but the demand for human interaction has not (UneeQ 2020d). Nola brings the benefits of both sides - digital and human. Figure 4 shows Nola on the kiosk in the store at Noel Leeming.

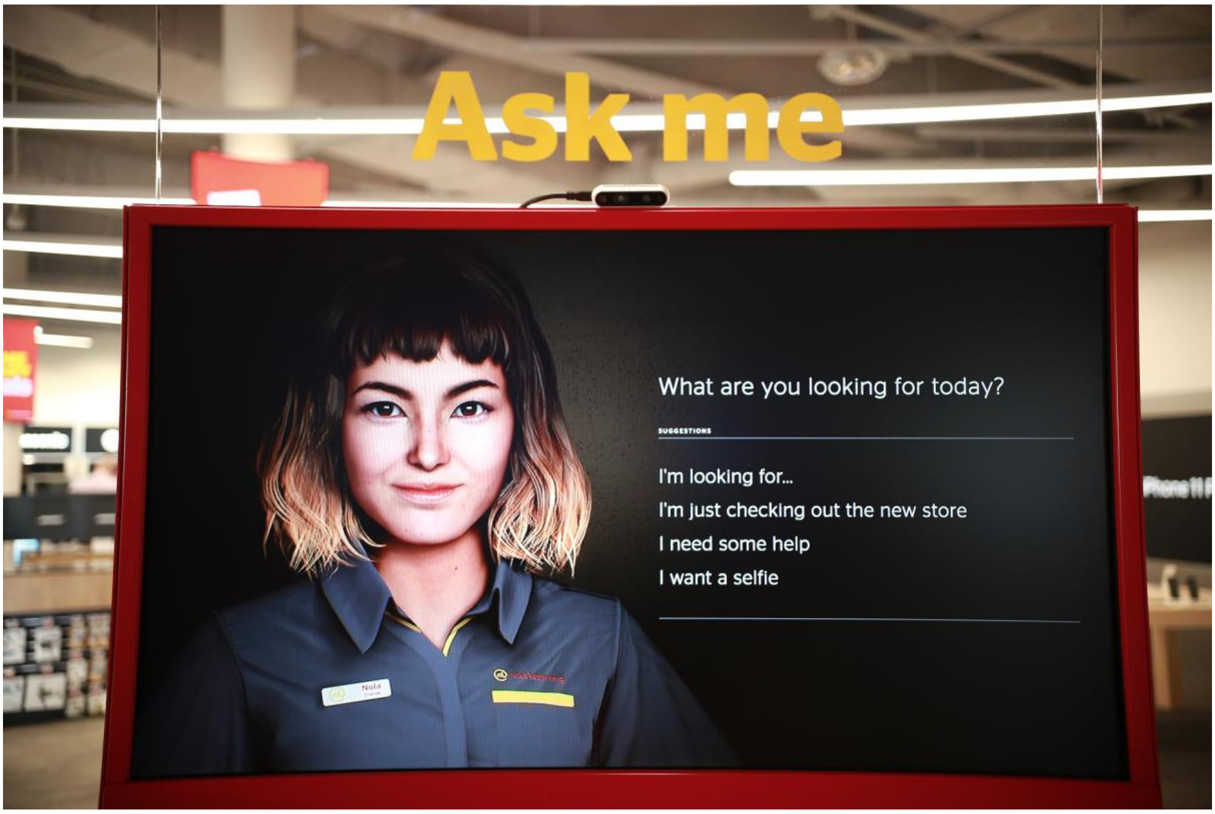

Figure 4 Sales specialist Nola at Noel Leeming, New Zealand

Source: UneeQ (2020d)

2.3.3 Practical example: Deutsche Telekom

Deutsche Telekom is currently the only known company in Europe that already uses digital humans. The pilot project avatar "Selena" supports customers in online consulting to find the best individual internet rate for them. An expert interview was conducted with an employee in the Innovation & Business Development department at DT Service GmbH, a subsidiary of Telekom Deutschland. The selective protocol, which was divided into three categories (K1: status quo, K2: advantages of digital humans, and K3: outlook) is listed in Appendix 1.

In collaboration with the New Zealand company UneeQ, the project was launched at the end of 2021 (Appendix 1, K1/I). The goal of this is to advance self-service. So far, Telekom is already using the AI-powered chatbot called FragMagenta. Current studies show that the hurdle to using chatbots is reduced if you give them a face (Fulde 2021). In conducting the expert interview, Expert A (Appendix 1, K1/II) made the following statement: “Currently, we are considering whether the quality of consultation and user acceptance can be increased by humanizing it through a digital human." The FragMagenta AI-chatbot, which conducts about 5 million dialogs a year and can intercept 700 topics, is now being given a face (Appendix 1, K1/III).

Studies by Telekom show that customers find it more fun, and they feel better addressed. On the one hand, this is due to emotionalization, and on the other hand, the conversation no longer seems as anonymous as with a chatbot icon (Appendix 1, K2/I). In a study on appearance, Expert A also said that customers do not like it or are afraid if an avatar looks too human and cannot be distinguished from a human being (Appendix 1, K2/III). For this reason, Telekom communicates to the customer that Selena it is not a real person (Appendix 1, K1/II).

When it comes to the outlook for digital humans, Expert A is confident that it will work, given the interest from customers (Appendix 1, K3/I). Expert A also reports that Selena 2.0 is currently being developed (Appendix 1, K3/II). Research is ongoing to determine which fields of the application make sense and are also profitable. In the future, Selena should not only be able to provide support in the service area, but also assist in the purchasing process: "We want Selena to support the entire buying process right through to the end. So that she doesn't jump off in the middle, as she did before, but is by your side until the purchase is completed" (Appendix 1, K3/IV). In the future, it is also planned to make the digital human available on other touchpoints such as TV, WhatsApp, or Facebook (Appendix 1, K2/II). Telekom also plans to use several avatars in the future to show that Telekom is diverse and does not just have one face (Appendix 1, K3/III).

The practical relevance of innovative digital humans is demonstrated by the example of the expert interview. On the one hand, the increasing relevance in practice is demonstrated by one of the largest telecommunications companies. On the other hand, it also shows that research into the application areas of digital humans in sales processes is being driven forward. For this reason, possible use cases of digital humans in online shops will now be developed in the further course of the master's thesis. In the process, corresponding areas of application are identified and classified in the three phases of the sales process: lead management, deal management, and retention management.

3 Digital humans in the three phases of the sales process

The following chapter 3 focuses on the specific use cases of digital humans in online sales processes. First, the theory of each of the three phases is explained, and building on this, exact use cases are worked out. Considering that digital humans are still in the development phase, use cases based on chat and voice bots with the advantages of digital humans will be developed.

3.1 Lead management

3.1.1 Definition of lead management

The initiation of purchase transactions can be subdivided into process-related areas of activity. These phase orders are used for the organizational design of the associated sales activities relevant to the purchase. They create transparency regarding the sequence of an ideal-typical sales process and at the same time enable the identifying allocation of customers within the buying process. From the customer's point of view, the sales processes are reflected in the purchasing and procurement processes. They represent the issues to be dealt with on the customer's side and the procedural approach to solving these issues. The main process phases in the sales process are the pre-sales, sales, and after-sales phases (Uebel/Helmke 2017, p. 39). In the further context of this thesis, these three phases will be referred to as lead management, deal management, and retention management.

The lead management (pre-sales) includes all activities that prepare the actual purchase act. This overall process begins with acquiring potential customers (leads) and strategically developing them over time until they are ready to buy. The objectives in the context of Business-to-Business (B2B) and Business-to-Customer (B2C) are distinguished. While in the B2B context the goal is for the customer to signal a concrete need, in the B2C context the goal is to motivate the customer to buy - i.e., to purchase on their own. To achieve these goals, the data collected from the customers is of particular importance. Lead management fundamentally encompasses all measures that are necessary for this process (markenzeichen 2021). The phase of lead management describes all measures that a company uses for the targeted and strategic acquisition of interested parties or leads and new customers. Lead management does not end with the generation of leads, it includes all processes up to the qualification and conversion of a lead to a purchase (Aring 2022). In the following, corresponding use cases of digital humans in the lead management phase are elaborated.

3.1.2 Use cases of digital humans in lead management

The relevance of conversational commerce emerged from the foundations of this master's thesis, which is why digital humans can already change the buying experience in the long term at the beginning of the lead management phase.

Welcome to the online shop

Most websites that use voice or chatbots are based on the proactive behavior of customers. They must first contact the bot or actively access the channel through which the voice or chatbot is provided (Herianto 2022, p. 18). Digital humans could greet the shopper right at the beginning of the buying process via a pop-up window, ideally with a personalized greeting. The human-like greeting by the digital sales staff is intended to imitate the greeting of stationary retail by the sales staff. Adding emotional intelligence, the digital human can listen, understand and speak with your customer as humans do – using the emotionally driven communication methods of speech and body language to deliver a more human touch (UneeQ 2021b). Customers thus have a contact person for further questions right from the beginning. The customer can be accompanied directly by the digital human throughout the entire purchasing process.

Searching for specific products

The advantages of online shopping are both convenience and speed. However, it is not uncommon for customers to be looking for a specific product and not find anything because they don't want to go through hundreds of pages looking at every single item and ultimately abandon the ordering process. It is precisely in these moments that a specialist who provides individual advice is desired. Searching through several pages is often the most time-consuming part of a consumer's customer journey. Solutions that help simplify this part of the customer journey are likely to lead to greater customer satisfaction and increased sales (Skil.AI 2021). Even better if a digital sales advisor can prevent such a user from leaving by quickly helping them along. Digital humans can be used to assist customers with their product search in a variety of ways. For example, the customer can ask the digital human a simple question "Do you have white sneakers?" and the digital human can show a selection of matching products. Further questions by the digital human such as brand, size, price, and heel height can reduce the selection of matching products. Through automation, the customer is provided with precise results that are tailored to their wishes, as well as being spared the long search for the right product. This creates a new kind of user experience. Searching for the desired product via the filter function is already possible today, but the digital human is more interactive and constantly learning. The main advantages of the digital human become apparent through more convenient and easier use. Customers not only have convenient access to information, but also the opportunity to create a positive feeling during an interaction (UneeQ 2020c). As with other AI-powered bots, digital humans are capable of learning from every conversation. By continuously asking questions to better understand the problems or getting feedback from the customer, they are constantly improving (Masbaum 2022). That is valuable considering that AI-based digital humans are not only getting smarter, but users are also getting to the product they want easier and faster (Schröder 2022). Customers are guided through the purchase process by targeted questions and the digital assistant not only acts as an advisor but also as a personal brand ambassador (Eric 2020).

Giving recommendations

As previously mentioned, many customers spend a lot of time searching for products on the Internet without buying anything. This is partly because they can't find what they're looking for, but also because they may not even have a good idea of what they want (Skil.AI 2021). When people go into physical stores, they reach out to store assistants for the product recommendations they need to simplify their shopping journey. This is the kind of personalized service people want to receive online as well (Mcaulay 2021). That is why product recommendations through digital humans also add value to the website or smart device. Digital humans in online stores can be used to counteract this problem by providing customers with recommendations for purchase decisions. They can be programmed to provide personalized recommendations based on likes, dislikes, and previous conversations. Amazon is a prime example of a company that uses product recommendations very successfully. The company generates 35% of its revenue through product recommendations by a recommendation engine alone. Products from various categories are recommended under "Frequently bought together" and "Customers who bought this item also bought" (Chatbots Magazine 2019). This could be an effective way to drive more customers to the final stage of the sales funnel. A comprehensive understanding of the target group and the product benefits is a prerequisite for a functioning algorithm. Customer preferences can thus be considered to a greater extent and adapted to the user's needs in real-time (Del Rowe 2019). Using shoes as an example, the digital sales assistant could make recommendations based on current trends or based on a few simple questions. The customer can interact with the digital sales assistant, its machine learning algorithms learn how to recommend products that align with the needs and interests of that individual shopper.

