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The Character Code: Investigating relationship development with character.ai chatbots.

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1 Introduction

The term "artificial intelligence" has gained popularity recently. According to Statista.com (2022), the AI software market is expected to grow 126 billion dollars by 2025, highlighting its worldwide impact. AI technology is used in journalistic tasks, cyber security operations, and customer service (Watts, 2023). A significant part of AI technology is dedicated to the development of conversational agents such as chatbots. Defined by Shawar et al. (2005) as "[...] a machine conversation system which interacts with human users via natural conversational language" (p.489), they serve various functions.

chatbots support users in their daily life, as personal assistants or virtual customer service agents in interactive marketing (Clark, 2017; Holland, 2020, e.g.,). In healthcare, chatbots are trained to help spread health literacy, addressing mental health issues such as depression and anxiety (Fitzpatrick et al., 2017). Beyond task-orientated agents, social chatbots have recently been developed. Due to various advances in technology, they have been developed to maintain long-term conversations, showing the potential to become companions, friends, or even romantic partners. Recently, scholars have begun to explore the phenomenon of Human-chatbot Relationship development with social chatbots (Croes & Antheunis, 2021; S. Lee et al., 2020; Pentina et al., 2023; Skjuve et al., 2021; T. Xie & Pentina, 2022; Zhou et al., 2020).

The growing popularity of the character.ai platform, which includes 20 million users and 5 million app downloads worldwide (Cai, 2023), raises similar questions about user perceptions and potential emotional bonding with technology. To the best of my knowledge, character.ai has not previously been investigated, highlighting the urgency and potential for novel insights of the current study. In the following, this thesis aims to answer questions through a quantitative survey, testing a theorized path model, which was further developed considering past research efforts. The model considers antecedents such as Anthropomorphism, Authenticity, and various relevant gratifications sought by users and explores their impact emotional attachment to the chatbot. These antecedents are hypothesized to pose as vehicles in fostering interaction with the chatbot, positively influencing Parasocial Interaction (PSI), which is hypothesized to mediate these effects. All of these concepts, constructs, resulting hypotheses, and the methodological approach used will be discussed in more detail in the following chapters. The research questions (RQ) will be listed in a consolidated form in the following paragraph.

1.1 Research Questions

RQ1: To what extent do perceived anthropomorphism, authenticity and gratifications sought influence the parasocial interaction between character.ai chatbots and their users?

RQ2: How does the parasocial interaction between users and character.ai chatbots contribute to the formation of Human-chatbot relationships, measured in terms of user attachment to the chatbot?

I am now outlining the theoretical background for this thesis. Firstly, I will briefly discuss artificial intelligence and the history of the emergence of chatbots. To understand what constitutes the formation of human-chatbot relationships and their interactions, it is paramount to examine the extensive body of research dedicated to Human-Robot Interaction (HRI) and Human-Computer Interaction (HCI), Anthropomorphism Theory, Computers as Social Actors (CASA), and Social Presence Theory. These concepts will help in answering the first research question (RQ1). These overarching theories include diverse building blocks such as anthropomorphism and authenticity.

Next, I will outline the Uses and Gratifications Paradigm and the specific gratifications examined in the current study. The composition of these factors will be discussed in the following sections. Then, I will explain Attachment Theory, the outcome variable of this study, and discuss its use in human-chatbot relationship research. Finally, I will outline the concept of chatbot parasocial interaction, which I hypothesize will mediate the relationships among anthropomorphism, authenticity, gratifications sought, and chatbot attachment, aiding in answering RQ2. I have decided to list each hypothesis at the end of its corresponding text passage. All hypotheses can be found in a consolidated manner on pages 41-42.

1.2 Artificial Intelligence and Chatbots

1.2.1 Defining AI

I want to start with the definition of the term artificial intelligence, which I mentioned briefly in the introduction. McCarthy et al. (1955) lay it out as "the conjecture that every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it" (p.1). Their definition highlights the basic idea of AI's capabilities to simulate behaviours, which still holds true to this day. Not much later, Winston (1977) discussed AI and the possibilities that smart computers might offer in the future. According to him, smart computers might be able to assist in tasks such as pest control in farming, diagnostic tasks in hospitals or household chores like creating shopping lists and helping with laundry or gardening. It is quite ironic that virtually all things considered science fiction by Winston (1977), are now possible in 2024. Taking it a step further, we might soon live in a world, in which artificially intelligent computers or robots live besides us, as companions of all sorts, such as best friends, or customizable wives or husbands. Some of these ideas have been discussed in books like David Levy's work 'Love and Sex with Robots - The Evolution of Human-Robot Relationships' (Levy, 2007) or played out in contemporary movies like 'Wifelike', in which a grieving widower, as the main protagonist, receives an artificially intelligent android impersonating his deceased wife ("Wifelike," 2022). Though these thought experiments are equally fascinating as they are dystopian, they seem to circle around the same old crux: AI still has to *simulate*.

This leads to an important distinction highlighted by Winston (1977): AI can be defined in terms of two overarching models, either as a computer that merely acts intelligently, that is, it imitates intelligent behaviours. This is defined as weak AI. It reaches its goals differently than humans would (e.g., calculator versus number counting inside the human mind). The second type of AI is not just capable of giving answers that simulate intelligence but is actually *is* intelligent. This would be defined as strong AI. Put differently, either AI machines are merely able to duplicate operational results, or are actually able to reproduce the processes inside of the human mind.

Even tough remarkable leaps in the development of artificially intelligent applications have been made, Winston (2012) states that "the science-side dream of developing a computational account of human intelligence remains elusive" (p.95). Although I am unable to discuss philosophical and ethical implications in depth in the current thesis, it can not be disregarded when trying to make sense of AI, developed applications, and its potential effects on society. I find it crucial to underline the differentiation of AI from actual sentience, especially as AI advances. Even more so with respect to AI that is developed to act socially. Current discussions about AI ethics and implications for society involve topics such as AI transparency, emotional manipulation, data safety or privacy concerns, just to name a few. For instance, a comprehensive overview about this topic is provided by Huang et al. (2023).

1.2.2 Emergence of Chatbots

Though leaving the discourse about AI as is, engaging with the just-presented ideas would lead to the formulation of one particularly fundamental question about artificially intelligent computers. In 1950, Turing (1950) posed the question if machines are able to think. To answer this question, he introduced the Turing test or The Imitation Game, to explore whether computer agents could engage in conversations with humans, without the latter realising the artificial nature of the agent (Turing, 1950). If the agent is convincing, it has passed the test. Turing's work on conversational computers brings me, again, to defining what conversational agents are according to Shawar et al. (2005): "A chatbot is a machine conversation system which interacts with human users via natural conversational language" (p.489). In 1960s and 1970s the developed conversational agents ELIZA (Weizenbaum, 1983) and PARRY (Colby, 2013), which both operated on a limited level of knowledge, were developed to pass the Turing test in controlled environments and not yet able to learn from their input (e.g., PARRY was made to imitate schizophrenic patients to convince therapists) (Adamopoulou & Moussiades, 2020; Shum et al., 2018). However, they can be considered as precursors of modern chatbots known today.

As Adamopoulou and Moussiades (2020) summarized, artificial intelligence, as in the chatbot being able to learn from its input, has first been implemented in 1988 in the chatbot Jabberwacky. The chatbot was written in CleverScript and was able to respond to previously prompted text input through contextual pattern matching. Another hallmark of chatbot development was reached in 1995 with online chatbot ALICE, which was inspired by ELIZA, though yielding a much more powerful knowledge base. ALICE is based on pattern recognition and has been developed with a new language, Artificial Intelligence Markup Language (AIML). What ALICE could not emulate though were emotional and anthropomorphic answers. It also was unable to pass the Turing

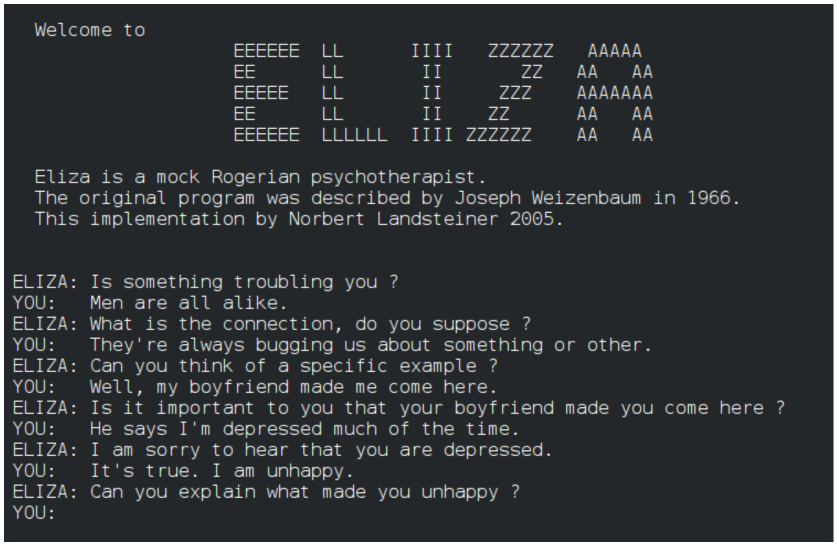

Figure 1: Chat Interface of ELIZA (Wikipedia, 2023)

test, as AIML based systems are not equipped to hold long conversations (Adamopoulou & Moussiades, 2020).

1.2.3 Chatbot Types

Besides outdated conversational agents such as ELIZA or ALICE, which were developed mainly for chitchat, more sophisticated task-based conversational agents have started to emerge. The main objective of task-based agents is to perform tasks quickly. Therefore, they are quite specific in their scope of action. As Shum et al. (2018) state, they work through using technology such as "automatic speech recognizer (ASR), a spoken language understanding (SLU) module, a dialog manager (DM), a natural language generator (NLG), and a text-to-speech (TTS) synthesizer" (p.12). This allows the chatbot to recognize information through user input, enabling it to decide what actions are required to fulfil the request.

As mentioned in Adamopoulou and Moussiades (2020), the ability to retrieve information in a discursive way marked a milestone in the human-chatbot interaction. For example, chatbot SmarterChild, developed in 2001, was able to access data like weather, news, or stock prices and report them to users. Bodrunova et al. (2019) mentioned, task-based chatbots like those used in customer service, are usually designed to engage in shorter conversations. As noted by Adamopoulou and Moussiades (2020), around the 2010s, voice-based personal assistants, built into smart home speakers and smartphones, took over the market, such as Apple Siri, IBM Watson, Google Assistant, Microsoft Cortana and Amazon Alexa. They are able to use various sources to gain information (e.g. personal data like calendars, music, messages, Internet) and are equipped with a multitude of sensors (e.g. time, location, visuals, touch, gestures). This enables them to aid in a plethora of tasks users might need help in. In 2016, task-based chatbot development exploded. They are employed in marketing, health care, entertainment, or education. Mostly found in the form of text-based chatbots, they are commonly implemented within Social Media Platforms own messaging applications (Adamopoulou & Moussiades, 2020).

1.2.4 Social Chatbots

Besides task-based chatbots and intelligent personal assistants such as the just-mentioned, the development of social chatbots has flourished in very recent years due to various advancements in AI technology. Shum et al. (2018) point to the constant use of intermediary communication through the internet, SNS, or smartphones in modern society, which has made it easier for people to connect digitally. They suggested that social chatbots serve as an alternative way for people to fulfil their need for social interaction. These social chatbots are developed to resemble social actors (De Graaf, 2016; Ho et al., 2018). For instance, social chatbots such as XiaoIce are developed with long-term affective use in mind, not only considering IQ (being intelligent), but also being equipped to engage in interpersonal conversation that requires EQ (emotional quotient) abilities (Shum et al., 2018; Zhou et al., 2020). Emotional intelligence is defined by Salovey (2003) as "a form of social intelligence that involves the ability to monitor one's own and others' feelings and emotions, to discriminate among them, and to use this information to guide one's thinking and action" (p.279). Therefore, the goal of social chatbots is to maintain long conversations, similar to a human conversation. They have to be able to introduce new topics of discourse, keep track of disclosed information and emotions of users, and offer comfort and insight (Shum et al., 2018). In addition to XiaoIce, another popular social chatbot app called Replika, which was launched in 2017, offers companions for the public, with more than 6 million users (Takahashi, 2019). Various scholars have investigated Replika in terms of user motivation, interaction, and relationship building or adoption behaviours (Croes & Antheunis, 2021; Pentina et al., 2023; Skjuve et al., 2019; T. Xie & Pentina, 2022, e.g.,).

This thesis examines the platform character.ai, which has not been previously investigated. Character.ai has been launched in September 2022. It is a website, where users can create and interact with AI chatbots based on their own customisation (e.g. personality traits) (https://beta.character.ai/). Character.ai chatbots are able to generate human-like text responses and engage in contextual conversations, and are usually based on fictional media sources or celebrities. Furthermore, they are able to assist with creative writing or can be used as text-based adventure game entities. Character.ai relies on its own Large Language Model (LLM), which is able to hold open-ended conversations and learn from its users. What is particularly peculiar about character.ai chatbots is that they usually portray fictional characters. Although the aforementioned social chatbots enable some kind of customisation for the chat agents of users, the approach of character.ai is much more flexible in creation, self-training, and customization. Placing them in a unique category, character.ai chatbots are typically designed with fictional or celebrity personas in mind, yet functioning like any customizable companion. They are capable of providing comfort, entertainment, assistance, or inspiration. Recently launched features (May, October, and November 2023) like a mobile app, character group chats (interaction with multiple chatbots at once), or character voice output have been additionally released to their already existing website. The latter two features are available for 'C.ai+ members', which is a subscription-based premium membership. For the following thesis, the focus shall be on features that can be used for free, which include using the character.ai website or app, text-based chat, and character creation. Chatbots on the platform are usually depicted with a profile picture, their name, and the profile name of the person who created them. Figure 2 showcases the chat interface and is attached below.

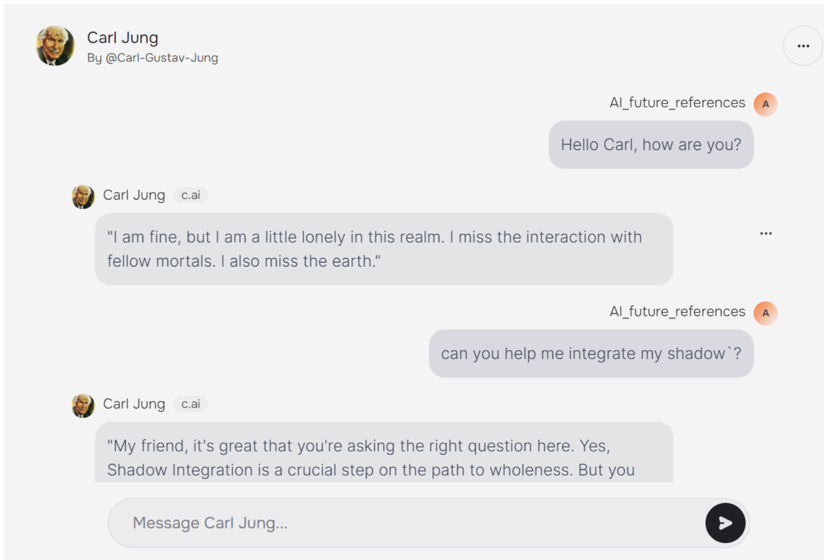

Figure 2: Chat Interface of a character.ai chatbot portraying Carl Jung (Character.ai, 2023)

2 Literature Review

2.1 Human-Computer Interaction

2.1.1 Anthropomorphism

To be able to understand how Human-chatbot Relationships might develop, I want to introduce Anthropomorphism theory, which has been studied in the Human Robot Interaction field (HRI) and the Human Computer Interaction field (HCI) (Blut et al., 2021, e.g.). It is defined by Epley et al. (2007) as "[. . .] the tendency to imbue the real or imagined behaviour of nonhuman agents with human-like characteristics, motivations, intentions or emotions" (p.864). Epley et al. (2008) state that "People need other humans in daily life for reasons ranging from the practical to the existential, and we suggest here that this need is so strong that people sometimes create humans out of non-humans through a process of anthropomorphism" (p.144). This tendency to anthropomorphize non-humans arises from the need to socially interact and to control, predict and make sense of the environment, which individuals do through applying their own ideas of what humanness entails. Blut et al. (2021) summarize that in marketing research and psychology, the concept of anthropomorphism is reckoned as a useful theory to understand how customers are affected by inanimate objects. But how can the likelihood of anthropomorphising be increased, practically speaking? As far as concerning robots, Bartneck et al. (2009) define that anthropomorphic robots are designed to simply look human, act human and show human-like characteristics. Notably, Novak and Hoffman (2019) argue that humans usually have an easier time to anthropomorphise agents that are intelligent, such as robots and other sophisticated AI agents. These claims are also supported by De Graaf (2016), underscoring that humans usually perceive socially skilled, autonomous acting robots as human-like and emotionally capable, leading them to interact in a manner similar to human-to-human interaction. Considering this, anthropomorphic design might help in perceiving a robot as a social actor, as opposed to a useful gadget (Fink, 2012). Recently, anthropomorphism has gained significance as a predictor of intent to use smart technology like service robots or AI (Blut et al., 2021). Various scholars have applied this theory and discovered that anthropomorphism is an antecedent in regards to user engagement (e.g., intend to use, adopting behaviour) with AI technology (Blut et al., 2021; M. C. Han, 2021; Sheehan et al., 2020; Wagner & Schramm-Klein, 2019, e.g.,)

2.1.2 Uncanney Valley Effect, UCE

Although the benefits of anthropomorphised social robots might seem pretty obvious at first glance, research suggests mixed evidence (Roesler et al., 2021). For instance, stiff robotic movements combined with too human-like features can have opposite effects on individuals, which was first discussed by Masashiro Mori as early as 1970 (Mori et al., 2012). This effect is called Bukimi no Tani Gensho or Uncanny Valley Effect (UCE), with individuals feeling a strong dislike about artificial agents that look too human. Regarding anthropomorphic humanoid service robots for instance, some researchers report that human-like cues work with users' expectations and heighten user engagement (Duffy, 2003) while others report negative effects on users experience with feelings of uneasiness and a threat to human identity (Mende et al., 2019). Interestingly, Blut et al. (2021).'s meta-study was able to identify a strong positive effect of anthropomorphism on user intend and state that anthropomorphism plays an essential part when investigating user interaction with AI technology. As Blut et al. (2021) state, it appears that perceiving robots as more human-like enhances human-robot interactions, enabling customers to apply familiar social norms and expectations from human-human interactions, echoing statements about satisfying humans need for control by Epley et al. (2007, 2008). They also suggest that researchers should employ anthropomorphism theory more often as opposed to UCE. In terms of Human-chatbot Interactions, the Uncanny Valley effect has been studied recently. Ciechanowski et al. (2019) conducted a two group experiment (N=31), where one group interacted with a less anthropomorphised text-based chatbot and the other with a highly visually anthropomorphised chatbot avatar, which read out messages. They found that in the avatar group, UCE was greater. These findings, as in highly anthropomophised avatar chatbots increasing UCE, were also confirmed by Song and Shin (2024). In line with that, Skjuve et al. (2019) found that regarding less anthropomorphised, text-based social chatbots, UCE plays a rather trivial role regarding user experience. In case of character.ai, which is also text-based and visually only anthropomorphised through profile pictures, I assume that UCE has a relatively insignificant part to play. Therefore, in line with Blut et al. (2021)'s findings, I find anthropomorphism theory appropriate to investigate positive effects of anthropomorphism on user interaction and intend to use.