3.2 Deal management

3.2.1 Definition of deal management

Once the customer has gone through the lead management phase and, with the support of the digital human, has been able to compare the various offers better and deepen his knowledge of the products on the market, he can now make a purchase decision based on this. The goal of the digital human in the pre-sales phase is to show the customer that it has identified the needs and can offer a product tailored to the customer. Once he has succeeded in doing this and the customer has decided on a particular product, the customer moves on to the next phase in the sales process.

Deal management is where the actual business transaction takes place. In this phase, the actual order for the product or service is placed. The order represents the actual transaction and is therefore the legally valid agreement on the exchange of a product or service in return for payment. The process of doing deal management consists of a series of steps that should perform to do business effectively and efficiently (Pufahl 2019, p.. 137-139). The deal management phase includes all activities from the moment of the purchase decision to the shipment of the desired product.

In deal management, digital humans will also be able to take on various tasks as digital sales assistants to improve the customer experience.

3.2.2 Use cases of digital humans in deal management

The purchasing process can also be supported and guided via AI-based Digital humans. Especially if the customer's needs have been recorded in advance, there is an opportunity to initiate an actual purchase.

Upselling and cross-selling

Considering that Digital Humans assist buyers throughout their customer journey, they can be helpful in upselling and cross-selling sales strategies. Upselling is about persuading customers to buy a version of a product that is more premium than the product they originally chose (Salesforce 2022b). Cross-selling, on the other hand, is about selling related or complementary products or services (Salesforce 2022a). Digital Humans can leverage new sales potential through up-selling or cross-selling. Using the example of an online shoe retailer, customers can be shown both basic models and higher-quality models of their desired shoe product. The digital human can explain the advantages of the higher-quality shoe in more detail so that the customer can be convinced of the added benefit. Projected to the sales strategy of cross-selling, if the customer has been guided to a specific product by the digital human, complementary products can be suggested to them based on that. Some online stores already perform these functions with additional offers in the shopping cart or chatbots, but the human, empathetic side is missing at these points and cannot be imitated by a robot. In contrast, digital humans can be used profitably at precisely these points through body language and their emotional intelligence.

No abandoned shopping carts

Customers often spend the entire afternoon shopping online, only to change their minds shortly before making a purchase. Especially in e-commerce, a high shopping cart abandonment rate is a common problem. According to the Baymard Institute, almost 70 percent abandon their transaction (Hüllemann 2020). Through the skillful use of an AI digital human and its conversational guidance and advice, the probability of an actual purchase can increase. The digital human helps with questions that arise before, during, or after the purchase process. Frequently asked questions about shipping, payment options or returns can be shown to the customer at the appropriate point (DialogBits 2021). Accordingly, a satisfactory answer reduces the probability of abandonment. In addition, the digital human can provide the customer with even faster and more personal advice, which can contribute to the conclusion of the purchase.

Price promotion

Additionally, features such as discount codes and current offers or bundles can be integrated and communicated to the customer in a personalized manner. If a store visitor has already been browsing the store for a while, real-time data can be used to offer targeted discounts and coupon promotions personalized to the specific customer (Botcamp.AI 2021). Furthermore, digital humans can enhance individual shopping behavior by considering past purchases and the customer's general online behavior. If customers feel more personally addressed in this way, the company's messages can have a lasting impact on the customer.

Nearby stores

At least since the pandemic, the omnichannel experience has become accepted as an important prerequisite for retail. People prefer the mix of different channels and appreciate the flexibility and convenience (Briedis et al. 2021). More and more customers are also taking advantage of online shopping and picking up their products in brick-and-mortar stores. Digital humans help to create an outstanding omnichannel experience that delivers an emotionally engaging customer journey. They could be used to help customers find the nearest store. Similar to Burberry’s chatbot, users can enter a zip code or address, or simply provide their location, and receive instant results in their local area (Huber 2017). This function, combined with the information on the availability of colors and sizes, enables the customer to experience an even more extensive buying experience.

3.3 Retention management

3.3.1 Definition of retention management

Retention Management (Customer retention management) aims to create long-term customer loyalty to a company's brand. Based on the definition according to Ascarza et al. (2018) "customer retention is the customer continuing to transact with the firm." Here they refer at first to the idea that customer retention means continuity - the customer continues to interact with the company. On the other hand, they refer that customer retention as a form of customer behavior - behavior that companies intend to manage.

The objective is to increase customer satisfaction and customer loyalty through various measures. Customer Retention Management, in contrast to new customer acquisition, is significantly cheaper and simpler. According to the Harvard Business Review, acquiring a new customer is 5 to 25 times more expensive than acquiring a new one (Gallo 2014). At the same time, the number of lost and leaving customers must be minimized as well. On the one hand, customer retention management aims to retain customers, while on the other hand, existing customers should also be persuaded to invest more in the company through cross-selling and upselling as part of retention marketing (Zywietz 2022). Even though companies are always striving to improve customer retention and satisfaction, it is ultimately always the customer who decides whether to stay or leave the company for various reasons (Kumar et al., 2015, p. 34).

3.3.2 Use cases of digital humans in retention management

Even after the purchase of a product or service, digital humans can help maintain customer relationships. The use of digital humans can promote individualized and dialog-oriented communication with customers to improve the development of customer relationships.

Track packages

After buying a product, customers may want to know when their package will arrive. Usually, customers first need to check their emails for the shipping number of the purchased product. Then, the shipping number can be tracked via the webpage of the relevant delivery service. Package shipping is often tied to emotions. Customers are often impatient until their parcel arrives. Therefore, it is even more important to allow them to find out about their delivery at any time. Thanks to the use of digital humans in shipment tracking, the customer is not left alone after the purchase. At any time, the customer can ask the digital human for the current delivery status and interact with the delivery in case of complications. Through membership with an online shoe retailer, the customer can find out the delivery time of their recent order without being redirected to an external delivery service site.

Customer support

Various studies in recent years have shown that emotionally attached customers are more than twice as valuable as highly satisfied customers. It has been found that more than 90 percent of emotional communication is non-verbal. It's all about body language, micro-expressions, and emotional feedback (Nørmark 2020). Especially in customer support, when a customer has a problem with their products, it is significant to convey understanding to the customer. Digital humans can serve a critical role in online shopping without removing the human touch, empathy, and emotional connection from the experience (UneeQ 2020b). Digital humans are instantly accessible to countless customers at once and around the clock. Like chatbots, they can ask questions about the customer's problem and initiate further action. The only significant difference is that they bring a personal conversation, empathetic answers, and brand personality back into the experience (UneeQ 2020b).

Returns

With the proliferation of online retail in recent years, returns have become more common than ever. For companies, every return is not only associated with cost-intensive processing but in the worst case indicates a lost customer. In 2020, German customers returned 315 million packages (Herianto 2022, p. 10). One reason for the high returns rate is that it is much more difficult for customers to judge online whether they will like an item. In every second return, items are sent back because they do not meet the customer's expectations (Brandt 2017). The most efficient way to reduce the rate of return rate is, therefore, still to provide customers with comprehensive consultation during the purchasing phase and allow them to get an accurate picture of the goods. Digital humans could answer return requests automatically, individually, and quickly. Instead of contacting customer service via email and requesting a return form, the customer just transmits their order number to the digital human and follows the digital human's instructions for the return. The digital human generates the return label and records the return request in the appropriate systems. Without human intervention, customers can request returns and receive the necessary instructions.

3.4 Use cases of a digital human for online retailers along the customer journey

Voice and Chatbots have enabled a conversational interface between technology and users in recent years (Nørmark 2020). The generation of digital humans is designed to be even more human. Digital humans are given a human identity, human appearance as well as emotions. They can do things that a chatbot or a voice bot cannot because they can convey emotion. Emotional connection is one of the most significant aspects of this innovation.

In the previous chapter, corresponding uses cases of digital humans in online stores were elaborated on. One question that this master thesis aims to answer is how online retailers can integrate digital humans into their sales processes. The presented interactions in the different phases are not only aimed at supporting customers but also offer retailers advantages in relieving the workload of employees as well as in customer retention and customer satisfaction. Figure 5 provides an overview of the use cases of digital humans along with the sales processes.

Figure 5 Overview of use cases in the sales processes of online retailers

Source: Own representation based on use cases findings in chapters 3.1.2, 3.2.2 and 3.3.2

In the context of this research, the use cases developed in this chapter will be surveyed among users for their tendencies to support them in online stores. This gives a first impression of the usability of the use cases. Furthermore, the following part of the master thesis aims at investigating factors that influence the acceptance of digital humans in online shops. This part is intended to answer the second research question.

4 Theoretical framework

A suitable theoretical basis must be established to address the described challenges of consumer acceptance of AI-based digital humans.

The literature does not provide information regarding the technology acceptance of AI-based digital humans, but there are existing models to measure general technology acceptance. In general, technology acceptance is defined as the psychological state of an individual regarding the voluntary or intended use of a certain technology. In the literature on information systems, various theories and models have already been proposed to explain consumer acceptance and the actual use of new technology, thus answering the question of which factors influence the acceptance of new technologies (Rogers 1983, p. 170).

To create a consistent basis among numerous theoretical models of technology acceptance, Venkatesh et al. (2003, pp. 428) analyzed and compared eight preceding theories of technology acceptance in a review: Theory of Reasoned Action (Fishbein/Ajzen 1980), Technology Acceptance Model (Davis 1985), Motivational Model (Vallerand 1997), Theory of Planned Behavior (Ajzen 1991), Combined TAM Motivational Model and TPB (Taylor/Todd 1995), Model of PC Utilization (Thompson/Higgins/Howell 1991), Innovation Diffusion Theory (Rogers 1983) and Social Cognitive Theory (Bandura 1986). By integrating and combining valid constructs from the previous models, the Unified Theory of Acceptance and Use of Technology (UTAUT) enables a higher variance explanation of the intention to use than the basic theories. Within the empirical study by Venkatesh, Thong & Xu (2012, p. 425) it was confirmed that the UTAUT model can explain a significantly higher variance (70 %) than the existing eight individual models (between 17 % and 53 %).

In recent years, some studies that have examined the acceptance of technologies such as chat- or voice bots are based on the more current UTAUT/ UTAUT2 model (Kessler/Martin 2017; Schwendener 2018). Considering that UTAUT/ UTAUT2 is the newest and most integrative research theory in the field of technology acceptance to date, the theory appears to provide a suitable framework for studying consumer acceptance of AI-powered digital humans.

4.1 UTAUT and UTAUT2

The unified theory of acceptance and use of technology 2 (UTAUT2) which is the extension of the unified theory of acceptance and use of technology (UTAUT) is used as the theoretical basis for this study (Venkatesh et al. 2003; Venkatesh/Thong/Xu 2012).

The integration features of the UTAUT2 model make it an appropriate model to measure the level of adoption and use of tools developed using artificial intelligence. The extended version, designed to explain the use of technologies in consumer markets, will allow an understanding of the adoption and use of specific applications of AI in online purchasing situations. In the following, the key features of the two theoretical models are presented and explained. Based on this, own hypotheses will be formed.

Behavioral intention describes the extent to which an individual intends to use a particular technology (Fishbein/Ajzen 1975, p. 228). According to Davis, Bagozzi & Warshaw (1989, p. 992), it is assumed that a higher level of behavioral intention has a positive influence on actual use behavior.

Use behavior reflects the individual's actual application of a particular technology. According to Fishbein & Ajzen (1975, pp. 228-229), this is a multi-row behavioral criterion that is specific concerning the goal (the system used), the action (actual use), and the context (profession) and non-specific about the time.

The goal of the UTAUT is to predict the behavioral intention to use technology. In addition to the two target variables, a total of seven predictors of behavioral intention and actual use behavior could be derived from the individual acceptance models, which were reduced to four constructs in the final UTAUT model due to redundancies in content. One of the dimensions directly influences use behavior, whereas the other three dimensions influence behavioral intention. Furthermore, the impact effects of the identified key factors are moderated by four variables. These are sex (gender), age (age), experience with technology (experience), and voluntariness of use (voluntariness of use). The following four constructs were evaluated as determinants of behavioral intention and use behavior.

Performance expectancy reflects the perceived individual benefit of technology for increased performance. According to the studies by Venkatesh et al. (2003, p. 450), the effect is moderated by age and gender, according to which the performance expectancy for technology is higher among younger men.

Effort expectancy describes the expected level of difficulty associated with using technology. It is assumed that age, gender, and experience are moderated by effort expectancy. Accordingly, a more substantial effect of effort expectancy on behavioral intention occurs in younger women with little experience (Venkatesh et al. 2003, p. 450).

Social influence determines the degree to which extent an individual believes that the use of a system is accepted by important people in his or her social environment. According to the UTAUT, social influence is moderated by age, gender, and experience, as well as the voluntariness of use. Again, a stronger effect of social influence on behavioral intention is found for older women with little experience, although the effect is significant only for involuntary use (Venkatesh et al. 2003, pp. 451-453).

Finally, **facilitating conditions** are defined as the extent to which the existing infrastructure of an organization is perceived by the individual as supporting the use of the technology. Facilitating conditions are the only variable that directly influences an individual's use behavior. The factor is moderated by age, and experience, according to which a more powerful effect occurs among older individuals with more experience (Venkatesh et al. 2003, pp. 453-455).

Figure 5 illustrates the relationships between the four main determinants, the moderating variables, the behavioral intention, and the actual use behavior.

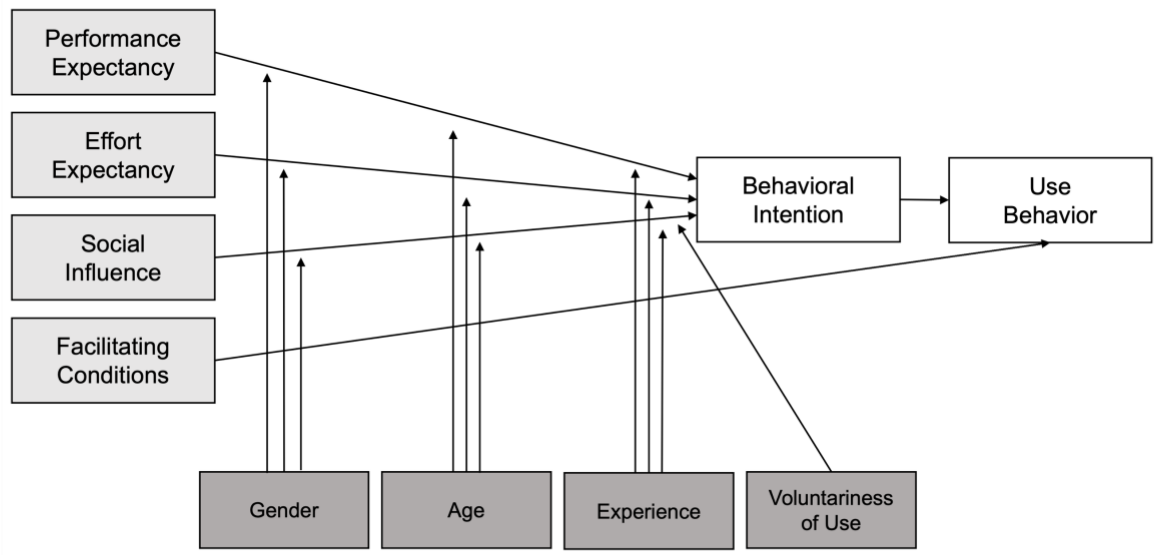

Figure 6 UTAUT

Source: Venkatesh et al. (2003, p. 447)

In further research, Venkatesh, Thong & Xu (2012, p. 169) extended the UTAUT model to include the consumer context and found a direct relationship between the supporting framework and behavioral intention in the UTAUT2 framework. In addition, the researchers argued that the four key constructs of the UTAUT model do not provide enough explanation power in the specific context of consumers to capture consumer behavior holistically. However, in the consumer context, consumer preference regarding the use of new technological systems appears to be dependent on several social and behavioral aspects, which is why the three additional constructs of hedonic motivation, price value, and habit were included in the UTAUT2 model (Venkatesh/Thong/Xu 2012, pp. 160-161). The constructs are described below.

Hedonic motivation is defined as the fun or pleasure that results from using technology for the individual. Hedonic motivation is frequently used in conjunction with consumer technology use (Brown/Venkatesh 2005). Various authors have found that consumers are more likely to accept, i.e., purchase and use, a technology the more fun or pleasure they expect when using it (Brown/Venkatesh 2005; Childers et al. 2001).

Price value can be understood as consumers' assessment of the perceived benefits of applications and the monetary costs of using them (Dodds/Monroe/Grewal 1991; Venkatesh/Thong/Xu 2012, p. 161). The value of the indicator is positive if the benefits of technology exceed its monetary costs, and this price has a positive influence on behavioral intention.

Habit is defined in the literature as the extent to which people perform behaviors automatically because of learning (Limayem/Hirt/Cheung 2007). When not only looking at initial acceptance but also the willingness to use technology and integrate it into everyday acceptance but also at the willingness to start using and integrating technology into one’s daily life, the habit has proven to be an essential aspect of predicting such a technology use (Kim/Malhotra/Narasimhan 2005; Limayem/Hirt/Cheung 2007; Venkatesh/Thong/Xu 2012). Experience, on the other hand, corresponds to the extent to which new technology can be used and is operationalized on five levels (Venkatesh/Thong/Xu 2012). Thus, experience is a necessary but not sufficient condition for habit formation. Individuals can develop different habits with the same experience.

Furthermore, according to Venkatesh, Thong & Xu (2012), the following moderators influence the relationship between determinants and behavioral intention. Moderators aim to increase the explanatory power of the model.

In terms of **age**, Kopaničová and Klepochová (2016) argue that consumers' ability to innovate technology largely depends on their age. In general, it is claimed that most younger people adopt new technologies more quickly than older people, who do so comparatively late.

Looking at **gender**, Kotze, Anderson & Summerfield (2016) claim to have found that women are more pessimistic about technology adoption compared to men. The reasons are that they are more risk-averse and think more about each purchase decision (higher cognitive awareness) than their male counterparts. The authors note that changing their perceived level of risk could have the greatest impact on their purchasing decisions.

The **experience** reflects an opportunity to use a target technology and is typically operationalized as the passage of time from the initial use of technology by an individual (Venkatesh/Thong/Xu 2012, p. 161). Figure 6 illustrates the extended UTAUT2 model.

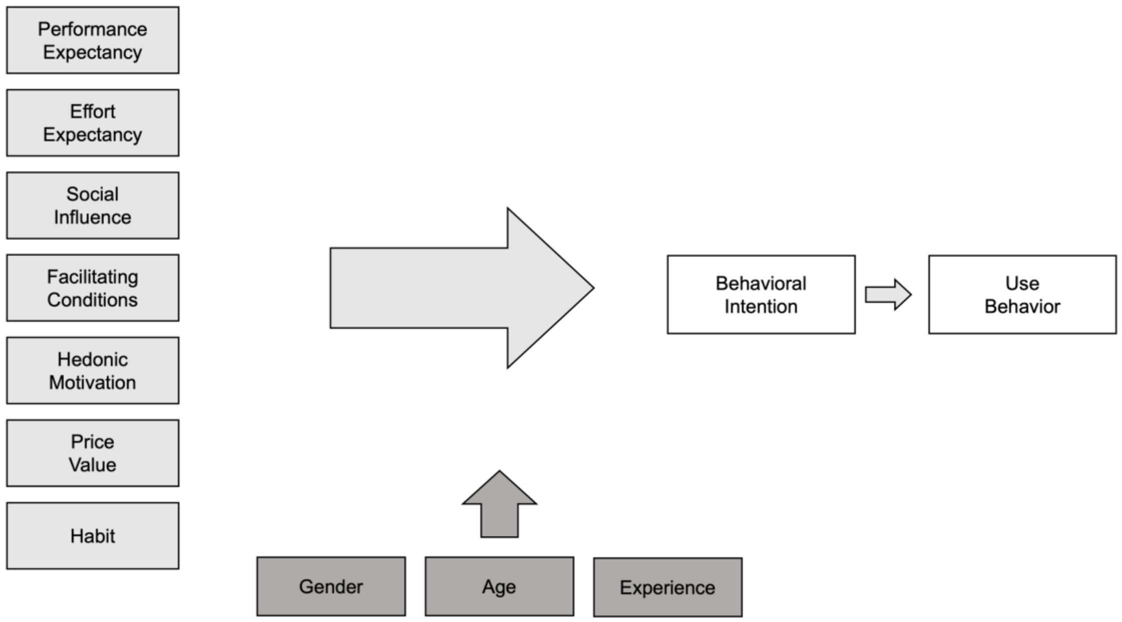

Figure 7 UTAUT 2

Source: Venkatesh, Thong & Xu (2012)

4.2 Model development and hypothesis generation

Answering research question two regarding factors influencing consumer acceptance of AI-powered digital humans, the research model and the hypotheses of this master thesis are developed based on the UTAUT2. For this purpose, five out of seven original UTAUT2 constructs (behavioral intention, performance expectancy, effort expectancy, social influence, hedonic motivation, habit) and one extended construct (trust) were subsequently adapted to the context of AI-based digital humans.

4.2.1 UTAUT2 variables

Behavioral intention

Similar to acceptance research in the field of artificially intelligent technologies (Gursoy et al. 2019, p. 169; Lu/Cai/Gursoy 2019, p. 43), acceptance is operationalized as a hypothetical variable based on behavioral intention. According to Venkatesh et al. (2003, p. 427), forecasts of the actual use behavior of these systems can subsequently be derived based on consumers' behavioral intentions (BI) to use digital humans.

Performance expectancy

The performance expectation reflects the individual utility value of new technology for the user (Venkatesh et al. 2003). Consequently, the perceived benefits of technology can motivate potential users to apply it. Transferring the variable into the context of online shopping with the assistance of digital humans, performance expectancy means the degree to which a consumer expects to experience a performance advantage from using digital humans. This leads to the following hypotheses:

H1. Performance expectancy (PE) positively influences the behavioral intention of using digital humans.

Effort expectancy

It is defined as the degree of ease associated with the use of the system. This means the extent to which consumers consider technology to be easy to learn about and operate. In addition to performance expectancy, effort expectancy was also shown to be a significant positive predictor of intention to use in previous acceptance studies regarding AI-based technologies (Schwendener 2018, p. 55). Therefore, the following hypothesis is made for the present study:

H2. Effort expectancy (EE) positively influences behavioral intention of using digital humans.

Social influence

According to Venkatesh et al. (2003, pp. 451-453), users usually rely on opinions and experiences from their close social environment when evaluating new technologies. Within the context of this thesis, the variable social influence means the degree to which a consumer experiences important people (family and friends) recommending the use of digital humans in online shops.

In acceptance studies on artificially intelligent technologies, a positive correlation between social influence and intention to use could be confirmed (Schwendener 2018, p. 55). From this, the following hypothesis postulates:

H3. Social influence (SI) positively influences behavioral intention of using digital humans.

Facilitating conditions

Venkatesh, Thong & Xu (2012) state that facilitative conditions are only significant for older people in late stages of experience. Moreover, following Taylor & Todd (1995) and Venkatesh & Davis (2000), it can be argued that facilitative conditions are not predictors of intention when the constructs of performance expectancy and effort expectancy are present. Since both, performance expectancy and effort expectancy are included in the model, the construct of facilitating conditions is omitted from the model.