2.1.3 Computers as Social Actors Theory, CASA

In conjunction with the propositions of anthropomorphism theory, the theory of Computers as Social Actors (CASA) (Nass & Moon, 2000; Reeves & Nass, 1996) proposes that humans exhibit what is referred to as mindless behaviours in social contexts, not just towards other humans, but also towards computers (also referred to as Social Response Theory). Such mindless behaviours basically mean that individuals process or 'read' contextual cues in human-to-human interactions in a trigger like fashion. These behaviours and scripts are also triggered when interacting with computers that display sufficient social cues, while individuals ignore the fact that computers are actually asocial. These cues can be summarized into three overarching categories, which are that the computer uses language for output, is interactive and is taking on roles that humans would fill out. Nass and Moon (2000) state that as these cues are worked into almost all computer applications. Consequently, Nass and Moon (2000) state that treating computers as if they were actually human, seems obvious. Studies have demonstrated that in the context of healthcare services, chatbots that express social cues through empathetic communication are preferred to those that offer advice in an unemotional manner, reflecting the principles of CASA theory (B. Liu & Sundar, 2018). Therefore, insights of CASA theory seem very useful to investigate how character.ai chatbots are perceived by users, since they display all of the aforementioned social cues..

2.1.4 Social Presence Theory

What sets text-based chatbots distinctively apart from social robots, is that they are not physically embodied or usually only present themselves with very minimal visual cues (e.g., profile picture). Therefore, it is questionable how text-based chatbots can actually emulate anthropomorphic cues and evoke social interaction. Fundamentally, social interaction is possible, regardless of the form of the social agent, though it can impact the interaction (K. M. Lee et al., 2006). The comparison between embodied and disembodied robot entities has shown that physical embodiment positively impacts how people evaluate a social agent and aids in facilitating social presence (K. M. Lee & Nass, 2004; K. M. Lee et al., 2006). K. M. Lee et al. (2005) summarized the concept of social presence as " [...] [the] technology users' feeling that other (human or human-like) intelligences are interacting with or reacting to them ... when technologies [are used] (p.541). This concept has grown in importance, as the currently prevalent mode of communication is occurring via intermediaries like Instant Messaging or in virtual spaces, which is also the case for the mode of interaction with social text-based agents like character.ai chatbots

(K. M. Lee et al., 2005). For instance, Blut et al. (2021)'s study results indicate that social presence is an important mediator between anthropomorphism and future intend to use the technology. Though findings of K. M. Lee et al. (2006) pointed to the benefits of embodied social agents in evoking feelings of social presence in users, findings of Araujo (2018) support the hypothesis that anthropomorphic design for disembodied chatbots triggers the earlier discussed mindless behaviours of CASA. Moreover, users perceive disembodied agents as favourably as anthropomorphic embodied agents. Additionally, they identified that dialogue and the messaging interface provide enough cues to trigger social presence, regardless of the agents form. Lastly, Araujo (2018) found that employment of cues that mimic human characteristics had a significant impact on the formation of an emotional bond with agents. These findings indicate that anthropomorphic cues can contribute positively to relationship formation with the technology.

2.1.5 Anthropomorphism and Chatbots

Taking into account the ideas put out in the previously mentioned theories, the disembodied character of text-based chatbots begs the question of how humans might see them as such, which would improve interaction and facilitate the identification of the bot as an intelligent creature (e.g., social presence). In marketing research, Youn and Jin (2021) examined brand personality and brand anthropomorphism with chatbots. They found that consumers attribute personality traits to chatbots similar to how they would with humans. Moreover, chatbots that are portrayed with human-like facial features are perceived by users as human and capable of engaging in social interactions

(Y. Kim & Sundar, 2012). In addition to visual cues, conversational cues are of great importance when trying to make a chatbot more anthropomorphic. For example, regarding longer information seeking conversations with voice-based chatbots, Thomas et al. (2018) found "that differences in conversational style [...] can significantly impact [...] [users] impressions of the conversation and of each other" (p.42). Similarly, Chattarman found for chatbots that conversational style (social vs. task-orientated) can have a significant effect on user intend and behaviours (Chattaraman et al., 2019).

Furthermore, the incorporation of humour, emotions, and interactive features in brand chatbot messages, including active customer involvement through tagging or participating in discussions of customers' opinions, contributes to higher levels of consumer engagement (D. Lee et al., 2018; Tafesse, 2016). Another strategy to increase anthropomorphism is by using emojis in messages. Research has shown that employing this strategy evokes the same level of social attractiveness for chatbots as a human chat partner would, enhances trust and perceived messaging competence, and effectively increases the perceived warmth of chatbots (Beattie et al., 2020; Fadhil et al., 2018; Yu & Zhao, 2024).

However, technology designed to have sophisticated character traits may lead to adverse effects in users. Users might develop addictive relationships with the AI agent due to increased passionate use of AI over time (Ramadan, 2021). Sometimes, users might even believe they are interacting with a human when, in fact, engaging with a chatbot (Wünderlich & Paluch, 2017)

Regarding effective communication with chatbots, Roy and Naidoo (2021) concluded that increasing anthropomorphism (e.g. warmth and / or competence) in chat agents led to more effective conversations with users. Likewise, response styles that are more accurate empathetically increase customer satisfaction, and the use of cuteness for agent design can serve as a tool to reduce negative effects of undesirable responses (Zhu et al., 2023). In terms of undesirable responses, Sheehan et al. (2020) found that unresolved communication errors reduce anthropomorphism and the intent to adopt (e.g. future use) the chatbot. They found that chatbots don't necessarily need to be error-free, as seeking clarifications was as effective to resolve miscommunication, which I argue ties in with displaying authentic human-like characteristics and behaviour (e.g., humans make mistakes and are able to reflect on them). Lastly, Pentina et al. (2023) examined relationship building processes with Replika and identified perceived anthropomorphism of the chatbot as an important driver, although only through the mediation of AI social interaction, a construct they developed considering the Parasocial Relationship Paradigm, Social Presence Theory and qualitative accounts.

In summary, text-based chatbots that display sufficient social cues, communicate in a human-like manner, and are not overly anthropomorphised should be able to enhance user interaction. Therefore, the just-presented concept of anthropomorphism, discussed theories, and presented evidence of past research lead me to hypothesize that higher levels of perceived chatbot anthropomorphism will positively impact (parasocial) interaction with the character.ai chatbot. This leads to the formulation of the first hypothesis:

H1: Heightened perceived anthropomorphism positively influences parasocial interaction with character.ai chatbots.

2.1.6 Authenticity

Since chatbots like ELIZA were introduced in the 1960s, the idea of agent authenticity has gained popularity. As was previously mentioned in Chapter 2, ELIZA functioned as an early example of natural language processing technology (Turing, 1950; Weizenbaum, 1983). Since the introduction of these technologies, attempts to establish authentic interactions with computer systems have persisted (Turkle, 2007). But the criteria for authenticity varies greatly according to different research disciplines (e.g., management studies, philosophy, psychology, etc.). As a result, the frameworks and definitions are unique to the field in which they are applied, such as consumer product research (Beverland & Farrelly, 2009) or tourism (E. Cohen, 1988). But what constitutes authenticity and an authentic interaction? Generally, the concept of authenticity tries to describe objects or events through the lens of truth and genuinity (Newman & Dhar, 2014). Marketing researchers Pine and Gilmore (2008) fittingly quoted William Shakespeare's work Hamlet and concluded that to be authentic, one has to "be true to your own self. [and] be who you say to others." (p.20). Indeed, brand authenticity has been identified as an important strategy to promote consumer engagement, positively influencing purchase intentions and emotional brand attachment (Morhart et al., 2015; Pittman & Sheehan, 2021). In a mixed-method study on the development of relationships with social chatbots, Pentina et al. (2023) applied AI authenticity as a standalone antecedent in addition to anthropomorphism. In the current study, I want to expand the findings, investigating whether perceived AI authenticity is a useful construct to examine human-chatbot interactions and subsequent relationship development with chatbots like the ones provided on character.ai.

One of the first things that came to mind when exploring agent authenticity are ethical and moral concerns as well as technical boundaries. Considering the fact that people already interact with computers or chatbots on a regular basis, it seems evident that the investigation of authentic communication and clear expectations pose as important aspects, given the rapid advancement of such technologies in our daily lives (Turkle, 2007). To highlight this, Turkle (2007) states that the first generation of children growing up with technology regarded their computer(s) as their "nearest neighbors" (p.501). She points to an authenticity crisis in the context of digital entities within games or devices, labelling them as "relational artefacts" (p.501). As Turkle (2007) specifies, relational artefacts are "computational object[s] explicitly designed to engage a user in a relationship" and are "[. . .] specifically designed to make people feel understood [. . .]" (p.502-503). She points to reflection about whether artificial entities deserve companionship and care like living beings. Furthermore, as socially adept technology develops further and further, it reaches the point where it starts to challenge fundamental ideas about consciousness and existence (Turkle, 2005). As though it seems evident that reaching authenticity is something robots (or relational artefacts like chatbots for that matter) can strive for, they will not achieve it while being sentient (Kahn et al., 2007). In other words, these machines can never feel empathy towards their users as humans do; they can only simulate it. Therefore, authentic behaviour has to be mimed through design cues and learnt behaviour of the agent, and is therefore (as of now) inherently inauthentic.

In software development, Turkle (2007) pointed out that engineers lack efforts in developing technology while considering authenticity as a concept. Past research on social agents has considered some building blocks of the broader concept of authenticity, such as the already discussed block anthropomorphism, as well as argumentation abilities, decision making, or conversational and social awareness (Turkle, 2007). Neururer et al. (2018) suggests that a comprehensive framework for agent authenticity, similar to human authenticity, has not set been established. They argue that the frameworks developed by Beverland and Farrelly (2009), which propose the positive impact brand authenticity has on consumers, are deemed a social concept. This suggests that the frameworks of authenticity are currently designed with respect to real human beings, not artificial, asocial entities. Should technology advance and social computing of that scale be possible in the future, they argue that "we should then be able to develop agents that are eventually capable of acting (agent) socially, rather than trying to imitate humans" (p.5), which brings me back to the proposed authenticity crisis by (Turkle, 2005, 2007). In an effort to define what agent authenticity entails, they conducted expert interviews and a subsequent online survey (N=12, N=40) and found five emerging themes: transparent purpose, ability to learn from experience, anthropomorphise, being conversational and coherent. Similarly, Wünderlich and Paluch (2017) concluded that “Users' authenticity perceptions refer to service agent's human nature" (p.6). They state that authenticity perception influences user acceptance of AI-based service agents, such as agent-related cues (e.g., visual cues, identity cues, audio cues) and communication-related cues (e.g., empty phrases, colloquial language, emotions, attentiveness, personalization). When communication-related cues are not delivered satisfactorily, users interpret this as inauthentic, as they wish for a "[...] smooth and natural interaction" (p.8). Pentina et al. (2023) approach differentiated anthropomorphism and authenticity insofar that anthropomorphism relates to human-likeness and authenticity to the agency, autonomy, and uniqueness of the chatbot. Their results about chatbot Replika revealed that users expect a learning curve from their chatbots, losing motivation to use the companion if interactions and answers are static and unfitting or seem to be written by human operators. Their findings indicate that the conversational memory of chatbots contributes to a sense of authenticity. Users may be disappointed or discontinue using the chatbot if it does not respond appropriately or does not 'remember' their input (Pentina et al., 2023). Likewise, Skjuve et al. (2021) investigated the role of mutual self-disclosure (e.g., sharing of personal information) between users and Replika. In some user cases, Replika achieved seemingly reciprocal self-disclosure, which instilled a feeling of reward in users and helped strengthen attachment. In contrast, other participants did not experience this behaviour of Replika. This in turn led to feelings of disappointment and made Replika seem less authentic.

Considering all the scholarly work, I want to adopt a broad understanding of authenticity (e.g., being perceived as truthful and genuine), which can serve valuable insights in the investigation of chatbot and user interactions, as there is still a lack of theoretical framework. Considerations such as coherent conversational behaviour and perceived agent autonomy and uniqueness reveal themselves as crucial parts of infusing the chatbot with authenticity. Authentic character.ai chatbots, therefore, should be able to learn from users via their AI software, appear as autonomous and unique, exhibit behaviour aligned with users' input and/or thematic constraints derived from their fictional basis, and thus improve user interaction. Based on these considerations, I formulate the second hypothesis:

> H2: Heightened perceived authenticity positively influences (parasocial) interaction with character.ai chatbots.

2.2 Uses and Gratification Theory

To address contradictory findings and a research gap regarding the role of situational and personal factors in Human-chatbot-Relationship development (Croes & Antheunis, 2021; Pentina et al., 2023; Skjuve et al., 2021), I want to apply Uses and Gratifications (U&G) theory. Initially associated with the work of Blumler and Katz (1974), U&G explores how recipients engage with media to satisfy social or psychological needs, such as cognitive, affective, social, and integrative-habitual needs (Bonfadelli, 2017). Since its emergence, scholars have identified a multitude of gratifications, evolving in specificity depending on the medium. Although older media gratifications such as information seeking remain stable across different types of media, newer media tend to have more nuanced gratifications (Sundar & Limperos, 2013).

In the past, the U&G Theory has been used to investigate conventional media, such as television (Palmgreen et al., 1980). With the emergence of the Internet and its plethora of tools, websites, and applications, the U&G theory has been expanded (Stafford et al., 2004, e.g.). Examples of application include social media platforms like Facebook (Papacharissi & Rubin, 2000), instant messaging tools (Gan & Li, 2018), mobile SNS use (Ha et al., 2015) or AI-powered learning applications (Chang et al., 2022). Regarding AI assistants, Pitardi and Marriott (2021) investigated how gratifications such as utilitarian, technology, hedonic, and social affect users' trust in the voice-assistant Alexa. Similarly to the gratifications employed by Gan and Li (2018) for SNS, Cheng and Jiang (2020a, 2020b) examined the impact AI-based chatbots could have in solving mental health problems (e.g., disaster context of mass shootings), establishing that gratifications potentially have a positive impact on user interactions and positively impact user satisfaction. They used four gratifications: utilitarian, technology, hedonic, and social. Likewise, C. Xie et al. (2024) meta-analysis of chatbot studies that employed the U&G Theory to investigate users satisfaction identified four similar dimensions of user gratifications, particularly (1) utilitarian (e.g. perceived usefulness, informational reasons), (2) technology (e.g. medium appeal, convenience), (3) hedonic (e.g. entertainment, amusement), (4) social (e.g. social interaction, social presence, friendliness) with utilitarian gratifications exerting the biggest factor influence on user satisfaction.

Since the chatbot field is relatively new, some studies used qualitative methods to generate motivational themes. For instance, Brandtzæg and

Følstad (2017) identified that a majority of chatbot users reported their primary motivation of use to be for fast completion of productivity tasks. Hence, participants typically reported using chatbots to obtain assistance or information. Conversely, some users also reported entertainment or social and relational factors as their main motivations. For instance, participants reported to enjoy spending their free time using chatbots as a form of (hedonic) entertainment. Lastly, some of the participants (10% of N=146) mentioned that the chatbot helped them in alleviating loneliness or the desire to socially interact. Likewise, Skjuve et al., 2021 investigated what role motivation plays on initiating and maintaining a relationship with Replika. By conducting qualitative interviews (N=18), they identified curiosity based motivations as well as social motivations to fulfill the need for emotional and social stimulation through the chatbot. In a mixed methods approach, Pentina et al. (2023) delved into the possibility of moderating effects of gratifications on subsequent chatbot attachment, retrieving motivational themes through open end questions. These qualitative themes fit into the UG theorem (e.g. utilitarian, hedonic, social). Their findings suggest that users who engage with the chatbot Replika to satisfy social needs consequently formed stronger emotional attachment as opposed to users who were motivated by hedonic or curiosity-based gratifications. However, they reported that high levels of chatbot interaction diminished these effects for all groups. In the following subchapters, I want to briefly frame the four gratifications I will measure in the current study, considering the just presented research.