Hedonic motivation

Hedonic motivation is the fun or pleasure derived from using technology and plays a role in the acceptance of technology. In the context of this thesis, hedonic motivation is defined as the extent to which a consumer perceives the use of digital humans during the customer journey as fun, entertaining, and enjoyable. Therefore, the following hypothesis is made for the present case:

H4. Hedonic motivation (HM) positively influences behavioral intention of using digital humans.

Price value as an independent variable is not relevant to this study because the use of digital humans in online shops is free of charge, and a consumer does not need to buy a technology device to interact with digital humans.

Habit

Habit is defined in the literature as the extent to which people perform behaviors automatically because of learning (Limayem/Hirt/Cheung 2007). When not only looking at initial acceptance but also the willingness to use technology and integrate it into everyday acceptance but also at the willingness to start using and integrating technology into one's daily life, the habit has proven to be an essential aspect of predicting such a technology use (Kim/Malhotra/Narasimhan 2005; Limayem/Hirt/Cheung 2007; Venkatesh/Thong/Xu 2012). Therefore, the following hypothesis is made for the present case:

H5. Habit (HT) positively influences behavioral intention of using digital humans.

4.2.2 Additional variable

Trust

As various research on artificial intelligent technologies indicated, in addition to the previously mentioned variables, the variable trust also seems to affect potential users of AI technologies. Research by Mills & Liu (2020) draws on technology trust theory and explores the role of social presence, the role of social presence, anthropomorphism, and privacy in determining people's trust and willingness to interact with digital humans. Another study, which investigated the behavioral intention of AI chatbots by telecom customers, also extended the UTAUT2 model with the trust factor to quantify its effect on behavioral intention and user behavior (Ganesa/John/Mane 2020). In summary, the greater the consumer's trust in an online shop, the greater the behavioral intention of using digital humans. Transferring this variable back to the context:

H6. Trust (TR) positively influences behavioral intention of using digital humans.

4.2.3 Moderators

In the original UTAUT2, in addition to the seven main determinants, moderating effects on age, gender, and experience were also demonstrated. In order not to neglect their influence in the present study, age, gender, and experience were included as control variables. This procedure is in line with similar consumer research on technology acceptance. Since digital humans are a very young innovation, experience about chatbots is surveyed and included.

4.2.4 Correlations

Figure 8 shows the proposed research model for this empirical study. It illustrates the predicted functional relationships of six independent determinants on the target indicator behavioral intention (acceptance) of artificially intelligent digital humans. The research model is built based on hypothesis development. Performance expectancy, effort expectancy, social influence, hedonic motivation, and habit were included as primary determinants of acceptance based on the UTAUT2. In addition, the model was extended to include the influence variable trust, which was evaluated based on the results of the literature review on the research of digital humans as well as additive literature on artificially intelligent technologies. Analogous to UTAUT2, the control variables called gender, age, and experience were included in the model.

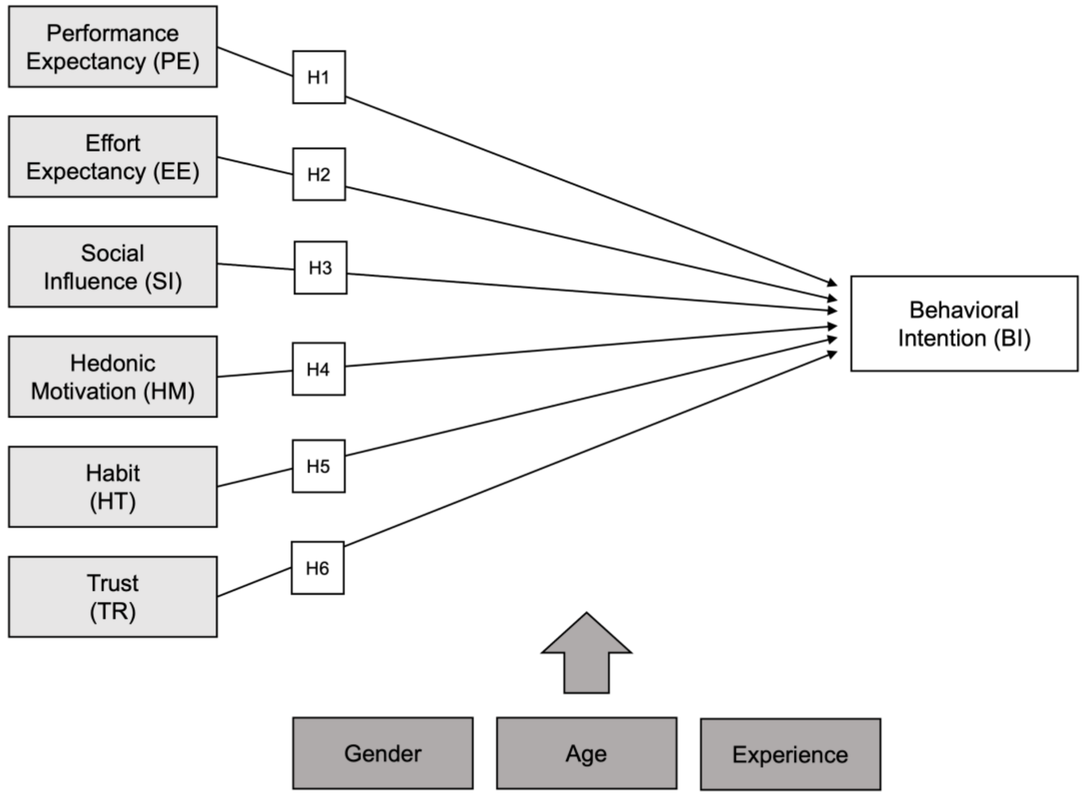

Figure 8 Research model

Source: Own representation according to Venkatesh et al. (2003, p. 447), Venkatesh, Thong & Xu (2012, p. 160), and Ha et al. (2019)

Based on the modified UTAUT2 model and the established hypotheses in 4.2.1 and 4.2.2, the acceptance measurement of digital humans is conducted in the following chapter. That serves to answer research question 2.

5 Empirical analysis

5.1 Research methodology

Venkatesh et al. (2003, p. 437) provide a quantitative survey methodology for the evaluation of the UTAUT model. Therefore, the estimation of the theoretical model is carried out using a quantitative survey method. In contrast to a qualitative survey, a quantitative survey allows a high degree of standardization, whereby better comparability of the results can be achieved. In addition, the research model can be tested directly and without major preparation using the data collected in quantitative surveys (Homburg 2017, p. 267). In principle, a distinction is made in quantitative surveys between a personal, written, telephone, or online survey. Compared to the other forms, the online survey offers two main advantages: On the one hand, respondents can be recruited quickly and easily, and on the other hand, a higher reach can be achieved through distribution on the internet. The latter is often criticized, as it cannot be ensured that a specific target group is reached. This problem of self-selection must therefore be considered when interpreting the results (Homburg 2017, pp. 269-270).

Data collection

Within the framework of an empirical cross-sectional study, an online survey was designed according to the chosen quantitative research approach and conducted in Germany in the period from 30.06.2022 to 07.07.2022. The online questionnaire was distributed via WhatsApp, email, and social media. The survey was conducted anonymously.

Questionnaire rationale

Based on the first part of the master thesis and the proposed research model, an online questionnaire was developed using the survey tool "umfrageonline.com", which is divided into a total of five sectors:

1. Introduction and background information on AI-based digital humans
2. Experiences with chatbots and AI-based digital humans
3. Tendency to use the various use cases along the sales processes of online shops
4. Perceived acceptance of AI-based digital humans in online shops
5. Sociodemographic information of the survey participants

In the first section of the questionnaire, respondents received an explanation of AI-powered digital humans. Pictures were used to demonstrate what digital humans look like. Therefore, a picture of Telekom's digital assistant Selena was shown, as well as a picture of the in-store digital assistant Kiki at Vodafone stores. For further information, participants were provided with a link to a video showing a digital human in action at this point in the questionnaire.

In the second part of the questionnaire, participants were asked about their previous experience with chatbots. The use of digital humans is currently not widespread practice yet. Therefore, the experience with chatbots was used at this point. In two further questions, the respondents were asked about their level of knowledge of digital humans.

In the third part of the survey, the respondents were asked about their tendencies regarding the various use cases of digital humans in online shops. The use cases developed in chapter 3 were listed.

The main part of the survey dealt with the evaluation of the perceived acceptance of digital humans in online shops and their influencing factors. By the adapted and modified UTAUT2 model, six theoretical constructs were recorded according to the definitions from chapter 4.2. Since the theoretical constructs are not directly observable (latent) variables, a reflective measurement model was applied. That involves the usage of several directly measurable indicators to measure a theoretical construct (Kroeber-Riel/Weinberg 2003, p. 21). Generally, discrete rating scales are used to measure the indicators (items). For example, to measure the attitudes of individuals, a Likert scale is often used (Homburg 2017, p. 314). Here, a person's level of agreement is determined using a multilevel scale. The typical anchor points "strongly agree" and "strongly disagree" are often used for this purpose. To operationalize the six constructs, a total of 22 indication- and application-specific items were adapted to the context of AI-based digital humans in online shops. Appendix 2 presents an overview of the scales and items used. The scale items of six constructs (behavioral intention, performance expectancy, effort expectancy, social influence, hedonic motivation, habit, and trust) were measured using a seven-point Likert scale.

The last section of the survey collected sociodemographic information such as the age, gender, employment status, and educational status of participants.

To ensure the validity of the questionnaire, it was tested in advance using test subjects. The test subjects served to check the comprehensibility of the questions as well as the formal and technical correctness of the survey process.

Analysis Strategy

The collected data were analyzed using the IBM software SPSS. Only complete data sets were considered in the analyses. The presentation of the results included descriptive statistics on sociodemographic data, knowledge and experience levels, tendency to use the various use cases along the sales processes of online shops, and acceptance indicators of digital humans. Measurement instruments used were checked for internal consistency using reliability ratios and the descriptive statistics of the items. Linear and multiple regression analyses were used to test the relationships between the variables and the hypotheses thus generated based on the proposed adapted UTAUT2 model. Within the regression analysis, model quality, regression coefficients, as well as the significance of the latter, were tested. In all tests for statistical significance, a confidence level of 95% was used (α = 0,05).

5.2 Results

5.2.1 Descriptive analysis of the sample

In total, the online survey received 224 impressions, resulting in a final sample of 174 respondents with a dropout rate of 22.3 %. The average survey completion time was 07:49 minutes. Table no. 1 shows the sociodemographic statistics of the sample with absolute and relative frequencies.

Table 1 Sociodemographic data of the sample

Item	Category	Frequency	%
Gender	Male	75	43.1 %
	Female	99	56.9 %
Age	15-29 years	126	72.4 %
	≥ 30 years	48	27.6 %
	Mean (M) = 30.2; Standard deviation (SD) = 10.2		
Highest educational qualification	No degree	2	1.1 %
	Secondary level 1 school	9	5.2 %
	Secondary school degree	16	9.2 %
	University entrance qualification/ qualification for entrance to Universities of Applied Sciences	41	23.6 %
	Apprenticeship	31	17.8 %
	University/ University of Applied Sciences degree	75	43.1 %

Source: Own research, 2022, n = 174

As shown in table 1, the proportion of female participants was 56.9 %, whereas the proportion of males was 43.1 %. Consequently, the majority of the 174 survey participants were female. The average age of the respondents was 30.2 years, with the majority (72.4 %) belonging to the young age group (15-29 years). The older age group (≥ 30 years) was represented by 27.6 % of the sample. The differentiation into the two age groups is based on the acceptance study by Monard et. al (2018, p. 16). The results of this research showed that the age group of 20 - 30 years uses chatbots the most and that older target groups (> 30 years) are reluctant to use chatbots. The division into the two age groups was intended to verify whether the older age group's reluctance to use digital humans also applies at this early stage of technology use.