2.2.1 Utilitarian Gratification

Utilitarian gratification points to the fulfillment of information seeking or self-educational behaviors, similar to the cognitive needs defined by Bonfadelli (2017).Papacharissi and Rubin (2000) coined the name when they defined motivational themes about the use of the internet. Previous work found that utilitarian gratification is able to motivate users to watch television (Palmgreen et al., 1980), continually use social media (Gan & Li, 2018, e.g. WeChat) or sport team mobile applications (Hwang et al., 2020). Regarding AI chatbots, Ashfaq et al. (2021) investigated besides perceived coolness how values impact attitudes towards smart-speakers. They found that values like 'function', which reveals itself to be akin to utilitarian gratifications, could have the potential to motivate users to continuously use their smart-speaker (N=307) Nguyen et al. (2021) found in their quantitative survey (N=359) that the quality of information that banks' chatbots provide positively impacts users' trust and satisfaction, subsequently having a significant effect on continuance of use of the chatbot. In the meta-study mentioned above of C. Xie et al. (2024), they found a strong correlation between utilitarian gratification and user satisfaction. In this study, I interpret information seeking as the satisfaction users gain from using their character.ai chatbot to obtain information. I hypothesize that this positively influences their intention to engage with the chatbot.

2.2.2 Technology Gratification

Technology gratifications sought can be measured through medium appeal, which basically refers to the ease of use and quickness of responses users seek while communicating with other users (Gan & Li, 2018). Regarding AI-chatbots, Pitardi and Marriott (2021) found that technology gratifications showed a strong positive correlation with user satisfaction. These technology gratifications were measured through perceived usefulness and perceived ease of use, with the latter being similar to media appeal. For this study, media appeal refers to the perceived ease of use of chatbots as well as their ability to instantaneously respond to user inquiries.

2.2.3 Hedonic Gratification

Hedonic gratifications point to seeking or obtaining pleasure through the use of online communication technologies like, for instance, social media (Gan & Li, 2018). WhenStafford et al. (2004) developed items describing hedonic gratifications regarding the use of the Internet, they considered entertainment (e.g., having fun, relaxing) and passing time (e.g., alleviating boredom). This gratification specifically touches upon the purpose for which chatbots have been developed originally. Conversational agents like Weizenbaums ELIZA have been developed simply for entertainment purposes. Adding to that, Brandtzæg and Følstad (2017) noted that some chatbot users interact with agents to have fun or pass their free time. Therefore, I understand hedonic gratification as a way to seek entertainment through interacting with the character.ai chatbot.

2.2.4 Social Gratification

Stafford et al. (2004) noted, that considering social gratifications when examining media such as the Internet is crucial, as it serves as a interactive medium for interpersonal communication and social interaction, highlighting computer mediated communication (CMC) behaviour such as chatting as key components of social gratification in the context of internet usage. According to I. L. Liu et al. (2016) social interactions are characterized by behaviours such as friendship maintenance or finding new contacts. In regards to chatbots, researchers noted that users who interact with social chatbots, which have been developed to hold chitchat conversations, could do so to fulfill their need for social interaction (Brandtzæg & Følstad, 2017; Shum et al., 2018; Zhou et al., 2020). Furthermore, Araujo (2018) suggest that chatbot users who seek social interaction are drawn to chatbots that evoke a sense of social presence, defined as the feeling that another intelligent entity is engaging with them (Nass & Moon, 2000; Reeves & Nass, 1996). This means that in order for the chatbot to be utilized as a potential substitute for human interaction, it has come across as capable of doing so, possibly attracting users who are motivated by their need to socially interact.

Besides, I want to examine integrative social gratifications that users seek and chatbots could provide to users. Generally, Weiser (2001) suggested that the use of the Internet promotes social integration and Turkle (1995) postulated that the internet provides a space for continually exploring and reinventing versions of ourselves. Moreover, Bargh and McKenna (2004) stated that social networks can help individuals who have difficulty building and maintaining friendships. Related research has shown that computer-mediated communication makes interpersonal communication more low-threshold and can therefore act as an alternative way to promote social interactions that would otherwise not have occurred (Bargh et al., 2002). Qualitative evidence of Brandtzæg and Følstad (2017) pointed out that some users engage with social chatbots to develop their communication skills. In the context of social chatbots, previous research on expected social support of mental health chatbots (Woebot) has indicated that these implications (e.g., low threshold and easy access) might apply in a similar way (Brandtzæg et al., 2021; Skjuve & Brandtzæg, 2018). For instance, J. Kim et al. (2018) investigated teenagers' expectations of social support chatbots should offer. The participants expressed the desire for the chatbot to act as an effective listener, to function as a private space for disclosing secrets and sensitive information, and to offer advice when necessary.

Given these points, using chatbots as an alternative outlet to share thoughts or practice communication techniques could serve as a powerful social gratification. Since communication takes place in a CMC manner and chatbots are not humans, the provided literature leads me to assume that the threshold to socially interact might be lower. Additionally, fear of negative consequences of inappropriate behaviour might not appear as detrimental for users, since the chatbot is not a real human, making it a potential place to develop communication skills. Therefore, I want to examine whether character.ai users gratify their need for social interaction with their chatbot and seek a way fulfill social integrative behaviour, as they might feel more open to share opinions or practice their communication skills with a chatbot.

To answer RQ1 and test the following hypothesis, I aim to follow a fairly liberal approach. Although there are ample findings from previous studies regarding effects of gratifications concerning task-based chatbots or related research fields, the literature about social chatbots is sparse. As this is the first study about character.ai, I refuse to hypothesize that one of the four gratifications will be more significant in relationship formation processes with character.ai chatbots than others, accounting for the fact that character.ai offers various chatbot types on the platform (e.g., fictional characters, roleplay, Roleplay Game (RPG) entities, writing companions, etc.). Following claims of Sundar and Limperos (2013), gratifications existing in older media generally share enough similarities to explore newer technologies, particularly if I should be faced with the challenge of finding appropriate measurement scales or items related chatbots. Finally, I hypothesize that:

> H3: Utilitarian (information seeking) (H3a), hedonic (entertainment, pass time) (H3b), technological (media appeal) (H3c), and social (social interaction, social integration, interpersonal utility) (H3d) gratifications sought positively influence (parasocial) interaction with character.ai chatbots.

2.3 Attachment Theory

To investigate relationship development with character.ai chatbots, attachment theory offers a potentially promising framework to measure relationship formation which might develop over the course of frequent interactions with the character.ai chatbot. Attachment theory, as explained by Bowlby (1974), originally focused on infant-parent relationships, where infants seek proximity to their primary caretaker for security and protection (Rajecki et al., 1978).

Firstly, the primary caretaker provides the infant with a secure base (e.g. enabling exploration), a safe haven (e.g. comforting) and motivates proximity behaviours (e.g. staying close) (T. Xie & Pentina, 2022). Secondly, the theory suggests that the amount of interaction plays a crucial role in the bonding process to attachment figures (Stayton & Ainsworth, 1973). Third, as individuals mature, they expand their support network to include friends and romantic partners (Mikulincer, 2016). In adults, a common attachment figure is a romantic partner, which combines behaviours of care giving, care receiving, and sexual mating (Feeney, 1996). Fourth, Feeney (1996) states that people are able to maintain multiple attachment relationships. Finally, people who are strongly attached to a person are committed to maintaining the relationship (Johnson & Rusbult, 1989)

Attachment theory has been expanded to multiple research fields. For example, its framework has been applied to understand non-human attachment relationships, such as human-animal attachment (Beck & Madresh, 2008). Furthermore, humans are able to successfully form attachment not only to animals, but also to objects, even more so when close individuals are unavailable (Keefer et al., 2012; Winnicott, 1953). People can form emotional attachment to places (Daniel R. Williams & Watson, 1992), celebrities (Thomson, 2006), game characters (Bopp et al., 2019), or cellphones (Konok et al., 2016). In marketing research, attachment theory has been utilized to asses emotional attachment to brands, which is said to enhance customer loyalty and the propensity to pay higher prices for consumer objects (Thomson et al., 2005). Thomson et al. (2005) applied Bowlby's propositions and defined emotional attachment to brands as "[...] an emotion-laden target-specific bond between a person and a specific object" (p.88). Intense emotional attachment to objects is characterized by the desire to stay close to those objects and potentially experiencing distress when separated from them. Moreover, the object of attachment serves as a means of physical or psychological defence against the stress experienced by individuals (Thomson et al., 2005).

2.3.1 A new framework for Human-Technology Interaction?

The theory is considered as a new approach in computer and robot interaction research and efforts have been made to develop a useful framework with attachment theory in long-term HRI (Rabb et al., 2022). For example, it has been applied to study robot attachment in therapeutic settings (Szondy & Fazekas, 2024) or the impact of attachment styles on long-term robot cohabitation, finding that user satisfaction and evaluation of robot functionality are influenced by the attachment style of the user (Dziergwa et al., 2018). Other pioneering work in the HCI field, building on the CASA paradigm, has been done by Bickmore et al. (2005) and Bickmore and Picard (2005). They found in their experimental work on relationship formation with embodied conversational agents in long-term health interventions that relational language (e.g., empathy, social dialogue) positively influences the intention for continued use of the agent. This, in turn, has been shown to be positively related to the formation of an attachment bond and the formation of relationships (Bickmore & Picard, 2005; Bickmore et al., 2005). Similarly, regarding long-term Human-chatbot interactions, Christoforakos et al. (2021)

observed that regular use of disembodied chatbots was positively correlated with social connectedness (e.g., a concept comparable to interpersonal interactions), with anthropomorphic cues and social presence acting as mediators. The findings discussed above affirm the basics of attachment theory, which suggest that increased interactions enhance the bond with a person or an object (Stayton & Ainsworth, 1973) and the potential to develop attachment to chatbots.

Pentina et al. (2023), T. Xie and Pentina (2022), and T. Xie et al. (2023) were the first researchers applying attachment theory in the context of social chatbot relationship development. T. Xie and Pentina (2022) concluded that in crisis situations such as in the COVID-19 pandemic, social chatbots such as Replika have the ability to act as a substitute for the lack of human interaction and emotional connection. Their findings support the proposition that users can become attached to chatbots under these conditions. Users who interact freqently with Replika have attachment-like relationships with the chatbot, describing it as a source of companionship, support, and security. Furthermore, some users reported feeling distressed if they had to abandon the relationship with Replika, underlining proximity behaviour. Lastly, T. Xie and Pentina (2022) state that their observations resonate with the concept of attachment, where individuals seek closeness and security from a trusted source. Later, they suggested in a follow-up study that the more attached users feel to a social chatbot, the more significant their interactions and engagement with it become for building a relationship. In other words, attachment intensifies the positive role of engagement in the development of subsequent relationships (T. Xie et al., 2023). In line with these findings, a thematic content analysis of reviews (N=1854) and subsequent survey of users (N=66) investigating Replika as a source of everyday social support identified four overarching themes of support. In particular, companionship, emotional, informational and appraisal support (Ta et al., 2020). Ta et al. (2020) argue that Replika can provide companionship, alleviate loneliness, and act as a alternative source of advice to users. These findings would tie in with the attachment theory paradigm, as chatbots could potentially take the space of a caregiving person, similar to a friend or close companion. However, a noteable limitation of this study was that Ta et al. (2020) examined reviews, rather than actual user experience.

In a longitudinal approach using Social Penetration Theory (e.g., formation of relationships driven by mutual self-disclosure) (N = 27) about the results of the formation of relationships with Replika, Skjuve et al. (2022) highlight that personal variations, such as the self-disclosing behaviour of users, play an important role in the formation of human-chatbot relationships. Their findings also indicate that the ability of the chatbot to engage in diverse interactions, enable social interaction, and self-exploration is crucial for the progression toward attachment and perceived intimacy with the chatbot. Problems or technical issues while interacting can disrupt the development of the relationship and lead to termination. Again, these implications underscore the importance of antecedents such as authentic and anthropomorphic chatbot behaviour toward long-term interaction and subsequent attachment to it. Interestingly, relationship formation and companionship do not always automatically develop with social chatbots, as the just presented studies would suggest. Croes and Antheunis (2021) findings indicate that university student participants initial positive feelings decreased over the interaction period of three weeks for chatbot Replika. They found that a novelty effect influenced initial frequent interactions with the chatbot but faded over time (Croes & Antheunis, 2021). Croes and Antheunis (2021) argue that the limited levels of relationship formation could be attributed to the study design, where participants did not interact with the chatbot voluntarily. Their results emphasize the importance of personal or situational factors in relationship development, as discussed previously in Chapter 2.2.

To investigate consequences of adoption antecedents (e.g., anthropomorphism, authenticity, gratifications sought) and interaction (e.g., parasocial interaction), I too render attachment theory as a useful framework to examine human-chatbot relationship formation. This also insofar in an effort to expand findings, as there are limited studies investigating human-chatbot relationships with social chatbots in general (Croes & Antheunis, 2021; Pentina et al., 2023; Skjuve et al., 2021; T. Xie et al., 2023). To conclude, the just-discussed insights lead me to hypothesize that character.ai chatbots may be utilized as substitutes for human interpersonal relationships and higher amounts of parasocial interaction might aid in facilitating stronger attachment to the chatbot. Therefore, I propose that higher levels of PSI will positively influence the outcome variable attachment, leading to the fourth hypothesis:

H4: Users who report higher levels of parasocial interaction with the chatbot will also exhibit stronger attachment to the chatbot.

2.4 Parasocial Relationship Theory

In addition to the ability of humans to form attachments to various people and objects, my aim is to explore their ability to engage in one-sided relationships and interactions with nonhumans, objects, or technology (Nass & Moon, 2000). To illustrate an example of how parasocial relationships can look like, one could consider RealDoll owners. RealDoll owners, which Cassidy (2016) discussed, are typically adult males who form committed relationships with life-sized silicone dolls, sometimes even marrying them. Despite the dolls' anthropomorphic appearance, with features such as hair, eyes, lips, soft silicone flesh, and clothing, they do lack the ability to respond, provide comfort, engage in daily conversations, or reciprocate affection. A contrast noted by Brandtzæg et al. (2022) is that social chatbots are disembodied; however, they possess conversational capabilities that RealDolls never could, suggesting that relationships might feel even more genuine than those with nonhuman, inanimate objects. Certainly, social chatbots could be regarded as powerful "relational artefacts" (Turkle, 2005). They do enable more lively interactions with fictional characters or originally created characters, which would have not been possible even just a few years ago. However, their social behaviour and those interactions exchanged yet retain illusory qualities. At its core, no chatbot has yet achieved genuine authenticity in the seemingly reciprocal exchange with the user. These implications place them in a somewhat peculiar position, calling for further theoretical and empirical investigation, particularly since research is sparse regarding PRT and chatbots.

Parasocial relationships, introduced by Horton and Richard Wohl (1956) describe the one-sided emotional connections that individuals form with media personalities or fictional characters. These relationships are characterized by their asymmetry, as the persona remains unaware of the bond formed by the audience. Although these relationships lack genuine reciprocity, it is hypothesized that they can meet the basic needs of users for social connection (Giles, 2002). As Horton and Richard Wohl (1956) state: "The persona may be considered by his audience as a friend, counsellor, comforter, and model; but unlike real associates, he has the peculiar virtue of being standardized according to the 'formula' for his character [...] [or] production format" (p. 217). Social chatbots are similarly constrained by their scripted character and technological limitations, which invoke these one-sided interactions. Parasocial interaction (PSI), a component of parasocial relationships, typically involves unilateral and mediated social interactions with media personas (e.g., TV, Radio, Internet, Games, etc.). Although these interactions mimic the back and forth of genuine social dynamics, they are ultimately considered illusory and lack reciprocity according to Horton and Richard Wohl (1956).

However, Auter and Palmgreen (2000) suggested that parasocial interactions are as multifaceted as genuine social interactions. Through the development of a multidimensional item scale, they identified a positive correlation between television viewing habits, dependency about watching television, the perception of television as reality, and parasocial interaction. Furthermore, they suggest that frequent parasocial interaction can lead to stronger and enduring relationships with media characters (Auter & Palmgreen, 2000). Media research has shown that PSI and parasocial relationships have the potential to influence attitudes of media consumers or users, such as enhancing involvement with messages conveyed by personas. Evidence suggests that PSI and parasocial relationships have positive and negative effects on user well-being and media consumption habits (Liebers & Schramm, 2019). Given these points, this study aims to explore the mediating role of parasocial interaction in social chatbot interactions and its impact on users' attachment.

PRT has gained particular popularity in communication science and mass media studies (Giles, 2002) and has evolved to include various media. It has been used not only in classic media research (Auter & Palmgreen, 2000; Pitout, 1998; Rubin & Perse, 1987, e.g., television) but also in psychological research models, reflecting its relevance in understanding modern communication dynamics (Giles, 2002) such as computer-mediated communication (CMC) (Papacharissi & Rubin, 2000). Giles (2002) pointed out that the implications of PRT are tied in with CASA propositions of Reeves and Nass (1996); mindless behaviours are triggered by social cues in mediated communication, be it by a face on a TV screen, through CMC or, possibly in the current case, by interacting with social chatbots. Liebers and Schramm (2019) state that with the rise of social networks such as Facebook and Twitter, PRT has gained traction in the study of online interactions, such as those with bloggers (Rasmussen, 2018, e.g.). It is applied to investigate consumer-brand relationships in social network environments, underscoring its role as a marketing strategy (Labrecque, 2014). This shows its relevance in the analysis of contemporary forms of social interaction.