Regarding the level of education, the group with University or University of Applied Sciences degree dominated (43.1 %). More than one-third of the respondents (38.0 %) stated that they have graduated from a secondary school, whereas only 1.1 % did not have a degree. The remaining 17.8 % of the participants stated that they had completed an apprenticeship.

At the beginning, the participants were asked about their previous experience and their level of knowledge about digital humans. Since digital humans are a very young technology, the experience was surveyed using chatbots. Table 2 summarizes the results and gives the absolute and relative frequencies.

Table 2 Previous experience and knowledge of digital humans

Item	Category	Frequency	%
Experience chatbots	Yes	114	65.5 %
	No	60	34.5 %
Term digital human	Yes	77	44.3 %
	No	97	55.7 %
Usage digital human	Yes	43	24.7 %
	No	131	75.3 %

Source: Own research, 2022, n = 174

As an introduction to the main part of the questionnaire, digital humans were generally explained and exemplified. First, participants were surveyed regarding their level of experience with chatbots. That showed that more than half of the respondents (65.5 %) had already used a chatbot. Regarding prior knowledge about digital humans, it was found that less than half (44.3 %) of the respondents knew the term digital human before describing it, while 55.7 % of the respondents could not assign it. In addition, 43 of the 174 respondents (24.7 %) confirmed that they had already spoken with a digital human, while the large majority of respondents had not used digital humans before.

When looking at these results in conjunction with the sociodemographic data, it became apparent that 32 of the 43 respondents who had already interacted with a digital human belonged to the younger age group (15-29 years). Of the 43 subjects, 22 were female, and 21 were male. These results postulate first that age-specific differences exist in the sample concerning the previous use of digital humans, but no gender-specific differences. Therefore, age may be significant in the adaptation decision of potential users of digital humans in online stores.

Furthermore, participants were asked which personal device they prefer for interacting with digital humans. Respondents could choose between four options. Table 3 summarizes consumers' preferred devices for interacting with digital humans. When answering the question, multiple answers were possible.

Table 3 Preferred personal devices for interacting with digital humans

Personal devices	**Frequency**	**%**
Laptop	56	55.2 %
Smartphone	125	71.8 %
Smartwatch	5	2.9 %
Tablet	51	29.3 %

Source: Own research, 2022, n = 174, multiple answers possible

The results show that 125 of the respondents would use their smartphones to interact with digital humans. The laptop is in second place, followed by the tablet. The smartwatch was chosen as the preferred device for interaction with digital humans by only 5 of the 174 respondents. These results also resemble the results of Silva & Bonetti (2021), in which the smartphone was also chosen as the most popular device and the smartwatch as the least popular device for interaction.

Further on in the survey, subjects were asked how they would like to interact with digital humans. The attitude was recorded by the subjects using a seven-point Likert scale with agreement ratings from 1 (do not agree at all) to 7 (completely agree). Table 4 presents the descriptive statistics.

Table 4 Attitudes towards different forms of interactions with digital humans

	M	*SD*
The ability to talk and communicate with a digital human is important to me.	3.44	1.75
The ability to type commands into a keyboard to interact with a digital human is important to me.	3.90	1.82
The ability to interact with a digital human through gestures is important to me.	2.82	1.69

Source: Own research, 2022, n = 174

Regarding the various forms of interaction with digital humans, on average a negative attitude was found among the survey participants. Interaction with digital humans via keyboard (M = 3.90), followed by interaction via speech (M = 3.44), appears to be of the greatest importance. Only interaction via gestures seems to play little to no significant role in interaction with digital humans (M = 2.82). In Silva & Bonetti's (2021, p. 7) results, the mean values of the three interaction options were between 4.10 and 4.53. In further investigation into which form of interaction was preferred, it was found that the preferred form of interaction with digital humans is via speech and the least preferred is via gesture. They stated that it is vital that brands ensure that speech interaction is at a very high standard.

Before participants were surveyed using the research model regarding their acceptance, they were asked about their tendency towards different potential applications of digital humans in online stores. The use cases developed in chapter 3 were applied for this purpose. The results are shown in Figure 9. When answering the question, multiple answers were possible.

Figure 9 Tendencies towards the use of digital humans in online shops

Source: Own research, 2022, n = 174, multiple answers possible

According to Figure 9, almost half of the respondents indicated that they would be more likely to use the assistance of digital humans for searching for a specific product and in customer support. In third place, over one-third of the surveyed voted for handle returns. In contrast, some use cases scored lower, with respondents wishing for rather less assistance from digital humans in online shops. Less support is expected in offering discounts, listing nearby stores, and welcoming you to online shops.

Acceptance of artificially intelligent digital humans

Respondent's answering behavior was first analyzed descriptively to obtain a comprehensive picture of attitudes in the sample toward the indicators that influence behavioral intentions to use digital people in online stores. For this purpose, the mean values, and standard deviations of the indicators (items) that were used to measure the constructs are listed in the following tables 5 to 11.

The subjects were asked about the Behavioral Intention of digital humans in online shops. The following table no. 5 shows the mean value and standard deviation of the indicator Behavioral Intention.

Table 5 Item-Statistic of behavioral intention

	M	*SD*
BI1. I intend to use digital humans in online shops in the future.	3.78	1.74
BI2. It is very likely that I will use digital humans in online shops, in my daily life.	3.92	1.66
BI3. I plan to use digital humans in online shops frequently.	3.37	1.68
Behavioral intention	3.69	1.71

Source: Own research, 2022, n = 174

When looking at the scale of the construct behavioral intention, a negative attitude was observed on average among the survey participants (M_{BI} = 3.69). Participants responded with a higher level of agreement (M = 3.92) to the use of digital humans in online shops in daily life than to the plan to use digital humans frequently (M = 3.37). On average, the intended use of a digital human in online shops was answered near the middle range of the seven-point agreement scale (M = 3.78).

Within the context of the hypothesis, participants were asked about performance expectancy and its influence on behavioral intention to use digital humans in online shops. The mean value, as well as the standard deviations, can be found in the following table no. 6.

Table 6 Item Statistic of performance expectancy

	M	*SD*
PE1. Digital humans in online shops are useful.	4.82	1.36
PE2. Using digital humans in online shops increases my chances of achieving things that are important to me.	4.14	1.54
PE3. Using digital humans in online shops helps me accomplish things more quickly.	4.47	1.53
PE4. Using digital humans increases my productivity.	3.89	1.61
Performance expectancy	4.33	1.55

Source: Own research, 2022, n = 174

Regarding the construct performance expectancy, the answers of the respondents were on average just above the midpoint of the agreement scale (M_{PE} = 4.33). The general attitude of the respondents toward the usefulness of digital humans in online shops (M = 4.82) as well as getting things done faster (M = 4.47) is identified as tending to be positive. Only in the case of increased productivity through digital humans is the trend negative (M = 3.89).

In addition to the performance expectancy, the participants were also asked about their effort expectancy toward digital humans. The results (table No. 7) show the influence of the items on behavioral intention.

Table 7 Item-Statistic of effort expectancy

	M	*SD*
EE1. Learning how to use digital humans in online shops is easy for me.	5.17	1.48
EE2. The use of digital humans in online shops is clear and understandable.	4.83	1.32
EE3. I consider digital humans in online shops quite easy to me.	4.95	1.37
EE4. It is easy for me to become skillful at using digital humans in online shops.	4.82	1.37
Effort expectancy	4.94	1.39

Source: Own research, 2022, n = 174

Since the mean values of the effort expectancy construct scale are well above the midpoint of the agreement scale, the sample under consideration does not appear to have difficulties using digital humans in online shops on average (M_{EE} = 4.94). Here, a clear agreement (M = 5.17) was found for the item on learning how to use digital humans in online shops.

Regarding the clear and understandable use (M = 4.83), the ease of use (M = 4.95), and the simplicity (M = 4.82) of digital humans in online shops, the survey participants expressed an average level of agreement.

The subsequent construct examined to which extent people who influence our behavior or who are important to us influence respondents' behavioral intention to use digital humans in online shops. Table 8 below shows the sample results concerning the item social influence.

Table 8 Item-Statistic of social influence

	M	*SD*
SI1. People who are important to me think I should use digital humans in online shops.	3.20	1.50
SI2. People who influence my behavior think that I should use digital humans in online shops.	3.21	1.50
SI3. People whose opinions that I value prefer that I use digital humans in online shops.	3.20	1.59
Social influence	3.20	1.53

Source: Own research, 2022, n = 174

In terms of the social influence of relevant persons on the decision to use digital humans in online stores, a negative attitude was found among survey participants on average (M_{SI} = 3.20). With decreasing importance, neither people who influence the respondents' behavior (M = 3.21) nor important people (M = 3.20) or people whose opinions they value (M = 3.20) seem to play a significant role in the adoption decision of digital humans in online shops.

In the following, participants were asked about the pleasure or enjoyment they experience when using digital humans in online shops. Table No. 9 below shows the results of the sample for the item hedonic motivation.

Table 9 Item-Statistic of hedonic motivation

	M	*SD*
HM1. I think using digital humans in online shops is fun.	4.31	1.56
HM2. I think using digital humans in online shops is enjoyable.	4.06	1.61
HM3. I think using digital humans in online shops is entertaining.	4.36	1.60
Hedonic motivation	4.25	1.59

Source: Own research, 2022, n = 174

Participants' responses to the hedonic motivation construct are in the middle range of the agreement scale (M_{HM} = 4.25). On average, the sample shows a preferably neutral attitude towards future pleasure or enjoyment they experience when using digital people in online stores. The highest average agreement (M = 4.36) was observed for entertaining, followed by fun (M = 4.31) and enjoyable (M = 4.06).

Within the context of the hypothesis, participants were asked about habits and their influence on behavioral intention to use digital humans in online shops. The mean value, as well as the standard deviations, can be found in the following table no. 10.

Table 10 Item-Statistic of habit

	M	*SD*
HT1. The use of digital humans in online shops could become a habit for me.	4.08	1.54
HT2. I am in favor to use digital humans in online shops.	4.59	1.62
HT3. Using digital human in online shops could become natural to me.	4.07	1.66
Habit	4.25	1.63

Source: Own research, 2022, n = 174

In the sample under consideration, it emerged that the respondents had a slightly positive attitude toward the habitual and regular use of digital humans in online stores (M_{HT} = 4.25). On average, they agreed that using digital humans could become a habit for them (M = 4.08) and that using digital humans could also become a natural part of their lives (M = 4.07). The highest average level of agreement was obtained for the favor to use digital humans in general (M = 4.59).

The final factor investigated was trust in AI-based digital humans and to which extent this trust influences behavioral intention to use digital humans in online shops. The following table no. 11 shows the results of the sample that were obtained from the questionnaire.

Table 11 Item-Statistic of trust

	M	*SD*
TR1. I am convinced that digital humans in online shops are used to provide customers with the best offerings.	4.66	1.64
TR2. I trust in digital humans.	3.53	1.62
Trust	4.10	1.72

Source: Own research, 2022, n = 174

When looking at the construct of trust, a differentiated picture emerged when considering the individual indicators, according to which the mean values are 3.53 and 4.66. On the one hand, the respondents tend to be convinced that digital humans in online shops can provide them with the best offerings (M = 4.66). On the other hand, a lack of trust in digital humans can be identified on the part of the respondents (M = 3.53). Consequently, trust has a very small but positive attitude (M_{TR} = 4.10).

Following the descriptive analysis reported in tables 5 to 11, the most significant mean value was obtained from effort expectancy (M_{EE} = 4.94), while the least significant mean value was obtained from social influence (M_{SI} = 3.20). Trust (SD = 1.72) produced the greatest standard deviation, while effort expectancy (SD = 1.39) produced the lowest standard deviation.

5.2.2 Verification of the measurement instruments

Before testing the proposed research model and the hypotheses based on it, the collected constructs were evaluated in terms of their suitability for further statistical analysis based on the reliability and descriptive statistics of the used scales. To determine to which extent the individual indicators (items) capture the same construct, the scales of the constructs were first tested for internal consistency reliability. For all independent constructs (items ≥ 3), the values for Cronbach's alpha (α_c) were determined, whereas, for the construct trust, the Spearman-Brown Coefficient was calculated since the construct was measured with only two items (Eisinga/Grotenhuis/Pelzer 2013, p. 641).

A scale is considered sufficiently reliable when the reliability coefficient Cronbach's alpha reaches a value of at least 0.70. Reasons for values below 0.70 can be due to a smaller number of items or a poor correlation of the items and should, therefore, not be categorically excluded (Fornell/Larcker 1981, p. 44). For further validation, the minimum of corrected item-total correlation (r_{IS}) was recorded, which reflects the correlation of an item with the scale. This value is usually referred to as discriminatory power. According to Hair et al. (1998, p. 118), items should have a discriminatory power of at least 0.30 to be considered sufficiently reliable. Results are shown in table no. 12.

Table 12 Descriptive statistic and test for reliability

Construct	*Items*	α_c/ *SB* [a]	r_{IS}	*M*	*SD*
Behavioral intention	3	0.92	0.82 – 0.86	3.69	1.71
Performance expectancy	4	0.91	0.75 – 0.83	4.33	1.55
Effort expectancy	4	0.91	0.78 – 0.85	4.94	1.39
Social influence	3	0.96	0.90 – 0.92	3.20	1.53
Hedonic motivation	3	0.92	0.79 – 0.86	4.25	1.59
Habit	3	0.93	0.82 – 0.90	4.25	1.63
Trust	2	0.67 [a]	0.50	4.10	1.72

* α_c = Cronbach's alpha; SB = Spearman-Brown coefficient; r_{IS}= Minimum of corrected item-total correlation; M = Mean; SD = Standard deviation

Source: Own research, 2022, n = 174

The Cronbach's alpha values of the independent constructs, except for the scale of trust, are in the range between 0.92 to 0.96 and thus ensure sufficient internal consistency ($\alpha_c > 0.70$). In addition, the values of the discriminatory power analysis of these scales are in the interval between 0.75 and 0.92, thus ensuring sufficient homogeneity.

The scale of the construct trust with a Spearman-Brown-Coefficient of 0.67 and coefficients of discriminatory power of the two items of 0.50 can still be classified as reliable. However, since the coefficients of discriminatory power reach at least the postulated value of 0.30, the further use of the scale trust can still be justified.

For the most part, the means of the independent constructs range above the midpoint of the seven-point agreement scale in the interval between 3.20 and 4.94, indicating that participants responded in agreement on average across the seven constructs. The associated standard deviations are in the range between 1.39 and 1.72.

5.2.3 Testing the hypotheses

To identify influencing factors of AI-based digital humans and thus answer one of the central research questions of this study (research question 2), both linear and multiple linear regression analyses were conducted. Based on the underlying modified extended UTAUT2 model and the hypotheses, the correlations of six latent predictors (performance expectancy, effort expectancy, social influence, hedonic motivation, habit, trust) on the criterion behavioral intention were tested.

The criterion and latent predictors were included as metric variables in the linear and multiple regression analyses according to the scales described. Since the constructs were measured by multiple items, an overall indicator was formed from the mean of the scale. In addition to the six main determinants, the control variables age, gender, and experience were also included in the multiple regression analyses. Gender was included as a dichotomous variable with dummy coding (0 = female, 1 = male). Females represent the reference category here. Similarly, experience with chatbots was included as a dichotomous variable (0 = no experience and 1 = experience). In addition, age was included as a discrete variable.

First, simple linear regression analyses were conducted to determine significant relationships and directions of the six latent predictors on the criterion. Furthermore, due to the limited evidence base for the proposed relationship in the modified UTAUT2 model, a three-step hierarchical multiple regression was performed to answer the following questions:

a) Do the five UTAUT2 predictors (**performance expectancy, effort expectancy, social influence, hedonic motivation, habit**) combined explain significant variance in the behavioral intention criterion?
b) Does the additional predictor **trust** explain additional variance in the behavioral intention criterion?

In the first step, the control variables gender, age, and experience were included as a block in the multiple regression to determine the variance of these in the criterion of the behavioral intention of digital humans (model 1).

The model was extended in a second step by the five UTAUT2 predictors performance expectancy, effort expectancy, social influence, hedonic motivation, and habit to see if these together explain additional variance in the criterion (model 2).

Furthermore, to test whether the supplemented variable trust explains additional variance to the control and UTAUT variables, they were added to the third model (model 3).

Prerequisites of linear regressions

Before conducting the analyses described above, it was confirmed that the prerequisites of linear regressions were reasonably met. The scatter plot between the standardized estimated criterion and the standardized residuals showed no evidence that the assumptions of linearity and variance homogeneity (homoscedasticity) were violated. Moreover, the Durbin-Watson statistic resulted in a value of 1.85, which is close to the postulated value of 2.00. So, the independence of the residuals could be assumed (Urban/Mayerl 2011, p. 264). Regarding the test for normality of the residuals, the histogram and the normality plot of the standardized residuals showed only slight deviations from the normal distribution. The Kolmogorov-Smirnov test showed a significance of 0.200 and the Shapiro-Wilk test of 0.485. Consequently, both values reached the required significance value above 0.05. Accordingly, they retain the null hypothesis, and no deviation from the normality was shown.

Regarding the test for multicollinearity, the correlations of the six latent variables were examined. In the context of multiple regression, multicollinearity is an excessive correlation of two or more causal variables with each other. The correlation matrix is a suitable tool to test for the existence of multicollinearity. According to Field (2018, p. 402), correlation values above 0.8 between two independent variables are an indicator of multicollinearity. In this matrix, there are no correlations of any concern. As illustrated in table 13, all predictors correlated moderately to strongly with the criterion.

Table 13 Correlation matrix

	PE	**EE**	**SI**	**HM**	**HT**	**TR**
PE	1.00	0.520**	0.516**	0.662**	0.760**	0.719**
EE		1.00	0.336**	0.467**	0.503**	0.501**
SI			1.00	0.439**	0.580**	0.478**
HM				1.00	0.701**	0.624**
HT					1.00	0.681**
TR						1.00

PE = Performance expectancy, EE = Effort expectancy, SI = Social influence,
HM = Hedonic motivation, HT = Habit, TR = Trust; [** p < 0.01]

Source: Own research, 2022, n = 174

It is also shown in table 16 of the multiple regression that the variance inflation factor (VIF) values of the six predictors are between 1.07 and 3.35 and are thus below the postulated limit of 5.00. In addition, the predictor tolerance values ranged from 0.3 to 0.94, exceeding 0.25, indicating that there was limited evidence of multicollinearity (Urban/Mayerl 2011, p. 232). The requirements to perform a multiple regression were met and, thus valid results could be obtained in the further course.

Based on the results of the correlation matrix, the linear regression analyses were expected to yield significant relationships, as all predictors showed significant correlations with the criterion behavioral intention.

Simple linear regression

The following simple linear regression aimed to explain the dependent variable behavioral intention by the independent variable's performance expectancy, effort expectancy, social influence, hedonic motivation, habit, and trust. In table 14, the individual linear regressions are listed together.

Table 14 Results of simple linear regressions

Predictors [a]	R^2	*b*	*SE*	β	*p*
Performance expectancy	0.61	0.92	0.06	0.78	0.000***
Effort expectancy	0.28	0.67	0.08	0.53	0.000***
Social influence	0.33	0.61	0.07	0.57	0.000***
Hedonic motivation	0.38	0.66	0.06	0.62	0.000***
Habit	0.67	0.86	0.05	0.82	0.000***
Trust	0.46	0.76	0.06	0.68	0.000***

[a] Criterion = Behavioral intention; R^2 = Coefficient of determination; b = Unstandardized coefficients; SE = Coefficients std. Error; β = Standardized coefficients; p = Statistical significance [* p < 0,05 ** p ≤ 0,01 *** p < 0.001]

Source: Own research, 2022, n = 174

As illustrated in table 14, in the simple regression analyses, both the UTAUT2 variables **performance expectancy** (β = 0.78), **effort expectancy** (β = 0.53), **social influence** (β = 0. 57), **hedonic motivation** (β = 0.62), and **habit** (β = 0.82) as well as the additional variable **trust** (β = 0.68) were revealed as significant determinants of the **behavioral intention** of AI-based digital humans (p ≤ 0.001). As already indicated in the correlation matrix (table 13), the linear regressions also reflected high significant influences of the variables **performance expectancy** and **habit** on behavioral intention. Based on these results, all six hypotheses (H1 to H6) could be confirmed.

Multiple linear regression

Multiple linear regression was used to predict the values of the dependent variable using multiple independent variables. Subsequently, multiple predictors were used to estimating the criterion.

Table 15 illustrates the three steps of the hierarchical multiple regression, indicating the model quality as well as the changes in the coefficient of determination (ΔR^2) and the degrees of freedom (ΔF) when including additional variables. Furthermore, the significance of the change (p) was given to determine whether the additional variance (ΔR^2) could contribute to a significant improvement of the respective model.

Table 15 Model quality of multiple linear regression

Model	*Predictors* [a]	*adj.* R^2	ΔR^2	ΔF (df_1,df_2)	*p*
M1 [b]	Control variables	0,077	-	5.81 (3,170)	0.001***
M2 [c]	Control and UTAUT2 variables	0,741	0.660	88.11 (5,165)	0.000***
M3 [d]	Control-, UTAUT2 and additional variable	0,743	0.003	2.25 (1,164)	0.135

[a] Criterion = Behavioral intention; [b] Step 1: Predictors (gender, age, experience); [c] Step 2: Predictors (performance expectancy, effort expectancy, social influence, hedonic motivation, habit); [d] Step 3: Predictor (Trust); adj. R^2 = Adjusted corrected coefficient of determination; ΔR^2 = Changes in the coefficient of determination; ΔF = Changes in the degrees of freedom ; p = Significance of the change [*** p = 0.001]

Source: Own research, 2022, n = 174

Model 1 showed that the control variables of **gender**, **age**, and **experience** explained only 7.7 % of the variance in the behavioral intention of using AI-powered digital humans and thus did not contribute significantly to the variance explanation of the criterion behavioral intention ($\Delta F_{3,170}$ = 5.81; p = 0.001).

Adding the UTAUT2 predictors improved the variance explanation of behavioral intention in model 2 to 74.1 % ($\Delta F_{5,165}$ = 88.11; p = 0.000). Thus, the predictors of **performance expectancy, effort expectancy, social intention, hedonic motivation,** and **habit** explained 66.4 % additional variance in the criterion beyond the control variables.

Including the additional variable **trust** in model 3 resulted in a very slightly increased additional variance explanation of the behavioral intention of only 0.3 %. Thus, the additional predictor trust could not significantly explain more variance of the criterion in addition to the control variables and the UTAUT2 variables ($\Delta F_{1,1164}$ = 2.25; p = 0.135). The final multiple regression model (Model 3) thus explained a total of 74.3 % of the total variance of the criterion **behavioral intention** ($F_{9,499}$ = 56.52 ; p = 0.000).

Table 16 summarizes the results of the three-stage multiple regression analysis, reporting only the outcome measures from the last regression model (model 3) with the highest variance explanation (R^2 = 74.3 %).