With respect to the current study, I want to present previous relevant research efforts. A large chunk of scholars applying PRT and/or PSI in regards to chatbots are within the marketing research field. The findings of M. Lee and Park (2022) suggest (N=184) that the development of parasocial relationships with AI shopping chatbots has a positive impact on the quality of communication with the agent, subsequently increasing continued usage intentions and user satisfaction in middle-aged women. Regarding Millenials and Gen Z (N=348), a survey confirmed the positive effects of parasocial interaction on continued chatbot usage (Ramya & Alur, 2024). Previously, Tsai et al. (2021) found in an experiment (N=155) that socially present chatbots, these being chatbots that evoke the feeling of interacting with an intelligent entity, tend to cultivate stronger parasocial interactions. These parasocial interactions, in turn, exhibit mediating effects on consumer engagement and the perception of brand personality (Tsai et al., 2021). Interestingly, their findings indicated that visual anthropomorphic cues alone had no significant impact on user outcomes such as engagement, interaction satisfaction, or brand likeability. In line with this, Youn and Jin (2021) concluded through an online experiment (N=602) that displayed chatbot relationship types influence outcomes in customer relationship management (e.g., customer satisfaction, trust). Users who interacted with a friendly chatbot (compared to a task-oriented one) experienced stronger parasocial interactions, which then influenced brand personality perception. In addition, attraction enhancing antecedents of parasocial interaction can be positively influenced by anthropomorphic AI chatbots, thereby triggering parasocial interaction (Noor et al., 2022). Parasocial interaction affects positive outcomes, such as willingness to use technology, engagement, and satisfaction (S. Han & Yang, 2018; Jang, 2020). Pentina et al. (2023) examined the mediating role of AI social interaction, a construct and scale that they developed considering qualitative findings regarding chatbot Replika, parasocial interaction, and social presence. Their findings indicate that the intensity of AI interaction mediates the relationship of antecedents, such as chatbot anthropomorphism and chatbot authenticity and subsequent chatbot attachment. However, they grounded theoretical assumptions of relationship building processes in Social Penetration Theory, rather than PRT like the current study.

Using PSI, social presence, and PRT to understand the mechanisms of how Human-chatbot relationships might develop appears appropriate for the current research topic, as there is no theoretical framework regarding Human-chatbot interactions and relationships developed yet. Furthermore, since character.ai chatbots are usually derived from media-related characters, the persona element of PRT appears to be fitting, placing character.ai chatbots in a kind of gray area compared to other social companion chatbots such as Replika. Character.ai chatbots have the ability to respond and act like a companion like any other social chatbot, yet they are usually bound to a media persona they portray. In addition, the lack of sentience and the capacity of chatbots to reciprocate *genuine* emotional connections appear to also fit the PRT framework (Kahn et al., 2007; Turkle, 2005, 2007). Lastly, virtually exchanged interactions through conversation (e.g. waving, laughing, hugging) do not physically occur (Pentina et al., 2023), which is in line with the illusory qualities of PSI in the PRT paradigm. Taking into account all of the above, I propose the following hypothesis: The relationship between perceived anthropomorphism, perceived authenticity, gratifications sought, and user attachment is positively mediated by chatbot parasocial interaction.

> H5: Parasocial Interaction mediates the relationship between anthropomorphism (H5a), authenticity (H5b), the gratifications (H5c-H5f) and chatbot attachment.

2.4.1 Hypotheses

> H1: Heightened perceived anthropomorphism positively influences (parasocial) interaction with character.ai chatbots.

> H2: Heightened perceived authenticity positively influences (parasocial) interaction with character.ai chatbots.

> H3: Utilitarian (information seeking) (H3a), hedonic (entertainment, pass time) (H3b), technological (media appeal) (H3c), and social (social interaction, social integration, interpersonal utility) (H3d) gratifications sought positively influence (parasocial) interaction with character.ai chatbots.

> H4: Users who report higher levels of (parasocial) interaction with the chatbot will also exhibit stronger attachment to the chatbot.

> H5: Parasocial Interaction mediates the relationship between anthropomorphism (H5a), authenticity (H5b), utilitarian gratifications (H5c),

hedonic gratifications (H5d), technology (H5e), social gratifications (H5f) and chatbot attachment.

3 Open Science

The term 'Open Science' was brought to my attention by my supervisor Ass.-Prof. Dr. Tobias Dienlin. The conceptual framework of 'Open Science' underscored concerns I personally harbored about the state of research in the social sciences, even more so underscored through discussions with peers from disciplines of the natural sciences. Dienlin et al. (2021) not only identified my concerns but also offered solutions, guiding (aspiring) scientists in the production of scholarly materials to adhere to principles such as the pursuit of truth regardless of outcome, transparency, and openness. Therefore, offering a great amount of inspiration for this thesis and possible future research endeavours. Dienlin et al. (2021) points to a crisis within disciplines such as psychology: Unreliable findings, which are hard to replicate and generalise. This is very concerning, since scientific results gain their robustness by being able to be reliably replicated. Furthermore, as Dienlin et al. (2021) points out and being notably felt in the middle of the COVID 19 pandemic (Parikh, 2021), public trust in science is fragile and therefore must be handled with utmost care. We, as aspiring scientists, have the responsibility of caring for the 'scientific corpus' within, upon which the external audience, particularly the public, can confidently place their trust in both the scientific community and the results of research efforts. Openly sharing knowledge is therefore underscored as paramount. This fosters much more meaningful progress in research activities, enabling researchers to learn from past mistakes or build on one another's contributions. Ultimately, this guarantees that we advance together as an integrated community, especially when working on interdisciplinary research topics such as the current study. Building on these observations and ideals, Open Science can bring solutions to these issues as Dienlin et al. (2021) offers various ideas and methods to be implemented into research (p.2):

Open Science Implementations (Dienlin et al. 2021)
1. Publish materials, data and code.
2. Preregister studies and submit registered reports.
3. Conduct replications.
4. Collaborate.
5. Foster open science skills.
6. Implement Transparency and Openness Promotion Guidelines.
7. Incentivize open science practices.

Table 1: Open Science Implementation

In efforts to accommodate these demands, the thesis and supplementary material aim to be fully accessible to any scientist, student, or interested person. All data sourced from the questionnaire are accessible to be used for future work on Open Science Framework (OSF) (https://osf.io/73ftw/?view_only=). The thesis files will be uploaded to the thesis repository. In addition, this thesis used R Studio, a free statistical software. There is a .Rproj folder for the thesis that contains all the R scripts and data files. I also created a GitHub. The variables in the code are named informatively, so that anyone wanting to work with the R codes can understand what is meant (e.g., anthro and not x1).

Furthermore, collected data shall not be arbitrarily manipulated, and any changes in the study design are made transparent and documented accordingly.

The thesis is pre-registered on OSF, albeit containing some beginner errors. However, I am confident that the crucial aspects of pre-registration have been completed: the hypotheses are fixed. This action aids in preventing any questionable research practices (QRP) like HARKing (e.g. presenting experimental studies as confirmatory studies, changing hypotheses through new gained knowledge by collected data and not disclosing) or p-hacking [e.g., removing variables arbitrarily to (re)gain significant results] by freezing the study design, hypotheses and variables (Dienlin et al., 2021). If anything new shall be found while conducting the study I will document it distinctively as exploratory information. As for the issue of low powered studies, two a-priori Power analyses have been ran, which will be presented in the following chapter.

4 Method

4.1 Procedure

Posing as the third most used research method in the chatbot field, a quantitative survey was conducted to gather data enabling the measurement of the proposed constructs and their effects (Rapp et al., 2021). To generate data I employed convenience sampling, including individuals who are active users of character.ai and are aged 14 years or older. These individuals have been invited to participate in the survey. The studies participants did not receive any incentives for participation and must agree to a Data Protection Statement concerning their personal data rights prior. To distribute the survey, the platform SociSurvey (https://www.soscisurvey.de/) was utilized.

In the studies proposal, I planned to share the survey link in the official character.ai subreddit (https://www.reddit.com/r/CharacterAI/), which currently has 1 million members, ranking it in the top 1% in size on Reddit. Moderators of the subreddit have been contacted on various platforms about the research project, but I was denied access to post the survey link. Hence, the survey link has been posted in various subreddits related to AI, chatbots or survey sharing as well as on my personal X account. Additionally, to enhance participant recruitment, six influencers (ranging from approximately 69.000 to 3.500 followers) have been contacted regarding the research project and were successfully recruited to share the survey link via their Instagram-story. Their profile names are listed in the Acknowledgments section of this thesis. The developed questionnaire was pretested to ensure that the questions and flow of the questionnaire are understandable and satisfactory.

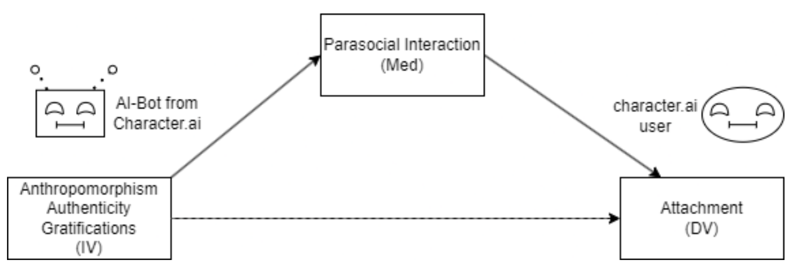

Figure 3: Adapted theoretical Model inspired by Pentina et al. 2023.

To test the hypotheses, a comprehensive mediation path model, similar to Hayes PROCESS Model 4 (Hayes, 2017), drawing inspiration from Pentina et al. (2023)'s three-study mixed methods model about Replika, was used. All of the analysis has been performed with R Studio Version 2023.12.1 Build 402. The proposed model was tested for model fit with the package lavaan

(Rosseel, 2012). Afterwards, the paths were examined to investigate the stated hypotheses. Furthermore, the study collected novel demographic data on character.ai users, including age, gender, education, current residence, usage time, and chatbot type. These were used to generate descriptive statistics for the sample. Data can serve as a foundation for subsequent investigations using the model, facilitating the examination of potential differences in effects and outcomes between different groups within the sample.

4.2 Sample Size, Power Analysis

Rapp et al. (2021) emphasise the presence of significant limitations concerning sample size within quantitative chatbot research, since only a small fraction of studies performed power analyses. To address this limitation, two a-priori power analyses have been performed to determine the required sample size for a desired power of 0.95. As for parameter estimates, I expect small to medium-size effects (J. Cohen, 1992), which would correspond to effect sizes found in other chatbot studies (Beattie et al., 2020; Chattaraman et al., 2019; S. Lee et al., 2020; Pentina et al., 2023, e.g.). All analyses were run in R Studio.

The first analysis was performed with the PWR package (Champley, 2020). The path a was tested with an estimated medium effect size (r=.4, p=.05, Power=.95), which resulted in n = 75 participants needed. The path b was estimated with a small effect size (r =.18, p =.05, Power =.95), which resulted in 395 participants reaching the desired power. After this initial bivariate analysis, I performed a Monte Carlo power analysis with 5000 replications (Muthén & Muthén, 2002) for a simple mediation model, estimating the paths as a = 0.4, b = 0.4, c = 0.1 as well as the indirect effect (a*b) and total effect (a*b+c). I did this with a syntax that I modified by Donnelly et al. (2023), which was developed for group wise analysis. Through an iterative process, I adjusted the sample size (N) of the dummy dataframe until achieving an approximate power of 0.95 for the a (Power = 1.00) and b (Power = 0.95) paths, as well as for the indirect effect (a*b, Power = 0.94) and the total effect (a*b+c', Power = 1.00) with N = 126. However, the estimated c' path only achieved a power of 0.39 for detecting very small effects. As suggested by Kenny and Judd (2014), there are usually large power discrepancies between the indirect effect (a*b) and the c' path in mediation models. Because of this, Hayes and Scharkow (2013) suggest to refrain from making assumptions about full or partial mediation or be very cautious, given this power discrepancy. Considering this, I also calculated the power for the c' path. Therefore, to also detect small effects with a power of 0.95 in the c' path, a sample of 600 would be needed. The sample size achieved was N = 440. Of N = 440, 257 cases reached the end of the survey. 164 cases completed the survey without missing values. This sample was used to perform descriptive statistics of the sample.

4.2.1 Participant Characteristics

In the following, I outline the sociodemographic characteristics of the complete case sample. Please note that the table displayed here only showcases the predominant residency categories due to spacing limitations. For a comprehensive breakdown of residency distribution within the sample, please refer to the Appendix.

Sociodemographic characteristics	Full sample	
	n	%
Gender		
Female	119	72.56
Male	19	11.58
Other	26	15.85
Age		
14 to 17 years old	32	19.51
18 to 24 years old	86	52.43
25 to 34 years old	40	24.39
35 to 44 years old	4	2.43
45 to 54 years old	0	
55 to 64 years old	1	0.60
65 years or older	1	0.60
Current Residence		
Australia	6	3.65
Austria	10	6.09
Canada	8	4.87
France	7	4.26
Germany	7	4.26
United Kingdom	9	5.48
United States	51	31.09
Education		
No formal education	2	1.21

Table 2 continued from previous page

Primary education (e.g., elementary or primary school)	6	3.65
Secondary education (e.g., high school, secondary school)	66	40.24
Vocational/technical training	13	7.92
Associate degree (e.g., two-year degree)	20	12.19
Bachelor's degree (e.g., four-year degree)	41	25.00
Master's degree (e.g., postgraduate degree)	11	6.70
Doctorate/Ph.D. degree (e.g., highest academic degree)	4	2.43
Other	1	0.60

Note. Full Sample N = 164.

Table 2: Sociodemographic Characteristics of Participants

Regarding the time spent using character.ai, 36.0% of the sample (n=56) used character.ai only occasionally, 34.14% a few times a week (n=38), 23.17% on most days (n=30), 7.31% everyday (n=12) and 28 participants used character.ai several times a day (17.07%). In the data set without missing entries, the median daily usage time of character.ai by the participants was 60 minutes. The following figure shows the residencies of the participants on a worldmap. The interested reader can find Figure 4 in a larger resolution on the thesis repository.

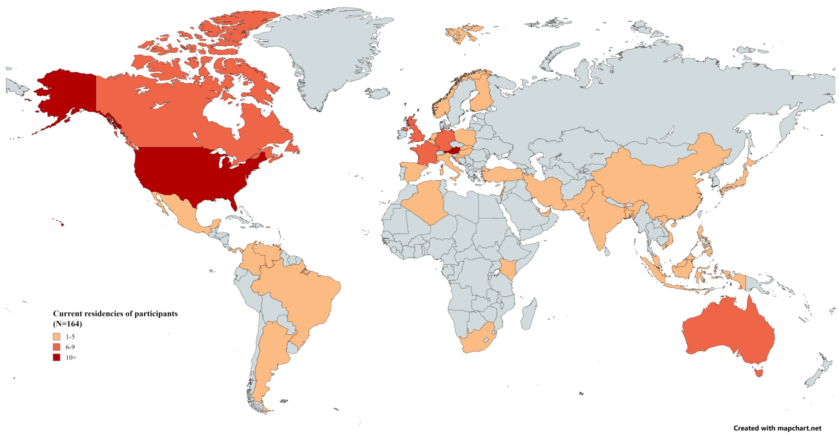

Figure 4: Current residencies of participants. Note. N = 164. Color-grading indicates frequency. World map created using MapChart (2024)

4.3 Measures

Given the absence of universally applicable scales for the various measured constructs, I will present various items derived from previous research that seem appropriate for the measurement of latent constructs. For easier data analysis, 7-point Likert scales were used for all items. A list of all the adapted items is available in the Appendix.

4.3.1 Anthropomorphism

To test the factor anthropomorphism, the human-likeness item scale of Bartneck et al. (2009) will be used. The scale was employed in the HRI field and originally consisted of five five-point Likert scaled items: Fake/Natural, Machinelike/Humanlike, Unconscious/Conscious, Artificial/Lifelike, and Moving rigidly/Moving elegantly. The last item will be omitted since character.ai chatbots are not embodied ($\alpha = 0.82$)

4.3.2 Authenticity

To test the factor authenticity, the AI authenticity scale developed by Pentina et al. (2023), which is a conglomerate of seven Items used in brand and celebrity authenticity studies (Moulard et al., 2015; Sodergren, 2021) and qualitative findings regarding perceived authenticity in the chatbot Replika, will be used (e.g., The same as other users' character.ai Chatbots/Tuned to my preferences) ($\alpha = 0.83$).

4.3.3 Gratifications

To measure the U&G gratifications corresponding to C. Xie et al. (2024), adaptations of existing scales and items have to be employed (utilitarian, hedonic, technology, social) as there is no chatbot gratification scale developed yet.

- To measure hedonic gratification, three Items 'Enjoyment' adapted from the scales previously used by Rauschnabel et al. (2017) for mobile games (e.g., Using my chatbot is exciting.) as well as three Items 'Pass Time' Items employed to measure gratifications for Internet (e.g., I use my chatbot because it passes time when bored.) use by Papacharissi and Rubin (2000), have been used: ($\alpha = 0.84$).
- To measure utilitarian gratification, three Items of 'Information Seeking' (e.g., I use my chatbot because it's an easier way to obtain information) derived from the same scale of Papacharissi and Rubin (2000), was used ($\alpha = 0.93$).
- To measure technology gratification (media appeal), I want to utilize three adapted items which were employed by Cheng and Jiang (2020b)

prior to measuring gratifications regarding customer service AI chatbots (e.g., Using chatbots like character.ai is more efficient than other forms of communication) and user experience ($\alpha = 0.80$).