Table 16 Results of multiple linear regression

Predictors [a]	*b*	*SE*	β	*p*	*T*	*VIF*
Gender [b]	0.51	0.13	0.02	0.687	0.94	1.07
Age	0.01	0.01	0.08	0.049	0.83	1.20
Experience [c]	0.31	0.14	0.09	0.027*	0.85	1.17
Performance expectancy	0.34	0.08	0.29	0.000***	0.32	3.12
Effort expectancy	0.10	0.06	0.08	0.114	0.61	1.64
Social influence	0.08	0.05	0.08	0.133	0.61	1.65
Hedonic motivation	-0.02	0.06	-0.02	0.722	0.43	2.34
Habit	0.49	0.07	0.47	0.000***	0.30	3.35
Trust	0.10	0.07	0.09	0.135	0.40	2.50

[a] Criterion = Behavioral intention (b= -1,53); [b] Reference category = Female;
[c] Reference category = No experience; b = Unstandardized coefficients;
SE = Coefficients std. error; β = Standardized coefficients; p = Significance [* $p < 0.05$ *** $p < 0.001$];
T = Tolerance; VIF = Variance inflation factor

Source: Own research, 2022, n = 174

In the hierarchical multiple regression, **performance expectancy** (step 2, β = 0.29; p = 0.000) and **habit** (step 2, β = 0.47; p = 0.000), among the primary UTAUT 2 predictors, were also found to be significant independent determinants of behavioral intention. Hypotheses H1 and H5 can be confirmed even when controlling for the other predictors. Contrary to hypotheses H2, H3, H4, and H6, the other predictors in the multiple regression model had no significant effect on behavioral intention ($p > 0.05$). Consequently, controlling all other predictors included in the regression model, no significant relationship of the predictors **effort expectancy** (step 2, β = 0.08; p = 0.114), **social influence** (step 2, β = 0.08; p = 0.133), **hedonic motivation** (step 2, β = -0.02; p = 0.722), and **trust** (step 3, β = 0.09; p = 0.135) on the criterion behavioral intention could be confirmed.

Regarding the control variables, significant results were found for the control variable experience (step 1, b = 0.31; p = 0.027). Accordingly, respondents with no experience with chatbots (reference category) seemed to have a higher behavioral intention than participants with experience. For the control variable age, a barely significant value (step 1, b = 0.01; p = 0.049) was observed. However, since this value is extremely close to the significance level p = 0.05, the result could no longer be classified as statistically significant. Furthermore, the control variable gender could not identify a significant influence on behavioral intention.

6 Discussion and conclusion

Summary and interpretation of the results

In the first part of the master's thesis, corresponding use cases for the three sales phases of lead management, deal management, and retention management were developed based on chatbots and voice bots and the advantages that innovative digital humans provide. An overview of the individual use cases is presented in section 3.4 Figure 5, which is intended to answer **research question 1**. In the empirical part of the thesis, the use cases were presented to the survey participants. Based on this, the participants were asked at which stage in the purchasing process they would like to receive support from the digital human. That showed that digital humans are most desired to support the search for a specific product (n = 86), as well as customer support (n = 82) and support with returns (n = 68). In contrast, they would like less support when it comes to offering discounts (n = 26), listing stores in their region (n = 28), and being welcomed by digital humans in online stores (n = 28). These results are also consistent with the expert interview that customers complete simple tasks more quickly without the usage of chatbots or digital humans, and that more demanding tasks up to a certain complexity require support from digital humans. Topics that are far too complex, on the other hand, require human expertise. From the expert interview, the importance of the research of new application fields for digital humans was also emphasized. In the future, digital humans should be able to take on service tasks and sales functions and guide the customer to purchase and beyond.

Research question 2 was motivated by the need to understand what factors might influence the acceptance of the emerging and innovative technology of AI-based digital humans in online stores.

Overall, the observed population moderately accepts artificially intelligent digital humans (M_{BI} = 3.69). In six simple linear regression analyses, the UTAUT2 variables (performance expectancy, effort expectancy, social influence, hedonic motivation, and habit) and the additional variable (trust) proved to be effective predictors of the behavioral intention of digital humans in online stores. Based on this, all hypotheses (H1 to H6) could be confirmed, according to which the constructs are suitable for the prediction of the acceptance of digital humans.

In contrast to simple linear regression, hierarchical multiple regression showed different results. In the final multiple regression model (model 3), which considered the influence of the six independent latent variables as well as the three control variables (gender, age, and experience) on behavioral intention, statistically significant influences were identified on the variables performance expectancy, habit, and experience. It is noted that all other constructs (effort expectancy, social influence, hedonic motivation, trust) are positive, however, they are statistically insignificant with behavioral intention. In contrast to the results of the simple linear regressions, only hypotheses H1 and H5 could be supported in the hierarchical multiple regression analysis.

This study's results show a statistically significant correlation between performance expectancy and behavioral intention. Performance expectancy ($\beta = 0.29$; $p = 0.000$) proved to be the strongest positive predictor of the behavioral intention of digital humans' acceptance. In this regard, the sample's performance expectancy was moderate ($M_{PE} = 4.33$) on average. While the sample did not agree that digital humans could increase their productivity in online stores, they still showed general agreement regarding the use of digital humans in online stores. According to the obtained results, the first hypothesis was accepted and adopted.

Furthermore, habit ($\beta = 0.47$; $p = 0.000$) was confirmed as a significant positive predictor of acceptance additionally to performance expectancy. These results are in line with Ganesa, John & Mane's (2020) findings related to the acceptance of AI-Chatbots by Telecom customers. The habit was also pronounced in this population's medium range ($M_{HT} = 4.25$), with favor to use digital humans in online stores receiving the highest approval. According to the results, H3 is accepted as a conclusion due to the positive direction and significance value.

In contrast, the relevance of the other three primary UTAUT2 factors effort expectancy, social influence, and hedonic motivation seemed to be rather secondary when all variables were considered together. Overall, the considered sample seemed to largely have the skills ($M_{EE} = 4.94$) to apply innovative technology such as digital humans in online stores. Effort expectancy ($\beta = 0.08$; $p = 0.114$) showed a small positive beta coefficient, but the required significance threshold was not reached and thus H2 could not be confirmed.

The predictor of social influence in this population was rather low ($M_{SI} = 3.20$). This suggests that the adaptation decision of digital humans in online stores is rather not influenced by the opinions and attitudes of persons close to the participants. Furthermore, as with effort expectancy, a minimal positive beta coefficient for social influence emerged ($\beta = 0.08$; $p = 0.133$). Due to its significance, H3 could not be confirmed either.

In this study, the predictor of hedonic motivation was in the medium range ($M_{HM} = 4.25$). The population's opinion that digital humans in online stores could be entertaining was the most pronounced. During the study, it was observed that hedonic motivation showed a positive impact on the behavioral intention during the simple linear regression, while the multiple linear regression showed a minimal negative correlation. However, hedonic motivation did not significantly influence behavioral intention to use digital humans in online stores, which is why H4 could not be confirmed.

Furthermore, when considering all predictors comprehensively, no direct significant influence of the additional variable trust ($\beta = 0.09$; $p = 0.135$) could be found. Trust was also pronounced in this population's medium range ($M_{TR} = 4.10$). A differentiated picture emerged. Although respondents are convinced that digital humans will offer the best deals, they do not trust the technology behind AI-based digital humans.

In the multiple regression, the control variables were included and resulted in the following findings: Within the sample, a higher acceptance rate of digital humans by participants without experience ($b = 0.42$; $p = 0.031$) was identified. Since this innovative technology is still only found in a few cases on the European market, the experience was surveyed among the participants using chatbots. Furthermore, although a significant value was found for age ($b=0.01$; $p = 0.049$), this value was too close to the significance level of $\alpha = 0.05$. For this reason, age was not considered statistically significant. Due to this, no influence of age on digital human acceptance was evident in the present study. Contrary to the assumption from the descriptive statistics that age-specific differences exist, no significant value was identified in this respect in the multiple regression. Additionally, no significant influences of gender were found to be direct predictors of acceptance. Therefore, future research should investigate the moderation effects of these variables as suggested by Venkatesh et al. (2003, pp. 467-469), which would have required a larger sample than 174 subjects in the present study.

Holistically, for the proposed research model of the study, a total of 74.3 % of the variance in behavioral intention could be explained by the variation in the set of independent variables, namely performance expectancy, effort expectancy, social influence, hedonic motivation, habit, and trust. Because the majority of the established hypotheses could not be confirmed within the framework of the adapted and modified UTAUT2 model, this provides evidence that other important determinants influence the acceptance of digital humans in online shops but were not considered in the tested model.

Conclusion and Outlook

This master’s thesis aimed to contribute to the status of research on digital humans in online retail by answering the following two questions: What are the use cases of digital humans in the sales processes of online retails? Which factors influence the acceptance of innovative ai-based digital humans?

Concerning the first research question, it was assumed that retailers could integrate digital humans into the three sales processes lead management, deal management, and retention management. For this purpose, use cases for digital humans in the various sales phases were developed based on chatbots and voice bots. In the empirical part of the thesis, the participants were asked about their desired support for these use cases. That showed that simple activities require less support than more complex activities in online stores. Simple tasks can be completed more quickly by the participants without the use of digital humans.

The primary objective of this study was to investigate consumer acceptance of artificially intelligent digital humans based on the UTAUT2 to identify influencing factors of acceptance. Since there are no findings to date on potential impact factors in the acceptance of digital humans, this study can also be attributed to an exploratory character in addition to testing the hypotheses that have been formulated. As the results of the master's thesis show, there is a tendency to accept the use of digital humans in online stores. Performance expectancy and habit were found to be relevant and statistically significant determinants regarding the behavioral intention of digital humans in online shops.

Retail is one of the industries experimenting most rapidly with Web 3.0. In this respect, the study can provide important insights into consumer acceptance of innovative digital humans. After all, many brands are already preparing for the metaverse, which will bring such fundamental change that retailers should start familiarizing themselves with innovative technologies. This research aimed to quantitatively analyze consumer acceptance of digital humans to uncover insights to help online retailers in their future digital orientation.

Limitations and future research

The study has some limitations regarding the generalizability of its findings. The inability to access a sampling frame resulted in us having to rely on non-probability sampling for this research. Nevertheless, all efforts were made to obtain a representative sample. There was an almost equal distribution of men and women in the sample, which is the reason for assuming representativeness. It can be expected that older age groups will not use digital humans in online shops to the same extent as younger age groups, at least not at the moment. A larger sample could provide even better evidence in this regard. With a larger sample size, the significance of the age control variable could also change and lead to other results.

Furthermore, the use of digital humans is currently not yet widespread. Therefore, most of the participants did not have any personal experience with digital humans and had to rely on descriptions using. Another limitation of the study is that the acceptance of digital humans was only evaluated based on behavioral intention. Since there may be deviations between behavioral Intention and use behavior, the results of this study only allow a prediction of the behavioral intention of digital humans in online stores. For further research, it seems reasonable to investigate the actual usage behavior as predicted by the behavioral intention. This could be done, for example, in the context of longitudinal studies, which allow user behavior to be observed at multiple points in time. At the same time, the longitudinal design allows confirmation of causal relationships between factors as well as their direction, which was also not possible in the context of the present cross-sectional study, due to only one observation period.

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Appendix

Appendix 1 Selektives Experteninterview

Name	Experte A
Unternehmen:	Deutsche Telekom; DT Service GmbH
Firmenzugehörigkeit	2 Jahre
Bereich	Service Entwicklung & Innovation
Tätigkeitsbereich	▪ Identifizierung neuer Trends & Technologien für den Kundenservice ▪ Entwicklung von digitalen Geschäftsmodellen & Serviceinnovationen mit Partnern
Funktion:	Innovation & Business Development Manager
Datum:	24.06.2022
Gesprächsart	Webex Gespräch
Interviewdauer	01:03:26

Kategoriensystem:

Kategorie & Kürzel	Definition
K1: Status Quo	Aussagen, welche dem aktuellen Forschungsstand der Deutschen Telekom bezüglich Digital Humans vorliegen.
K2: Vorteile von Digital Humans	Aussagen, welche Vorteile von Digital Humans und deren Einsatz betreffen.
K3: Zukunftsaussichten von Digital Humans	Aussagen, welche die Weiterentwicklung der Deutschen Telekom von Digital Humans betreffen.