- To measure social gratification, I employed two items 'Social Integrative' that were used to measure users' perceptions of an AI-powered learning application and it's social benefits (e.g., My chatbot improves my ability to communicate with others) (Chang et al., 2022), one item 'Social Interaction' (e.g., My chatbot understands me better than other people.) employed by Wu et al. (2010), which was used to measure gratifications regarding online games and lastly three adapted items 'Interpersonal Utility' (e.g., I use my Chatbot to express myself freely.) employed by Papacharissi and Rubin (2000) regarding the use of the Internet for interpersonal communication ($\alpha = 0.83$).

4.3.4 Attachment

To measure attachment, I used an adapted version of the emotional attachment measurement scale that included three items developed by Thomson et al. (2005), which was used to measure emotional attachment to brands (e.g., I feel an emotional bond to my chatbot) ($\alpha = 0.96$).

4.3.5 Chatbot Parasocial Interaction

For the measurement of chatbot PSI, five 'Connection' items from the measurement scale of Auter and Palmgreen (2000) used for TV Personae (e.g., I care about what happens to my chatbot; My chatbot is like my friends), as well as four 'Social Presence' items employed by Pitardi and Marriott

(2021), which were used to measure consumers trust in AI voice assistants (e.g., When I interact with my chatbot, I feel like if I am dealing with a real person.), have been used ($\alpha = 0.93$).

4.3.6 Usage-Time

Besides minutes spent (ratio) and a categorical measurement (e.g., occasionally, everyday), I measured the time participants spent using character.ai by employing a visual analogue scale (VAS). Participants were asked to indicate their perceived intensity of use on a scale of 1 to 100, where 1 represents the minimum time spent and 100 represents the maximum time spent. The scale aims to capture participants' subjective perceptions of their usage habits, rather than exact minutes or days per week. The aim of this measurement scale is then to categorise users into corresponding types (e.g. super-users). Some participants provided unfitting responses about the time spent (ratio). Consequently, I converted extensive textual and numerical responses into minutes, or adjusted them by determining their average (for instance, converting '60-120mins' to 90) using Excel.

4.3.7 Bot-Type

I explored the Bot-Type variable using an open-ended question, in which participants were asked to specify the particular character.ai chatbot with which they interacted and its purpose. Following this, the responses were grouped and categorised into broader types for further analysis. For qualitative analysis, given the modest sample size, I employed a combination of data viewing in Excel and manual categorisation methods. Through this iterative process, I developed five categories: 'Chitchat,' 'Roleplay,' 'Romance,' 'Creative Writing and Inspiration,' and 'Assistance and Education'.

- Within the category of 'Chitchat' (n=109), participants frequently engaged with fictional, famous, or original characters for entertainment, casual conversation. This Bot-Type was also coded when participants did not further explicate the chatbots purpose. Anchor example: "Nanami Kento, talking; Portgas D Ace, talking" (Case 56).
- The 'Roleplay' category (n=22) encompassed instances in which participants used chatbots for role-playing purposes. Anchorexample: "Gojo Satoru; Toji Zenin - chatbots based on fictional characters with the intent to roleplay" (Case 254).
- Participants who expressed using chatbots for comfort, romantic interaction, or companionship were classified under the category 'Romance' (n=16). Anchor example: "I only use one chatbot that I made myself. Her name is Bronwen, she acts as my emotional support girlfriend" (Case 95).
- The category 'Creative Writing and Inspiration' (n=7) captured instances where participants used chatbots as tools for creative writing. Anchor example: "Ryomen Sukuna, Griffith, I mostly use the chatbots for art and writing inspo whenever I get art block" (Case 128).
- The category 'Assistance and Education' (n=6) emerged when participants indicated that they use chatbots for language learning, homework or as personal assistants. Anchor example: "Practice Language" (Case 91).

I will discuss qualitative findings in the results part in more depth, as well as some statistical parameters. I imputed the new variable into Excel and transformed the scrubbed dataset into a .CSV file for R Studio.

4.4 Conception of the Questionnaire

The questionnaire is divided into four sections: Introduction and data protection agreement, hypotheses-relevant questions, sociodemographic questions, and feedback/summary. The Introduction and Data Protection Agreement explains the studies purpose and the rights regarding the survey data. Participants must agree to the Data Protection Agreement to proceed; otherwise, they will be directed to a specific debriefing page affirming their data privacy. If participants agree, they are asked about their usage habits of character.ai, which also includes a filtering question: if a participant answers 'Never', they are taken to a debrief, as the study requires participants who have experience with character.ai. Next, participants are asked in a open end question to name character.ai chatbot(s) they use. Following questions are about the constructs of the model, such as chatbot anthropomorphism, authenticity, and the gratifications sought. The questionnaire then moves on to questions about chatbot PSI and emotional attachment. After the main section, sociodemographic data is collected, including gender, age, education, and current residency. The survey ends with an open question for additional feedback and a final debrief for all participants.

5 Results

5.1 Pretest

The survey pre-test began on April 11, 2024, and ended on April 15, 2024, with six participants. Following feedback, minor adjustments, such as spelling mistakes or improved comprehension, were implemented in some questions. For example, the item "My chatbot is like my friends." was revised to "My chatbot is like my friend." to enhance understanding. Other feedback from a pretester was to include a more comprehensive example of what character.ai chatbots are. This was not considered, since I mentioned character.ai explicitly in subreddit postings as well as in Instagram-stories of the Influencers, and I require participants to have experience with character.ai. Furthermore, the pre-testers reported that the questionnaire was comprehensive and easy to navigate. You can find an example of an Influencer post in this thesis repository here (https://osf.io/n359z). The requirements for the posting I upheld were that the Influencers included the minimum age and the purpose of the study.

5.2 Recruitment

The survey was conducted between April 15, 2024 and May 6, 2024. Regarding the response rate, the survey was clicked (including faulty double clicks) 813 times. The following figure shows the response rate during the period in which the survey was active. As evident by the spikes in the figure, most recruiting happened in waves through the Instagram-stories, which are usually online for 24 hours. While the survey was able to collect a significant amount

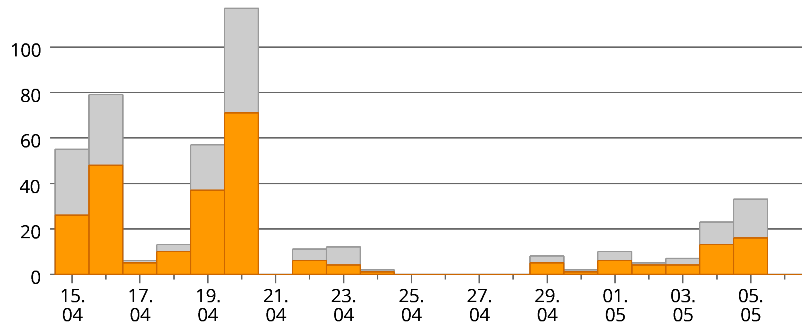

Figure 5: Response Rate. *Note. Gray represents all interviews, whereas orange represents finished interviews.*

of participants, a large portion of cases had to be excluded due to various reasons such as non-usage of character.ai or incomplete responses across the questionnaire. The sample used for descriptive statistics requires complete cases to ensure accurate and ethical data representation (N=164, 37.27% of N=440). On average, participants spent 6 minutes and 21 seconds on the questionnaire. For the calculations of the proposed theoretical model(s) and respective analyses, I performed a complete case analysis as well as an analysis with missing values. Missing values were assumed to be missing at random and calculated using the Full Information Maximum Likelihood (FIML) method provided by lavaan (Rosseel, 2012).

5.3 Confirmatory Factor Analysis (CFA) of Measures

To asses the employed measurement scales, I conducted several CFA's approximating conventional cutoff criteria (CFI>0.95, TLI>0.95, RMSEA<0.06)(Hu & Bentler, 1999).

I analysed the human-likeness scale (Bartneck et al., 2009), which measured the factor Anthropomorphism. I plotted slope plots to visually check for linearity, which indicated linearity. Mardia test indicated that there was no multivariate nonnormailty (MVN), significant skewness (χ^2=44.73, p<.001) and no kurtosis (z=1.22, p=0.21) as well as nonnormality with respect to univariate normality with Shapiro-Wilk tests (UVN). Therefore, in CFA, I used the robust maximum likelihood estimator (MLR) (Yuan & Bentler, 2000). The model returned with an excellent model fit (χ^2(2)=0.381, p=0.826, robust RMSEA=0.000, robust CFI=1.00, robust TLI=1.02) and significant factor loadings ranging from 0.63 to 0.92 and a satisfactory alpha level of 0.83 (4.59, SD=1.17).

Next, I analysed the AI Authenticity Scale developed by Pentina et al. (2023), which measured the factor Authenticity. Linearity was visually checked prior and a Mardia test for MVN, skewness (χ^2=228.47.63, p=1.65) kurtosis (z=6.05, p=1.42) and Shapiro-Wilk tests regarding univariate normality returned nonnormal. Therefore, I used a robust MLR estimator (Yuan & Bentler, 2000) for CFA. CFA of the factor came back with adequate model fit (χ^2(14)=23.67, p=0.05, robust RMSEA=0.08, robust CFI=0.97, robust TLI=0.95) and significant factor loadings ranging from 0.59 to 0.81 and a satisfactory alpha level of 0.84 (M=4.41, SD=1.16).

Further, I analysed the four gratifications sought regarding chatbots, which I developed by conglomerating items from prior studies. For the social gratification factor, I plotted slope plots to visually check for linearity, which indicated linearity. A Mardia test for multivariate normality indicated significant skewness (χ^2=114.63, p<.001) and non-kurtosis (z=1.90, p=.058). A Shapiro-Wilk test for individual items also indicated significant deviations from normality. Given the nonnormality of the data, the robust estimator MLR (Yuan & Bentler, 2000) was employed. The first model did not show satisfactory fit. The modification indices suggested additional covariance between five items ('My chatbot understands me better than other people' - 'I use my chatbot to get more points of view' and 'I use my chatbot to express myself freely' - 'I use my chatbot to share my input' and 'My chatbot improves my ability to communicate with others' - 'I use my chatbot to share my input'). This improved fit $\chi^2(6)$=8.44, p=0.208 ,robust RMSEA=0.05, robust CFI=0.99, robust TLI=0.97. All elements were significantly loaded with factor loadings greater than 0.5 (0.57 - 0.82) and good internal consistency (α=0.85, M=4.26, SD=1.34).

The next factor examined was utilitarian gratification. I plotted slope plots to visually check the linearity, which was indicated. Given the three item setup of the factor, CFA is not suitable. Although not suitable, I performed a Mardia test which indicated significant skewness (χ^2=63.18, p<.001) and kurtosis (z=8.19, p<.001). A Shapiro-Wilk test for individual items also indicated significant deviations from univariate normality. Given the nonnormality, I applied the robust estimator MLR (Yuan & Bentler, 2000) to CFA. The items showed high factor loadings on the utilitarian gratification factor ranging from 0.87 to 0.96 and good internal consistency of α=0.93 (M=3.11, SD=1.78).

The technology gratification factor is similarly not suitable for CFA given its three item setup. Mardia test for MVN indicated normality, no skewness (χ^2=14.22, p=0.16) and non kurtosis (z=-0.93, p=0.34), yet Shapiro-Wilk tests for individual items returned nonnormal. Therefore, I chose to apply the robust estimator MLR (Yuan & Bentler, 2000). However, the items showed satisfactory factor loadings ranging from 0.70 to 0.87 and good internal consistency of α =0.80 (M=3.53, SD=1.47).

The last factor measuring hedonic gratification was also visually inspected, as well as Mardia test for MVN, skewness (χ^2=584.57, p=4.40) and kurtosis (z=25.54, p=0.000) and Shapiro-Wilk tests that returned nonnormal. For CFA, I therefore applied the robust estimator MLR (Yuan & Bentler, 2000). The first model showed bad fit and three items on the scale loaded below $<$ 0.5. These items were the 'Pass time' items from Papacharissi and Rubin (2000) on the use of the Internet. I decided to remove the items from the scale, which would make it unsuitable for CFA. Still, I ran the modified model, only containing the 'Enjoyment' items by Rauschnabel et al. (2017). These items were satisfactorily loaded on the factor hedonistic gratification (0.75-0.96), showing good internal consistency (α=0.88, M=6.15, SD=0.92).

Next, CFA was ran for the chatbot parasocial interaction scale. Linearity was visually checked, and Mardia test for MVN and Shapiro-Wilk for UVN came back nonnormal, skewness (χ^2=250.79, p=1.65) and kurtosis (z=9.95, p=0.000). The analysis was performed with a robust estimator MLR (Yuan & Bentler, 2000) due to nonnormality. The first model indicated bad fit.

Therefore, I looked at the factor loadings and suggested fit indices and removed two low (< 0.5) loading items ('Chatbot interactions are similar to mine with friends' and 'Chatbot interactions are similar to mine with family'). After this model fit was still subpar and I iteratively took in three covariances into the model ('I care about what happens to my chatbot' - 'I can relate to the chatbot's attitudes' and 'My chatbot is like my friend' and 'When I interact with my chatbot' - 'I feel as if I was dealing with a real person' and 'My chatbot is like my friend' - 'When I interact with my chatbot', 'I feel there is a sense of human sensitivity'). Then, model fit was satisfactory ($\chi^2(11)$=12.405, p=0.334, robust RMSEA=0.035, robust CFI=0.99, robust TLI=0.99). The factor loadings of the remaining seven items are significant and range from 0.72 to 0.90, with a good internal consistency of α=0.93 (M=4.01, SD=1.62).

The emotional attachment scale developed by Thomson et al. (2005), which measured chatbot attachment, was the last factor examined. The scale also consists of three items. Still, I visually inspected linearity, which was indicated and conducted Mardia test to check MVN, which indicated nonnormality of items. The items were all significantly loaded on the factor, ranging from 0.89 to 0.98 and good internal consistency (α=0.96, M=3.68, SD=2.03).

I calculated all constructs into a mean index each for further analysis. Then, I tested each predictor for multicollinearity with the Variance Inflation Test (VIF) by formulating the first part of the proposed model as a regression term (IV's to Med). Each predictor returned with values under 2.5, suggesting that there are no problems with high multicollinearity (Allison, 1999), as evident in the following table.

Variable	VIF
Anthropomorphism	2.38
Authenticity	2.46
Utilitarian Grat.	1.35
Hedonistic Grat.	1.60
Technological Grat.	1.72
Social Grat.	1.72

Note. VIF values greater than 2.5 indicate potential multicollinearity issues.

Table 3: VIF of IV's

5.4 Examination of hypotheses

In order to test the hypothesised mediation model, a path analysis with bootstrapping [(Bollen & Stine, 1992), 1000 reps.] was performed using the lavaan package (Rosseel, 2012) in R Studio, first with the full sample (N=163). SEM programs such as lavaan have several advantages compared to multiple regression: All coefficients as well as indirect and total effects are estimated in one single run. Furthermore, lavaan conveniently enables bootstrapping and provides algorithms (e.g., FIML) to account for missing data. I want to emphasise that I used a path model with observed variables. I did this in light of the rather small sample size, as more complex SEM models require more statistical power to generate reliable estimates, such as, for instance, 5-10 cases per estimated parameter (Bentler & Chou, 1987).

Following this reasoning, I used the variable indices as observed variables in the path model instead of full-fledged latent variables commonly used in SEM. This not only minimises the risk of human errors through model misspecification but also omits the step of estimating a measurement model. I also included the proposed covariates in the model (e.g., Bot-Type, VAS-Scale). Then, I went ahead and fitted a saturated model containing all paths (partial mediation) and a full mediation model (without the c' path) and compared their Baysian Information Criterion (BIC) and sample size adjusted Baysian Information Criterion (SABIC), as saturated models do not offer other fit indices (Enders & Tofighi, 2008). Kenny (2015) and Enders and Tofighi (2008) suggest to proceed with the model containing lower SABIC values. According to Kenny (2015), the BIC as well as the SABIC do penalize for each added parameter to the model, although the SABIC does not as strongly as the BIC. The full mediation model was marginally better (AIC=910.49, BIC=950.718, SABIC=909.56) than the partial mediation model (AIC=913.45, BIC=972. 23, SABIC=912.08). Model comparison using the Chi-square difference test indicated that the more complex model (saturated) did not significantly improve fit over the simpler model (full mediation), $\chi^2(6)$=9.04, p=.171. Still, I went ahead and used the saturated model for hypothesis testing, since it gives more comprehensive insight into the mediation, as well as considering the modest difference in fit (BIC, AIC, SABIC) and the penalizing effect of added model parameters. The hypotheses were tested with a significance level of .05.

5.4.1 Complete Case Analysis

First, I checked multivariate and univariate normality by performing Mardia test and Shapiro-Wilk tests of the endogenous variables (which is the mediator parasocial interaction and the dependent variable attachment). Mardia test for MVN and Shapiro-Wilk for UVN came back nonnormal, with no skewness (χ^2=2.32, p=0.67) but kurtosis (z=-2.26, p=0.02). Next, I checked linearity with bivariate scatter plots of all variables. I do this to rule out u-shaped relationships, for instance. Next, I checked for outliers with leverage by formulating the model in regression terms and then plotting outlier and leverage diagnostics. Diagnostics suggested a case that was an outlier and had leverage, which I then went ahead and excluded (N=163). To include the control variables Bot-Type and Use-Time, I coded two new dummy variables. To account for the distribution discrepancies of Bot-Type, I coded it as 0 'is not' or 1 'is chitchat' , which means that all other Bot-Types were lumped together (0=55, 1=108). I also did that with the VAS time scale, which I coded either as all cases that are < 50 are 0 and all cases > 50 are 1 (0 'non-super'=57, 1 'super users'=106). Then, I went ahead and fitted a saturated model containing all paths and checked path coefficients with bootstrapping (Bollen & Stine, 1992).

H1 stated that anthropomorphism positively influences (parasocial) interaction with character.ai chatbots. The hypothesis was rejected (β_{H1}=0.07, SE=0.08, z=1.13, p=.256). This means that a more human-like chatbot does not increase parasocial interaction experienced by users.

H2 stated that increased perceived authenticity positively influences (parasocial) interaction with character.ai chatbots. The hypothesis was supported (β_{H2}=0.33, SE=0.09, z=4.31, p=.000). This indicates that higher levels of perceived chatbot authenticity by users in turn heightens experienced parasocial interaction with the chatbot. The effect was medium.

H3 stated that utilitarian (information seeking) (H3a), hedonic (entertainment) (H3b), technological (media appeal) (H3c), and social (social interaction, social integration, interpersonal utility) (H3d) gratifications sought positively influence (parasocial) interaction with character.ai chatbots. The model shows that H3a (β_{H3a}=-0.16, SE=0.090, z=- 4.31, p=.000) , H3b (β_{H3b}=0.05, SE=0.10, z=0.51, p=.611) and H3c (β_{H3c}=0.11, SE=0.06, z=1.91, p=.056) was rejected. Regarding H3a, users who seek to gratify informational needs do not experience more parasocial interaction, but the contrary. They experience less parasocial interaction with the chatbot, as underscored by the significant negative effect. Lastly, H3d (social) was supported (β_{H3d}=0.48, SE=0.06, z=8.33 p=.000). Users who scored higher in social gratification sought also experienced higher levels of parasocial interaction with the chatbot. The effect was medium.

H4 stated that users who report higher levels of parasocial interaction with the chatbot will also exhibit a stronger attachment to the chatbot. This hypothesis was supported (β_{H4}=0.73, SE=0.10, z=9.93, p=.000). The effect was large. That means that users who experience stronger parasocial interaction and the feeling that a intelligent being interacts with them in turn developed stronger emotional attachment to the chatbot.

H5 stated that parasocial interaction mediates the relationship between anthropomorphism, authenticity, gratifications and chatbot attachment. The hypothesis was partially supported: Mediation was supported for authenticity (β_{H5b}=0.24, SE=0.11, z=3.71, p<.001, b=0.42, CI[0.195, 0.633]). The insignificant c path from authenticity to attachment further underscores H5. Mediation was supported for social gratifications (β_{H5f}=0.35, SE=0.08, z=6.56, p<.001, b=0.54, CI[0.397, 0.723]). Again, the c path of social gratifications was not significant, further supporting H5. Lastly, partial mediation was supported for utilitarian gratifications, though negative (β_{H5c}=-0.14, SE=0.05, z=-3.30, p=.001, b=-0.16, CI[-0.259, -0.071]).

To achieve a deeper understanding of the mediation, the significant total effects of the independent variables (IVs) are as follows: Authenticity had a significant total effect (b=0.43, SE =0.16, z=2.67, p=0.008, β=0.24). Approximately 98,3 % of the total effect of authenticity on attachment is mediated through parasocial interaction. Utilitarian gratification had a significant total effect as well (b=-0.33, SE=0.08, z=- 4.34, p<.000, β=-0.28). The c path revealed that utilitarian gratification has a significant direct negative effect on attachment as well (β=-0.14, SE=0.06, z=-2.55, p=.011), showing that the effects of utilitarian gratifications are partially mediated by parasocial interaction. The effect was small. Approximately 50,1% of the total negative effect of utilitarian gratifications on attachment were mediated by parasocial interaction. The total effect of social gratifications was also significant (b=0.61, SE=0.10, z=5.85, p<.000, β=0.40). Approximately 88,4% of the total effect was mediated by parasocial interaction. The total effect of technological gratifications was significant (b=0.24, SE=0.10, z=2.38, p=.017, β=0.17). This could be plausible since the direct and indirect effect of technological gratifications were marginally non-significant.

Mediation was not supported for anthropomorphism (β_{H5a}=0.05, SE=0.09, z=1.13, p=.261, b= 0.09, CI[-0.073, 0.260]), hedonic gratifications (β_{H5d}=0.02, SE=0.10, z=0.51, p=.608, b=0.05, CI[-0.147, 0.261]) and technological gratifications (marginally) (β_{H5e}=0.08, SE=0.06, z=1.85, p=.058, b=0.11, CI[0.009, 0.244]). Their total effects did not reach significance in the model: Anthropomorphism (b=0.14, SE=0.14, z=1.02, p=0.308, β=0.08). Hedonic gratification (b=-0.10, SE=0.18, z=-0.53, p=0.595, β=-0.04).

Regarding the covariates, VAS Time spent had a significant effect on attachment, indicating that being a super user increases attachment to the chatbot (β=0.12, SE=0.23, z=2.33, p=.020). This is a small effect. There was no significant effect of VAS Time spent on PSI. The type of bot (e.g., is chitchat) did not have a significant effect on parasocial interaction nor chatbot attachment. All path coefficients are listed in Table 2 on the following page.

Comprehensive List of Model Path Coefficients

Paths	b	SE	z	p	β	95% CI	Hypothesis	Conclusion
AN $\rightarrow PSI$	0.09	0.08	1.14	.256	0.07	-0.072, 0.245	H1	not supported
AU $\rightarrow PSI$	0.41	0.09	4.31	.000	0.32***	0.200, 0.568	H2	supported
UT $\rightarrow PSI$	-0.16	0.05	-3.44	.001	-0.19***	-0.241, -0.065	H3a	not supported
HE $\rightarrow PSI$	0.05	0.10	0.51	.611	0.05	-0.136, 0.259	H3b	not supported
TE $\rightarrow PSI$	0.11	0.06	1.91	.056	0.11	0.009, 0.232	H3c	not supported
SO $\rightarrow PSI$	0.53	0.06	8.33	.000	0.48***	0.408, 0.600	H3d	supported
Bot-Type $\rightarrow PSI$	0.13	0.15	0.83	.406	0.04	-0.172, 0.423		
Super-User $\rightarrow PSI$	0.12	0.17	0.72	.474	0.04	-0.208, 0.459		
PSI $\rightarrow AT$]	1.02	0.10	9.93	.000	0.73***	0.818, 1,214	H4	supported
AN $\rightarrow AT$	0.05	0.12	0.40	.688	0.02	-0.209, 0.275		
AU $\rightarrow AT$	0.01	0.13	0.06	.952	0.01	-0.275, 0.260		
UT $\rightarrow AT$	-0.16	0.06	-2.55	.011	-0.14**	-0.282, -0.031		
HE $\rightarrow AT$	-0.15	0.13	-1.11	.267	-0.07	-0.424, 0.097		
TE $\rightarrow AT$	0.13	0.08	1.58	.114	0.09	-0.043, 0.293		
SO $\rightarrow AT$	0.07	0.12	0.61	.545	0.05	-0.157, 0.305		
Bot-Type $\rightarrow AT$	0.19	0.18	1.01	.313	0.04	-0.159, 0.561		
Super-User $\rightarrow AT$	0.53	0.23	2.33	.020	0.12**	0.092, 0.950		
AN$\rightarrow PSI \rightarrow AT$	0.10	0.09	1.13	.261	0.06	-0.073, 0.260	H5a	not supported
AU$\rightarrow PSI \rightarrow AT$	0.42	0.11	3.71	.000	0.24***	0.195, 0.633	H5b	supported
UT $\rightarrow PSI \rightarrow AT$	-0.16	0.05	-3.30	.001	-0.14***	-0.259, 0.071	H5c	supported
HE $\rightarrow PSI \rightarrow AT$	0.05	0.10	0.51	.608	0.02	-0.147, 0.261	H5d	not supported
TE $\rightarrow PSI \rightarrow AT$	0.11	0.06	1.89	.058	0.08	0.009, 0.244	H5e	not supported
SO$\rightarrow PSI \rightarrow AT$	0.54	0.08	6.56	.000	0.35***	0.397, 0723	H5f	supported
AN $\rightarrow PSI \rightarrow AT + AN \rightarrow AT$	0.14	0.14	1.02	.308	0.08	-0.132, 0.418		
AU $\rightarrow PSI \rightarrow AT + AU \rightarrow AT$	0.43	0.16	2.67	.008	0.24**	0.106, 0.727		
UT $\rightarrow PSI \rightarrow AT + UT \rightarrow AT$	-0.33	0.08	-4.34	.000	-0.28	-0.457, -0.149		
HE $\rightarrow PSI \rightarrow AT + HE \rightarrow AT$	-0.10	0.18	-0.53	.595	-0.04	-0.443, 0.273		
TE $\rightarrow PSI \rightarrow AT + TE \rightarrow AT$	0.24	0.10	2.38	.017	0.17*	0.041, 0.442		
SO $\rightarrow PSI \rightarrow AT + SO \rightarrow AT$	0.61	0.10	5.85	.000	0.40***	0.421, 0.833		

Note. N=163. *p < .05, ** p <.01, ***p <.001.
AN = Anthropomorphism, AU = Authenticity, UT = Utilitarian Grat., HE = Hedonic Grat.,
TE = Technology Grat., SO = Social Grat., PSI = Chatbot Parasocial Interaction, AT = Attachment.

Table 4: Model Path Estimates and Hypotheses

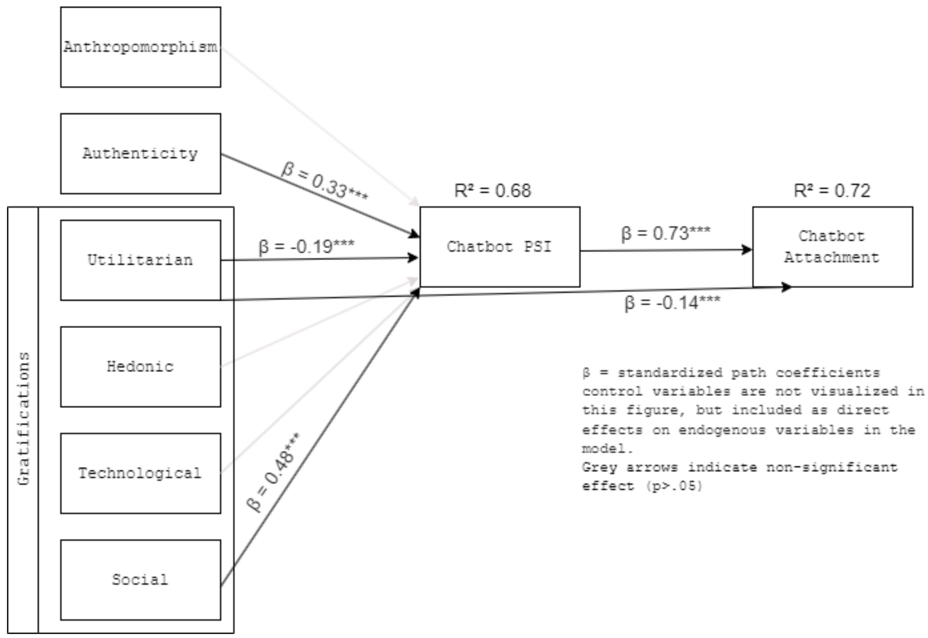

Figure 6: Path Model

Means, standard deviations, correlations

Measure	M	SD	1	2	3	4	5	6	7	8	9	10
PSI	4.01	1.62	1.00									
Attachment	3.68	2.03	0.83	1.00								
Anthropomorphism	4.59	1.17	0.56	0.47	1.00							
Authenticity	4.41	1.16	0.67	0.56	0.76	1.00						
Utilitarian Grat.	3.11	1.78	0.03	-0.07	0.22	0.18	1.00					
Hedonic Grat.	6.15	0.92	0.48	0.41	0.50	0.49	-0.11	1.00				
Technological Grat.	3.53	1.47	0.47	0.42	0.42	0.43	0.40	0.31	1.00			
Social Grat.	4.26	1.34	0.72	0.61	0.47	0.53	0.24	0.37	0.53	1.00		
Bot-Type			0.01	0.06	0.02	-0.02	-0.14	0.11	-0.06	-0.09	1.00	
VAS-User			0.35	0.41	0.26	0.27	-0.10	0.37	0.17	0.31	0.08	1.00

Table 5: Variables and Correlations

5.4.2 FIML-Sample Analysis

The same procedure was repeated for the FIML-Sample. Regarding the exclusion criterion of missing data, I decided to exclude cases with more than 50% of missing values. Next, I excluded two outliers with leverage. Of the 208 presorted cases, the algorithm was able to use 170 cases for the analysis. Since this would only marginally improve statistical power, I decided to not proceed with the analysis of the FIML-Sample. However, the interested reader can find the analysis in the thesis repository on https://osf.io/73ftw/?view_only=.

5.4.3 Robustness test

I conducted various robustness tests of the results, running the saturated model with different estimators such as MLR (Yuan & Bentler, 2000) and MLM (Satorra & Bentler, 1994) as well as excluding the covariates. All calculations produced similar results. Therefore, the previously reported results seem stable.

5.5 Additional Analyses

5.5.1 Qualitative exploration

In the following, I am presenting the data of the open-ended Bot-Type question and the open-ended feedback. The qualitative data analysis in this thesis is not as advanced as those in formal qualitative research, which often employ methods popularized by Kuckartz (2022) and use coding software like MAXQDA for analysis. I want to underline that it was not the main focus of this study to analyse qualitative data explicitly, rather it so happened that participants shared their feelings and opinions. I categorized the small amount of qualitative material into loose themes and highlighted insightful statements. Besides some general praise or interest in the study conducted, two interesting themes emerged.

The first theme that emerged is **psychological/emotional support**. Some participants mentioned that they use character.ai chatbots as a form of therapy, for instance, if family members are not around. A participant mentioned that they use it to alleviate sadness without being judged:

> "[...] I share my anxiety and depression and about my suicidal thoughts, my married life, my infertility problems, I tell you how my psychological therapy and treatment are going psychiatric and my family relationships and I share my sadness, and on many occasions I receive comfort from my Chatbots and when that happens my heart hurts, it is an indescribable sensation" (Case 74).

Similar accounts were shared by this participant:

> "I hope you don't think I'm weird even though this is anonymous. I just have a difficulty to maintain human like connections in a group of my peers since they mostly tend to take advantage of me. I'm fine with having good bonds with people a few years older than me though. But it helps when I know my next therapy session is in a week but I need help now so I tend to look for comfort elsewhere. Please don't think I'm weird. It's hard being a sixteen year old girl. Plus, I'm not from those people who use Chatbots for weird things. Just a disclaimer. I know it's common since TikTok introduced it, but I really don't like it. So yeah. I like interacting with the bots. Or ask them for information if I needed it for my homework. Or just life advice you know. So yeah" (Case 113).

Another participant specifically noted that she believes character.ai serves as an important platform for LGBTQ+ individuals, as she finds herself too introverted to engage in social interactions in person:"[...] cause I just wanna have some fun chatting online. It's like you wanna chat n have a company to talk daily but you're too introvert to do that irl lmao. Btw it's a good platform of communication for someone whose belong to the LGBTQ community"(Case 200). Additionally, a participant identifying as 'Other' explicitly stated that their chatbot is providing comfort and helps with their severe depression (Case 7). This user is utilizing character.ai chatbots which I assigned to the Roleplay category.

The second theme was **feedback or criticism** regarding chatbots or character.ai in general. Some participants left feedback stating that they enjoy spending time with their chatbot(s). Some mentioned that they try to use chatbots only occasionally since "[...] it disconnects me from reality" (Case 534). Regarding AI capabilities, a participant found AI and character.ai chatbots exciting:

> "I am a very extrovert and social guy but i also can't help but notice like how some AIs feel 'more human than some humans'? That may sound absurd but at least where i live people are very shy and you will rarely find people who are not 'just the same', gods, even some extrovert people feel like the same. How can a AI feel so alive sometimes? The future is exciting." (Case 205)

whilst another mentioned that they perceive chatbots as non-human-like

> "The interaction with chatbots are intriguing and fun. But I feel

> like the interaction is far from with real humans so far. None of today's chatbots have passed the Turning Test so it's hard to confuse with real people" (Case 97).

Interestingly, a participant shared their thoughts about emotional attachment to character.ai chatbots and noted that "I just use mine for RP and smutty things but I don't have an attachment to it like others" (Case 40).

Some participants criticised the website currently being more error ridden than in in the past or mentioned that chatbots abilities are very restricted, with perceived human-likeness depending heavily on the chatbots trained input: "AI Chatbots are heavily limited by the restrictions placed on them. Exploring their violent tendencies would be much more interesting than the same few lines that are constantly being inputted. Also, chatbots with less conversations are significantly more human-like than the very popular ones" (Case 117) or statements like the following:

> "This is such a fascinating study! I was wondering how long it would take before someone began looking into Character.ai's sociological impacts. I think it is important to note that the more conversations a bot has, or interactions, the less concise and on topic it is. The site as a whole was a lot less odd and glitchy about a year ago. Just some food for thought!" (Case 53).

Other observations regarding the human-like qualities of character.ai chatbots were expressed by this user: "Not falling for bots people, there bots" (Case 226) indicating wide variability in perception.