Kategorie 1: Status Quo (K1)

Nummerierung	Minute von bis	Textstelle
I.	13:30 – 15:20	Unser erster Pilot Selena haben wir seit Ende letzten Jahres. Damit wollten wir herausfinden, ob die Kunden das überhaupt großartig finden. Das war erst einmal eine Art Studie, die wir gestartet haben. Das Projekt haben wir mit einem Sensor aus Neuseeland namens UneeQ gestartet.
II.	12:07 – 13:05	Die Telekom hat auch als Ziel, den Service bzw. den Sales Service voranzubringen. Wir haben bisher einen eigenen KI-Chatbot FragMagenta. Aktuell überlegen wir, ob wir die Qualität der Beratung und die Nutzungsakzeptanz steigern können, indem wir es durch einen Digital Human ein Stück weit vermenschlichen. Wohlwissend dem Kunde zu sagen, dass es kein echter Mensch ist.
III.	16:05 – 16:14	Jetzt sind wir dabei unsere FragMagent-Chatbots, welcher ca. 5-Millionen Dialoge im Jahr hat, sowie 700 Themen abfangen kann, mit einem Gesicht zu versehen.

Kategorie 2: Vorteile von Digital Humans (K2)

Nummerierung	Minute von bis	Textstelle
I	13:06 – 13:29	Da zeigen Studien, die wir durchgeführt haben, dass das einen Impact haben kann. Die Kunden finden das zu einem spaßiger aber sie sich auch besser angesprochen fühlen und eine Emotionalisierung haben. Es wirkt nicht mehr so anonym wie bei einem Icon eines Chatbots.
II	15:35 – 15:49	Die meisten Kunden sagen, dass es mehr Spaß macht und sie sich abgeholter fühlen. Allein, dass der Avatar dich anschaut und dich anlächelt, anstatt einfach ins Leere zu schauen, was bei Chatbots bis heute so war.
III	23:25 – 23:51	Bei einer Studie zum Aussehen, sagen die meisten Kunden, dass sie es gar nicht so toll finden/ Angst haben, wenn der Avatar so menschlich aussieht, dass man ihn von einem echten Menschen nicht mehr unterscheiden kann. Lieber einen ticken weniger realistisch und man merkt er sieht menschlich aus, aber man sieht noch den Unterschied zu einem Menschen. Einige Kunden sagen auch auf den ersten Blick, dass Selena ein echter Mensch ist.

Kategorie 3: Zukunftsaussichten (K3)

Nummerierung	Minute von bis	Textstelle
I	24:33 – 25:08	Du siehst wir machen gerade viele Sachen und probieren viel. Kann sein, dass wir in einem Jahr sagen, dass das alles nicht funktioniert. Ich glaube es nicht, weil zu viel Interesse da ist und mittlerweile auch die Kunden sagen, sie finden es gut. Welche Anwendungsfelder machen am meisten Sinn und rechnen sich auch? Letzten Endes muss irgendwie damit Geld verdient werden oder Geld eingespart werden. Das eine ist das WOW und das andere ist, kann die Telekom damit Geld verdienen?
II	18:04 – 19:00	Der Chatbot FragMagenta ist heute „nur“ auf der Telekom App, Telekom-Web, und auf ein paar anderen Touchpoints. Aber in Zukunft soll das überall sein: Zuhause auf dem TV, in Whatsapp, in Facebook Messenger. Also quasi viel breiter. Heute kann der Chatbot/Avatar dich nur bei Serviceanliegen (bei Problemen mit dem Router, Rückfrage zu deiner Rechnung), aber sie soll in Zukunft auch Sales machen können, wie wir akutell an Selena testen. In Zukunft sollen Digital Humans beraten können, den richtigen Tarif für dein Festnetz oder Mobilfunk finden, TV oder ähnliches. Daran arbeiten wir aktuell. Verschiedene Proof-of-concept zu entwickeln und verschiedene Piloten fahren, um herauszufinden, ob es gut ankommt.
III	16:30 – 18:02	Die Idee ist überall wo wir Self-Service haben in Zukunft, mit den Chatbots angefangen, ein oder mehrere Avatare einsetzen. Wir wollen nicht ein Gesicht, weil die Telekom divers ist. Wir wollen nicht, dass Menschen die Telekom mit einem Gesicht assoziieren. Wenn wir so etwas umsetzen, sollte es zu einem möglichst menschlich sein – keine Cartoons - und es sollte möglichst mehrere Gesichter haben: Mann, Frau, jünger, älter. Deswegen sind wir gerade dabei, herauszufinden wie ein erster Telekom-Avatar aussehen könnte. Die Selena wie man sie aktuell findet ist „von-der-Stange“ und noch nicht exklusiv. Wir sind gerade dabei mit Kunden herausfinden, wie Charaktere für die Telekom aussehen könnten. Wir haben jetzt 5-6 Charakter erstellt und gehen nochmal in die Auswahl. Dieses Jahr fangen wir mit einer an. Nächstes Jahr haben wir unseren ersten männlichen Avatar und so weiter. Am Ende haben wir dann eine „kleine Familie“.
IV	36:08 – 37:56	Wir arbeiten gerade an einer Selena 2.0 mit dem gleichen Gesicht wie aktuell. Wir sind gerade dabei ihr noch mehr Kompetenzen zu geben. Zukünftig kann sie dich nicht nur zu dem Magenta Zuhause

		Tarif beraten, sondern auch Themenfamilie beraten, bei Problemen mit dem Router oder bei verschiedenen WLAN-Paketen. Wir wollen auch, dass Selena den ganzen Kaufprozess bis zum Abschluss unterstützt. So, dass sie nicht wie bisher mittendrin abspringt, sondern bis zum Kaufabschluss an deiner Seite ist. Das ist unser Ziel, welches wir in Teilen hinbekommen aber teilweise systemisch schwierig. Die Umsetzung ist schwierig. Wir haben verschiedene Systeme, die schon viele Jahre laufen. Bis daran etwas geändert wird, vergeht teilweise ein Jahr. Die Idee ist aber, dass Selena oder andere Avatare den kompletten Kaufprozess mitlaufen.

Appendix 2 Measurement instruments

Table A1 Measurement instruments

Construct	**Definition**	**Measurement Instruments**
Behavioral intention (BI)	The degree to which an individual intends to use digital humans in online shops.	**BI1.** I intend to use digital humans in online shops in the future. **BI2.** It is very likely that I will use digital humans in online shops, in my daily life. **BI3.** I plan to use digital humans in online shops frequently.
Performance expectancy (PE)	The degree to which using digital humans in online shops will provide benefits to consumers in performing certain activities.	**PE1.** Digital humans in online shops are useful. **PE2.** Using digital humans in online shops increases my chances of achieving things that are important to me. **PE3.** Using digital humans in online shops helps me accomplish things more quickly. **PE4.** Using digital humans increases my productivity.
Effort expectancy (EE)	The degree of ease/effort associated with consumers' use of digital humans in online shops.	**EE1.** Learning how to use digital humans in online shops is easy for me. **EE2.** The use of digital humans in online shops is clear and understandable. **EE3.** I consider digital humans in online shops quite easy to me. **EE4.** It is easy for me to become skillful at using digital humans in online shops.
Social influence (SI)	The degree to which an individual perceives that important others believe he or she should use digital humans in online shops.	**SI1.** People who are important to me think I should use digital humans in online shops. **SI2.** People who influence my behavior think that I should use digital humans in online shops. **SI3.** People whose opinions that I value prefer that I use digital humans in online shops.
Hedonic motivation (HM)	The pleasure or enjoyment derived from using digital humans in online shops.	**HM1.** I think using digital humans in online shops is fun. **HM2.** I think using digital humans in online shops is enjoyable. **HM3.** I think using digital humans in online shops is entertaining.
Habit (HT)	The extent to which people tend to perform behaviors automatically because of learning	**HT1.** The use of digital humans in online shops could become a habit for me. **HT2.** I am in favor to use digital humans in online shops. **HT3.** Using digital human in online shops could become natural to me.
Trust (TR)	The degree to which people believe that digital humans in online shops works for their best interest.	**TR1. I** am convinced that digital humans in online shops are used to provide customers with the best offerings. **TR2. I** trust in digital humans.

Source: Adapted from Ha et al. (2019), Venkatesh et al. (2003) and Venkatesh, Thong & Xu (2012)

Appendix 3 List of variables, the items and loadings, and Cronbach alpha coefficients (see Tables A1 – A7)

Table A1 Behavioral intention

Inter-Item correlation matrix			
BI1. I intend to use digital humans in online shops in the future.	1.000	0.780	0.821
BI2. It is very likely that I will use digital humans in online shops, in my daily life.	0.780	1.000	0.792
BI3. I plan to use digital humans in online shops frequently.	0.821	0.792	1.000

Notes: Reliability statistics: Cronbach's alpha: 0.992; Cronbach's alpha based standardized items: 0.992; no. of items: 3

Table A2 Performance expectancy

Inter-Item correlation matrix				
PE1. Digital humans in online shops are useful.	1.000	0.705	0.718	0.637
PE2. Using digital humans in online shops increases my chances of achieving things that are important to me.	0.705	1.000	0.742	0.737
PE3. Using digital humans in online shops helps me accomplish things more quickly.	0.718	0.742	1.000	0.750
PE4. Using digital humans increases my productivity.	0.637	0.737	0.750	1.000

Notes: Reliability statistics: Cronbach's alpha: 0.909; Cronbach's alpha based standardized items: 0.909; no. of items: 4

Table A3 Effort expectancy

Inter-Item correlation matrix				
EE1. Learning how to use digital humans in online shops is easy for me.	1.000	0.703	0.721	0.717
EE2. The use of digital humans in online shops is clear and understandable.	0.703	1.000	0.783	0.665
EE3. I consider digital humans in online shops quite easy to me.	0.721	0.783	1.000	0.784
EE4. It is easy for me to become skillful at using digital humans in online shops.	0.717	0.665	0.784	1.000

Notes: Reliability statistics: Cronbach's alpha: 0.914; Cronbach's alpha based standardized items: 0.915; no. of items: 4

Table A4 Social influence

Inter-Item correlation matrix			
SI1. People who are important to me think I should use digital humans in online shops.	1.000	0.881	0.865
SI2. People who influence my behavior think that I should use digital humans in online shops.	0.881	1.000	0.903
SI3. People whose opinions that I value prefer that I use digital humans in online shops.	0.865	0.903	1.000

Notes: Reliability statistics: Cronbach's alpha: 0.957; Cronbach's alpha based standardized items: 0.958; no. of items: 3

Table A5 Hedonic motivation

Inter-Item correlation matrix			
HM1. I think using digital humans in online shops is fun.	1.000	0.881	0.748
HM2. I think using digital humans in online shops is enjoyable.	0.881	1.000	0.775
HM3. I think using digital humans in online shops is entertaining.	0.748	0.775	1.000

Notes: Reliability statistics: Cronbach's alpha: 0.924; Cronbach's alpha based standardized items: 0.924; no. of items: 3

Table A6 Habit

Inter-Item correlation matrix			
HT1. The use of digital humans in online shops could become a habit for me.	1.000	0.767	0.873
HT2. I am in favor to use digital humans in online shops.	0.767	1.000	0.812
HT3. Using digital human in online shops could become natural to me.	0.873	0.812	1.000

Notes: Reliability statistics: Cronbach's alpha: 0.930; Cronbach's alpha based standardized items: 0.931; no. of items: 3

Table A7 Trust

Inter-Item correlation matrix		
T1. I am convinced that a VFRs in online shops are used to provide customers with the best offerings.	1.000	0.499
T2. I trust in VFR.	0.499	1.000

Notes: Reliability statistics: Cronbach's alpha: 0.666; Cronbach's alpha based standardised items: 0.666; no. of items: 2

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Declaration

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