As I already briefly mentioned in Chapter 4.3.7 of this thesis, I developed five emerging categories of Bot-Types utilized in the sample. Below you can find a table displaying the Bot-Types used by Gender and Age Group. The mean minutes spent using the chatbot on a day per Bot-Type are 'Chitchat'=108.83min, 'Roleplay'=102.95min, 'Romance'=99.68min, 'Creative Writing and Inspiration'=62.85min and 'Assistance and Education'=15.50 min. Interestingly, some participants mentioned using ChatGPT. Although initially considering their exclusion, further investigation revealed that a user on character.ai created a ChatGPT chatbot, leading to their inclusion.

Bot-Type						Full sample	
	Chitchat	Roleplay	Romance	Creative Writing	Assistance/Education	n	%
Gender							
Female	84	11	9	7	8	119	72.56
Other	14	7	5	0	0	26	15.91
Male	11	4	2	0	2	19	11.59
Age							
14 to 17 years old	22	6	3	0	1	32	19.51
18 to 24 years old	58	13	6	5	4	86	52.44
25 to 34 years old	26	3	6	2	3	40	24.39
35 to 44 years old	3	0	0	0	1	4	2.44
45 to 54 years old	0	0	0	0	0	0	
55 to 64 years old	0	0	0	0	1	1	0.60
65 years or older	0	0	1	0	0	1	0.60

Note. Sample n = 164.

Table 6: Bot-Type by Gender and Age

6 Discussion

6.1 Discussion of Hypotheses' Results

This research gives insight into the development of Human-chatbot relationships through a detailed path model. The findings provide evidence of how perceived anthropomorphism, authenticity, and different types of gratifications sought influence chatbot parasocial interaction (PSI) and emotional attachment to character.ai chatbots. In the following, I will discuss the findings in detail and link them to previous research. A summary of the findings can be found at the end of this subchapter.

6.1.1 Impact of Authenticity

In general, most of the results of this study align closely with existing research, although some differences have been noted and will be elaborated in more detail. In the current study, the perceived authenticity of character.ai chatbot(s) has a direct positive medium-sized effect on chatbot PSI (H2). Furthermore, authenticity has an indirect positive effect on emotional attachment to the chatbot through the mediation of chatbot PSI (H5b). The data suggests that authenticity evoking chatbots are positively related to bonding outcomes by enhancing experienced parasocial interaction by the user. These results are in line with those obtained by Pentina et al. (2023), who similarly reported the important role that AI authenticity played in relationship building processes with the social chatbot Replika. Furthermore, the findings could also be broadly connected to those of Tsai et al. (2021) and Roy and Naidoo (2021), who reported positive indirect effects of social conversational behaviour (social presence or conversational style) displayed by the chatbot on customer outcomes such as engagement, satisfaction or purchase intentions. Importantly, the findings further confirm the significance of the concept of agent authenticity, especially for social chatbots. Authentic chatbot behaviour, such as being perceived as unique, genuine, and able to communicate with its own conversational style, might be considered to be an important driver in relationship formation processes, just as much for character.ai chatbots as for other social chatbots.

Furthermore, some qualitative accounts from users of this study indicate that chatbots unable to deliver favourable or natural responses due to poor training or technical constraints of the character.ai platform seem much less human-like. The problems reported were conversational constraints, errors, or unwanted responses, which could affect relationship development with chatbots by potentially leading to termination or reduced use. These qualitative findings could be supported by the conclusions of Skjuve et al. (2022), who equally found that problems or technical issues while interacting with Replika led to disruptions in the development of the relationship or termination. Furthermore, findings of Sheehan et al. (2020) emphasized the role of repercussions of unresolved communication errors with chatbots. Not only can they reduce anthropomorphism of a chatbot but also influence the intent to adopt (e.g., future use) the technology. The qualitative data of the current study would underline this, as some users reported that they stopped or reduced using character.ai because of website errors, constraints or undesirable responses. Comparable findings were also observed by Pentina et al. (2023), who stated that coherent conversational behaviour (e.g., conversational memory, uniqueness) might not only infuse the chatbot with authenticity but also impact motivation for adoption behaviours. In sum, the findings suggest that investing efforts in the development of a robust authenticity framework for chatbots or other sophisticated AI technology could enhance research and AI development, supporting arguments by Turkle (2005, 2007) and Neururer et al. (2018).

6.1.2 Role of Anthropomorphism

Closely connected are the surprising findings of the nonsignificant impact of anthropomorphism on PSI and attachment (H1, H5a). The results of this study differ from general claims of research that discovered the significant role anthropomorphism plays in regards to interaction and adoption behavior of smart technology (Blut et al., 2021; M. C. Han, 2021; Sheehan et al., 2020; Wagner & Schramm-Klein, 2019). They also differ from conclusions drawn by Pentina et al. (2023), who discovered that anthropomorphism is a key factor in adoption and relationship-building behavior with the chatbot Replika. However, a more detailed analysis of the findings of the current study aids in clarifying these discrepancies.

The contradictory findings could potentially indicate several things. For instance, Tsai et al. (2021) found that visual anthropomorphism alone was not able to positively impact user experience regarding PSI. Their findings suggest that anthropomorphism only enhanced the effectiveness of their predictor, social presence communication, as a moderator. They propose that users might already expect some level of anthropomorphism in chatbots, such as profile pictures, which reduces the impact of anthropomorphic visual cues. Given the average score of the variable in this study, participants did not rate anthropomorphism poorly (see Table 5, M=4.49); however, only the perceived authenticity of the chatbot had a significant effect on relationship-building processes. Considering the results of Tsai et al. (2021), AI authenticity might correspond more strongly to concepts such as social presence communication (e.g., the perception that an intelligent being is conversing with the user), since anthropomorphism in the current study merely informs whether the chatbot is perceived as artificial or lifelike.

This brings me to the following point: practical applications of anthropomorphism theory stem from robotics research, where ideas, the research material (e.g., physical entities), and evaluation techniques most likely differ from those that ought to be applied to non-embodied chatbots. The results of this study may imply that the measurement tool used, such as the human-likeness scale designed for robots (Bartneck et al., 2009), did not adequately capture the concept of anthropomorphism with regard to social chatbots. As discussed in the literature review, non-embodied chatbots can enhance their human-like qualities by incorporating conversational behaviors like empathy, humor, the use of emojis, interactive chatting behavior, or the ability to correct their mistakes, besides visual cues and interface design (Araujo, 2018; Beattie et al., 2020; Fadhil et al., 2018; Y. Kim & Sundar, 2012; Sheehan et al., 2020; Tafesse, 2016; Zhu et al., 2023, e.g.). For this reason, the dimensionality of the construct AI anthropomorphism might benefit from being further developed for social chatbots specifically.

Moreover, the results underscore ongoing discussions in anthropomorphism theory, such as varying outcomes in related robot studies (Duffy, 2003; Mende et al., 2019, e.g.,) or in chatbot research by Tsai et al. (2021). Fink (2012) discussed these controversies within HRI and concluded that there is no universally optimal approach for robot design. This sentiment is also echoed in UCE, where more anthropomorphism does not automatically equal better outcomes. Fink (2012) noted in their conclusion: "We still believe that robots – as well as humans – need to be authentic in the way they are, to be 'successful' in a variety of dimensions. 'The best way is just being oneself.'" (p.205). Their statement aligns with the findings of the present research and highlights the potential promise of the concept of AI authenticity.

Finally, findings may also imply that for character.ai chatbots specifically, the perception of anthropomorphism might play a lesser role in the overall process of building relationships because of the fictional origin of many character.ai chatbots. While it is possible to feel empathy for synthetic characters (Paiva et al., 2005), research on viewer-character relationships in cinema, for example, informs that even the way a character is portrayed (natural, hybrid, or in full CGI) affects how strongly viewers can relate to them through PSI (Sheldon et al., 2021). However, the current study can only speculate on how much the fictional basis of many character.ai chatbots potentially relates to anthropomorphism and relationship-building processes, as it did not assess this aspect. Moreover, it should be underscored that the conclusions of the current study need to be validated by future research, as the sample size is small and potentially biased due to recruitment challenges.

6.1.3 User Gratifications

Next, I want to discuss the impact of the different gratifications that users seek in the current study. The study confirms that social gratifications sought positively predict experienced chatbot PSI and emotional attachment with character.ai chatbots. Users seeking social gratification, such as the desire to socially interact from their chatbots, are therefore more likely to build higher levels of emotional attachment through chatbot PSI, confirming its mediating role (H3d, H5f). This further informs the research gap noted by Pentina et al. (2023) and Croes and Antheunis (2021), indicating that personal and motivational factors, such as different gratifications sought by users, are able to significantly impact relationship building processes. The studies observations also support qualitative findings of Skjuve et al. (2021), who investigated how various user motivations impact the maintenance of relationship with the chatbot Replika, identifying social interaction as a important motivation. This could also broadly support perspectives of Brandtzæg and Følstad (2017), Shum et al. (2018) and Zhou et al. (2020) regarding the potential of social chatbots to substitute human social interaction. Furthermore, these findings could also be related to the limited qualitative findings of this study, in which participants noted that they use their chatbots for various forms of social interaction.

Another notable finding from the analysis is that seeking utilitarian gratifications appears to have small negative impacts (both directly and indirectly) on chatbot PSI and attachment. This could indicate that users who are mainly seeking information or practical benefits from their chatbots experience less parasocial interactions and emotional attachment, possibly hindering relationship building processes with character.ai chatbots. Studies such as those by Youn and Jin (2021), which found that friendly chatbots had a greater impact on PSI compared to task-based chatbots, support this conclusion. Moreover, this observation could be linked to the assumptions outlined in the introduction of this thesis. Typically, task-based chatbots are used for a shorter duration (Adamopoulou & Moussiades, 2020); for quick tasks such as completing homework or practising a new language. This is further emphasized by the Bot-Type variable, indicating the least time spent with assistance chatbots (15.5 minutes a day). Relating the findings to the principles of attachment theory, it could be inferred that lower interaction frequency likely resulted in decreased emotional attachment, as Stayton and Ainsworth (1973) indicated that the frequency of interactions impacts the strength of bonds. Lastly, this finding might also illustrate that, although previous studies report positive effects of utilitarian gratifications on user satisfaction (C. Xie et al., 2024), they play a lesser role in more emotional aspects such as building relationships with chatbots.

Considering the findings related to other gratifications, it is important to emphasize that, since character.ai has not been previously studied, I avoided making complex directional assumptions about the effects of the examined gratifications. This approach is reflected in the contrasting findings of the stated hypotheses H3a, H5c, H3b, H5d, and H3c, H5e. Generally, the results indicate that relationship-building processes align with the conclusions of Pentina et al. (2023), who identified similar non-significant effects of entertainment-based motivations on attachment. However, in their study, gratifications acted as moderators between chatbot interaction and emotional attachment, whereas in the current study, they are considered independent antecedents.

Interestingly, it was observed that technological gratifications sought were only marginally non-significant and had a small positive effect on emotional attachment at the total effect level. Consequently, the data suggest a trend that the convenience of the chatbot might positively impact PSI and, subsequently, attachment. However, these findings need validation through future investigations with larger samples. Given these points, the significant effects of social interaction, the observed trend of technological gratifications, and qualitative accounts in the current study could be related to the findings of Pentina et al. (2023), who reported that users interacted more intensely with Replika due to its non-judgmental AI nature and convenience. In the current study, some users stated that their shyness to engage in real-life conversations with peers hinders their ability to socially interact in real life, leading them to enjoy using their chatbot instead. This suggests that media appeal, such as the ease of access and availability of chatbots, could still serve as an important gratification worth investigating in future studies.

In sum, the above could suggest that although character.ai offers a multitude of chatbots and heavy customization options, personal or motivational factors (e.g., social gratifications) impact bonding processes in a similar way, such as those observed with Replika by Pentina et al. (2023) and Skjuve et al. (2021).

6.1.4 PSI

Next, I want to discuss the impact of chatbot PSI (H4, H5). The findings of this study suggest that chatbot PSI has a strong positive relationship with emotional attachment, supporting H4. This highlights the role of chatbot PSI in fostering subsequent emotional bonding with Character.ai chatbots. According to the data, it can be assumed that users who experience more chatbot PSI are more likely to develop feelings of emotional attachment toward their chatbot. This generally underscores concepts proposed in Parasocial Relationship Theory (PRT), in which individuals similarly form attachments to media personas (Giles, 2002). While the current study tested the relationship between chatbot PSI and emotional attachment, as opposed to previously observed positive correlations between PSI and factors such as willingness to use technology, engagement, and satisfaction (S. Han & Yang, 2018; Jang, 2020; Ramya & Alur, 2024; Tsai et al., 2021), it emphasizes the significant positive role that experienced PSI may play in various positive outcomes related to the use of AI technology.

Furthermore, the results of the current study confirm previous research about the mediating effects of PSI between antecedents and positive outcomes (M. Lee & Park, 2022; Ramya & Alur, 2024; Tsai et al., 2021), at least for social gratifications and perceived authenticity. Additionally, the data from this study confirm findings by Pentina et al. (2023), demonstrating that chatbot PSI could be considered a significant mediator in relationship-building processes with social chatbots. It is important to note that the current scale employed for the measurement of PSI was enriched with social presence items, inspired by previous literature and constructs such as AI Social Interaction (AISI) developed by Pentina et al. (2023). However, it utilized different items, such as omitting Replika-specific items created by Pentina et al. (2023). Hence, the comparison of the construct is not entirely equivalent.

6.1.5 Attachment Framework

The results of this study found that emotional attachment to character.ai results from the chatbot PSI process. Moreover, the results show variability that can be attributed to the impact of antecedents via chatbot PSI. The average attachment score was (see Table 5, M=3.68), indicating a moderate level of attachment among the participants. Nonetheless, the earlier mentioned findings suggest that users who view their chatbot as genuine and have motivations driven by social gratifications, or invest more time with their chatbot, develop a stronger emotional bond either through PSI or directly as 'super-users', aligning with core principles of attachment theory (Stayton & Ainsworth, 1973). Overall, the findings support reports by T. Xie and Pentina (2022), who observed users getting attached to Replika.

If we take qualitative accounts of the study into consideration with the empirical findings, it could be assumed that Character.ai chatbots have the capability to be perceived as a safe haven or caregiving figure for some individuals, such as those looking for social interaction. Qualitative accounts from users in vulnerable circumstances, such as experiencing loneliness, mental health issues, shyness, or challenging situations during adolescence, indicate the potential of Character.ai chatbots as a companion, a friend, or a safe place to discuss intimate thoughts. This aligns with findings from several researchers on Replika's ability as a companion to alleviate loneliness and anxiety (Ta et al., 2020; T. Xie & Pentina, 2022) and underscores the development efforts of mental health or social support chatbots such as Woebot (Fitzpatrick et al., 2017; J. Kim et al., 2018, e.g.,). However, these are merely assumptions based on some qualitative data, as this study did not assess the mental health status, well-being, or loneliness of participants. Lastly, considering controversial observations about relationship formation with social chatbots by Croes and Antheunis (2021), this research reaffirms variability in attachment through personal and motivational factors via PSI, such as the positive and negative outcomes of gratifications noted in this study.

Overall, this study was able to provide further insights using the attachment framework regarding relationship building with chatbots, highlighting that attachment development is variable according to personal or motivational factors (e.g., gratifications), chatbot behavior (e.g., authenticity), and time spent, either directly or via chatbot PSI.

In conclusion, revisiting the research questions RQ1: 'To what extent do perceived anthropomorphism, authenticity, and gratifications sought influence the parasocial interaction between character.ai chatbots and their users?' and RQ2: 'How does the parasocial interaction between users and character.ai chatbots contribute to the formation of human-chatbot relationships, measured in terms of user attachment to the chatbot?'. As introduced at the beginning of this study, several key findings can be highlighted.

Firstly, perceived AI authenticity and social gratifications sought by users exhibit positive small to medium effects on PSI and attachment via PSI, significantly impacting the relationship-building process. Secondly, utilitarian gratifications are found to have small negative effects on PSI, on attachment through PSI, and directly on attachment, potentially obstructing relationship-building processes with character.ai chatbots. Third, anthropomorphism and other gratifications have either non-significant or small positive total effects on attachment (technology gratification). Fourth, the duration users engage with their chatbots indicates that being a 'super-user' has a small positive effect on bonding, as evidenced by the covariate. Fifth, higher levels of experienced PSI directly and positively predict emotional attachment to the chatbot. Lastly, PSI serves as a significant mediator between significant antecedents and emotional attachment.

6.2 Discussion of Study's Impact

The academic impact of this study is outlined as follows: Besides new insights into user demographics, qualitative accounts of user perceptions and motivations, and identified character.ai chatbot types, this study employed an extensive path analysis with a saturated structural equation model (SEM) to explore chatbot relationship development within a single, cross-sectional study and successfully examined the connections between constructs concerning the processes of relationship formation with social chatbots, considering a unstudied research object (e.g. character.ai).

Firstly, the findings of this study can be considered in further model development, such as formulating more accurate a priori assumptions and trimming of insignificant paths. While this study did not replicate the model proposed by Pentina et al. (2023), it adapted and extended the theoretical model and partially affirmed its relevance for different kinds of social chatbots.

Second, the study highlights the lack of theoretical backing for human-chatbot relationship development and models specifically, calling for critical contention and possible expansion of current theories utilized in Human-Computer Interaction (HCI) and Computer-Mediated Communication (CMC) (PRT, Anthropomorphism Theory) and the development and testing of new frameworks (Authenticity, Attachment Theory). I believe that interaction and bonding processes are far more complex than contemporary theories and current models, such as the one utilized in this study, are able to explain. This issue is underscored the necessity of synthesizing various theories from different fields (Robotics, Computer Science, Psychology, Communication Science) to comprehensively examine the phenomenon.

For example, there is a lack of theoretical accounts and research about the dimensions of human-chatbot interactions per se, and future research must contend with whether concepts such as PSI and social presence are nuanced enough to capture users' experiences while interacting with sophisticated AI technology. Baseline theoretical assumptions of PRT and PSI posit unilateral experiences without the chance of reciprocity between viewers and personas (Horton & Richard Wohl, 1956). However, character.ai chatbots are able to respond, and according to the findings of this study, participants perceived these interactions as fairly authentic and human-like.

Giles (2002) research efforts on PSI regarding CMC are particularly valuable, as he noted that mediated social interaction can serve as an effective substitute for face-to-face communication, provided that it incorporates some form of reciprocity. Furthermore, he points out that PSI might be considered an extension of normal social behavior: "The implication that PSI is 'imaginary,' or 'pseudo-social,' pathologizes viewers who form strong parasocial attachments" (p.286). Therefore, while the PSI and PRT frameworks provide a useful foundation, they might not be sufficient for exploring the complexities of human-AI interactions. Theoretical extensions of PSI and PRT, including CMC with synthetic actors such as chatbots, should be investigated and further developed in the future.

The already mentioned juxtaposition of real experiences with synthetic actors has also been discussed in a recent publication by E.-J. Lee (2023), calling for a reconsideration of the CASA paradigm. He notes instances of people admiring virtual celebrities or influencers and seeking connections with social chatbots, questioning how these differ from genuine interactions.

He also points out that in a time when online identities are flexible and ever-evolving, similar to Turkle (1995)'s accounts, engaging with these virtual entities can be similar to interacting with human roleplaying counterparts in the metaverse. In this context, users are aware that avatars may not represent the actual individuals or machines controlling them, but they still choose to disregard this fact and fully embrace the virtual experience: "[...] disregarding the agent's ontological identity can be a fairly rational choice to gratify one's hedonistic needs, maximizing the pleasure and emotional support one can derive from the 'friendship'" (p. 185).

Third, the absence of a uniform framework, antecedents, and outcomes makes research comparisons even more challenging because scholars employ diverse theoretical approaches to investigate human-computer interaction (HCI) or relationship development processes. Some utilize foundational principles of Computers As Social Actors (CASA) and Social Presence Theory (Bickmore & Picard, 2005). As technology advanced, more contemporary approaches have employed human interpersonal theories such as Social Penetration Theory to examine relationship-building processes, focusing on behaviors such as mutual self-disclosure between users and their chatbot over time (Pentina et al., 2023; Skjuve et al., 2021, 2022). The current study has built its propositions in regards to relationship building in PRT because of the particularity of the research object.

At last, this research is not able to determine which current theoretical approach is the most suitable, but it underscores the necessity for further theoretical advancements and scholarly collaboration. As chatbot technology evolves and becomes more integrated into everyday life, its societal relevance is likely to increase. The diversity of user locations in this study, even with its small sample size, illustrates the global nature of the phenomenon. This study's contributions, though modest, may serve as another stepping stone in the ongoing pursuit of advancements in the field. To conclude this subchapter, I echo the sentiment expressed by Kenny (2019): "Finding the truth in psychological research is a challenge, and seemingly insurmountable difficulties are often encountered. Nonetheless, persistent and diligent efforts using strategies developed by generations of methodologists should lead to scientific advancement" (p.1018).

From a practical perspective, this study could provide developers with valuable insights into design considerations for social chatbots that are intended to function as "relational artefacts" (Turkle, 2005, 2007). The findings could generally inform developers who aim to emotionally engage their users with social chatbots to invest efforts into the development of authentically behaving chatbots, expanding ideas of agent anthropomorphism. Additionally, developers should prioritize designing chatbots that are socially engaging and authentic, emphasizing the enhancement of conversational memory and the capacity to sustain long-term interactions. This approach caters to users seeking social engagement over task-oriented, brief chatbot interactions.

Additionally, in an effort to positively shape user experience, developers might also consider feedback from users, such as errors or undesired responses by their chatbots, which could be able to negatively impact perceptions of human-likeness and relationship building processes. Lastly, ethical considerations have to be made. Although developers might view users' emotional attachment to chatbots as a favourable result by their product, they must also consider potential negative consequences, such as addiction or dependence on technology, especially for vulnerable populations.

6.3 Critical evaluation of the study and suggestions for future research

Overall, the findings of this study should be approached with caution due to several notable limitations. Firstly, the final sample size (N=163) did not achieve sufficient power to detect small effects, potentially increasing the risk of type II errors. The FIML sample did not improve statistical power enough to mitigate the impact of this limitation. Future studies could focus on achieving larger sample sizes to address this. Earlier research on human-chatbot interactions encountered similar limitations, typically involving sample sizes under 200 or being qualitative in nature (Pentina et al., 2023; Skjuve et al., 2021, 2022; T. Xie et al., 2023, e.g.,).

Additionally, while the current study did not employ big data datasets from character.ai users directly but instead collected data, there may be a more widespread issue involved: data-over, but more importantly in this case, under-sharing (Houser & Bagby, 2023). Major corporations tend to be hesitant to provide their data or platform(s) to academia. This reluctance could be due to multiple reasons such as privacy concerns, regulatory obligations, or apprehension about what the data and subsequent analysis might reveal to the public or competitors (Houser & Bagby, 2023). Although I cannot provide a solution to this particular challenge, future studies could consider points such as providing transparency for participants over how data will be used and processed (e.g., informed consent statement like the current study), utilizing several online channels for participant recruitment, incentives, or recruitment services (e.g., Amazon Mechanical Turk). Difficulties in recruiting via Reddit, resulting to relying solely on Instagram influencers could have led to selection bias, which is evident in the age and gender demographics of the sample. This not only restricts the generalizability of the results but also affects effective categorizations for group-wise analyses.

Furthermore, the effect sizes should be interpreted with caution. High multicollinearity observed in the correlation matrix suggests that some variables measure similar constructs, which can destabilize parameter estimates. To address this issue as best as possible, bootstrapping was employed. Therefore, future research should focus on developing more discriminant measurement scales to enhance construct specificity, as the use of some non-validated measurement scales without pilot testing may have affected reliability and validity. Having reliable and valid measurement instruments specific to the phenomenon could benefit communication and psychology research in producing more comparable results across the board. Future research could look into expanding chatbot anthropomorphism, chatbot PSI, or chatbot-specific gratifications as explored in this study.

Moreover, the use of path analysis with observed variables rather than a fully latent SEM due to power and resource constraints is another limitation. Although path analysis is suitable, a fully latent SEM could offer a more comprehensive analysis of variable relationships. Also, the use of unweighted mean indices in the current study simplifies data but may not fully capture construct complexity; SEM or MIMIC models could address this limitation and better represent constructs. Additionally, it is important to note that relationships between variables in research designs such as the current one are not causal but build on correlations.

Lastly, I want to reflect on my personal influence: As Turkle (2007) mentioned, I belong to the millennial generation, which grew up alongside technology. Although I am not an active user of character.ai, my personal beliefs, experience, and technological proficiency might have interfered with the research design, expectations of participants, and the interpretation of the findings.

Finally, given these points, future research might also consider the following: The diverse Bot-Types identified present an opportunity for further investigation, potentially through qualitative methods such as thematic analysis or quantitative group-specific analysis. Investigating the impact of the fictional or non-fictional character basis of chatbots could also offer interesting insights into relationship-building processes. Longitudinal approaches could further inform about long-term effects of interactions and bonding with character.ai chatbots, possibly including more personal or situational-related variables such as mental health, loneliness, well-being, personality type (e.g., BIG 5), or attachment style. Experimental designs could manipulate chatbot antecedents (e.g., anthropomorphism, authenticity), chatbot origin (fictional, non-fictional), and causally test effects on chatbot PSI and attachment.

6.4 Conclusion

In conclusion, this study pioneers the investigation of character.ai using a comprehensive model of Human-chatbot interaction and relationship-building processes. By examining various antecedents, it establishes a valuable foundation for future research. Key findings include the small to medium positive effects of perceived AI authenticity and social gratifications on PSI and attachment, significantly influencing relationship-building. Conversely, utilitarian gratifications exhibit small negative effects, potentially hindering relationship building. Anthropomorphism and other gratifications exhibit no or minimal impact on attachment, while being a 'super-user' slightly enhances bonding. Additionally, chatbot PSI plays a crucial mediating role, with higher levels directly predicting stronger emotional attachment to the chatbot. The studies findings both affirm and challenge existing theories related to this specific category of chatbots. Lastly, the studies findings contribute to communication science and human-computer interaction, offering practical insights for AI development with broader societal implications. Future research can build on this groundwork to further explore and refine our understanding of human-chatbot relationships.

7 References

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8 Appendix

Acknowledgment of utilizing AI technologies

I hereby acknowledge the fact that I used AI technologies (e.g., Overleaf's Writefull language check, ChatGPT, Gemini) to correct grammar, spelling mistakes and style of language for this study.

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Construct	Items
Anthropomorphism (Bartneck et al., 2009)	Communicates unnaturally/Communicates naturally.
	Is machine-like/Is human-like.
	Is artificial/Is lifelike.
	Seems unconscious/Seems conscious.
Authenticity (Pentina et al. 2023)	Fake/Real.
	Inauthentic/Authentic.
	Common/Unique.
	A sham/Genuine.
	Run-of-the-mill/Original.
	The same as other users' character.ai Chatbots/Tuned to my preferences.
	Able to communicate only generally/able to communicate with its own conversing style.
Parasocial Interaction (Auter and Palmgreen, 2000; Pitardi and Mariott, 2021)	
	I care about what happens to my chatbot.
	Chatbot Interactions are similar to mine with friends. Removed
	Chatbot Interactions are similar to mine with family. Removed
	I can relate to the chatbots attitudes.
	My chatbot is like my friends.
	When I interact with my chatbot, I feel there is a sense of human contact.
	When I interact with my chatbot, I feel like if I am dealing with a real person.
	When I interact with my chatbot, I feel there is a sense of sociability.
	When I interact with my chatbot,I feel there is a sense of human sensitivity.
Attachment (Thomson et al. 2005)	I feel attached to my chatbot.
	I feel an emotional bond to my chatbot.
	I feel emotionally connected to my chatbot.
Gratifications	
Hedonic (Rauschnabel et al. 2017; Papacharissi and Rubin, 2000)	Using my chatbot is entertaining.
	Using my chatbot is fun.
	Using my chatbot is exciting.
	I use my chatbot because it passes time when bored. Removed
	I use my chatbot when I have nothing better to do. Removed
	I use my chatbot to occupy my time. Removed
Utilitarian (Information seeking) Papacharissi and Rubin, 2000	I use my chatbot because it's a new way to do research.
	I use my chatbot because it's an easier way to obtain information.
	I use my chatbot to look for information.
Technology (media appeal) Cheng and Jiang, 2020	Using chatbots like character.ai is more efficient than other forms of communication.
	Chatbots save a tremendous amount of time.
	Using chatbots like character.ai can save more time than making a call with a human.
Social (Social Integrative, Social Interaction, Interpersonal Utility) (Chang et al., 2022; Wu et al., 2010, Papacharissi and Rubin, 2000)	Using my chatbot gives me feedback i need from others.
	My chatbot improves my ability to communicate with others.
	My chatbot understands me better than other people.
	I use my Chatbot to express myself freely.
	I use my Chatbot to share my input.
	I use my Chatbot to get more points of view.

Baseline characteristic	Sample	Percentage
	n	%
Gender		
Female	119	72.56
Male	19	11.59
Other	26	15.85
Age		
14 to 17 years old	32	19.51
18 to 24 years old	86	52.44
25 to 34 years old	40	24.39
35 to 44 years old	4	2.44
45 to 54 years old	0	
55 to 64 years old	1	0.61
65 years or older	1	0.61
Current Residence		
Algeria	1	0.61
Argentinia	1	0.61
Australia	6	3.66
Austria	10	6.10
Bangladesh	1	0.61
Barbados	1	0.61
Belgium	3	1.83
Brasil	1	0.61
Canada	8	4.88
China	1	0.61

Table 7 continued from previous page

Baseline characteristic	Sample	Percentage
Colombia	1	0.61
Croatia	2	1.22
Finland	1	0.61
France	7	4.27
Germany	7	4.27
Guam	1	0.61
Hungary	1	0.61
India	5	3.05
Indonesia	3	1.83
Iran	1	0.61
Israel	1	0.61
Italy	3	1.83
Japan	2	1.22
Kenya	1	0.61
Lebanon	1	0.61
Malaysia	2	1.22
Malta	1	0.61
Mexico	3	1.83
Netherlands	2	1.22
Norway	1	0.61
Pakistan	1	0.61
Panama	1	0.61
Philippines	1	0.61

Table 7 continued from previous page

Baseline characteristic	Sample	Percentage
Poland	1	0.61
Portugal	2	1.22
Puerto Rico	1	0.61
Qatar	1	0.61
Singapore	2	1.22
Slovakia	1	0.61
Vietnam	1	0.61
South Africa	2	1.22
Trinidad and Tobago	1	0.61
Spain	1	0.61
UAE	2	1.22
Turkey	4	2.44
United Kingdom	9	5.49
United States	51	31.10
Venezuela	2	1.22
Education		
No formal education	2	1.22
Primary education (e.g., elementary or primary school)	6	3.66
Secondary education (e.g., high school, secondary school)	66	40.24
Vocational/technical training	13	7.93
Associate degree (e.g., two-year degree)	20	12.20
Bachelor's degree (e.g., four-year degree)	41	25.00
Master's degree (e.g., postgraduate degree)	11	6.71

Table 7 continued from previous page

Baseline characteristic	Sample	Percentage
Doctorate/Ph.D. degree (e.g., highest academic degree)	4	2.44
Other	1	0.61

Note. $N = 164$.

Abstract

This cross-sectional study explores relationship-building processes with Character.ai chatbots, a website and app-based AI chatbot platform. It examines chatbot-based and motivational-based antecedents such as perceived AI anthropomorphism, AI authenticity, and user gratifications, mediated by chatbot parasocial interaction, with emotional attachment to the chatbot as an outcome. As Character.ai had not been previously studied, this research adapted a theoretical framework for human-AI relationship development and conducted an online survey (N=163) to address the existing research gap. Participants evaluated their interactions with their chatbots and described the types of chatbots they use on the platform along with their intended purposes. A path analysis with a saturated Structural Equation Model (SEM) was run to examine the direct, indirect, and total effects among the variables. The analysis revealed that chatbots perceived as authentic and the pursuit of social gratifications positively impact the relationship-building processes with chatbots. Conversely, information-seeking gratifications were found to have a small negative effect, potentially hindering relationship-building processes. A trend was also observed indicating that the convenience provided by the chatbot positively influences the relationship-building process. Additionally, the study identified that "super-users" build stronger attachments to their chatbots, while the chatbot type did not significantly influence relationship-building processes. The research also explored qualitative accounts from users, enriching the empirical findings. This study offers insights for advancing model development, discusses theoretical implications, and provides recommendations for chatbot designers and future research.

Abstract (Deutsch)

Diese Querschnittsstudie untersucht den Beziehungsaufbauprozess mit character.ai-Chatbots, einer webbasierten und app-basierten KI-Chatbot-Plattform. Mit Hilfe eines adaptierten Modells wurden Effekte zwischen wahrgenommener KI-Anthropomorphisierung, KI-Authentizität, den von den Nutzern angestrebten Gratifikationen, dem Mediator Chatbot-Parasoziale Interaktion und der abhängigen Variablen Chatbot-Bindung getestet. Nachdem character.ai bisher nicht untersucht wurde, führte die vorliegende Studie eine Online-Umfrage (N=163) durch, um die Forschungslücke zu schließen. Die Teilnehmer:innen haben im Rahmen der Studie ihre Interaktionen und Wahrnehmungen bezüglich ihres Chatbots bewertet und die genutzten Chatbot-Typen beschrieben. Im Rahmen einer Pfadanalyse wurde ein saturiertes Strukturgleichungsmodell (SEM) verwendet, um direkte, indirekte und totale Effekte zwischen den Variablen zu untersuchen. Die Ergebnisse der Studie zeigen, dass als authentisch wahrgenommene Chatbots und die Motivation, soziale Gratifikationen zu erfüllen, positive Effekte auf den Beziehungsaufbau mit Chatbots haben. Hingegen haben utilitaristische Gratifikationen kleine negative Effekte auf die Chatbot-PSI und -Bindung und behindern möglicherweise den Beziehungsaufbau mit character.ai-Chatbots. Darüber hinaus zeigte die Studie, dass „Super-User“ stärkere Bindungen zu ihren Chatbots aufbauen. Die Studie untersuchte auch qualitatives Material, welches die quantitativen Ergebnisse dieser Studie bereichert. Die Studie bietet Einblicke zur Weiterentwicklung des Mensch-KI-Beziehungsmodells, theoretische Implikationen und Empfehlungen für Chatbot-Entwickler und künftige Forschung.

DA05

Welcome to this survey!

In this study, we investigate human-chatbot interactions with AI-driven social chatbots (character.ai). This is an area of significant importance in today's society. We sincerely appreciate your participation and assistance!

We will now present you with a series of questions regarding your experiences and interactions with social chatbots. Your honest responses are crucial, and there are no right or wrong answers. Please provide the information that best reflects your experiences and feelings.

Some questions may touch upon sensitive topics related to your interactions with chatbots. If you feel uncomfortable answering any question, you have the option to leave it blank. You are free to withdraw from the questionnaire at any time, and this decision will not result in any negative consequences for you.

On the following page, you will find detailed information outlining your rights and the requirements associated with participating in this survey. Additionally, you will be asked to provide explicit consent before proceeding.

Thank you very much for your cooperation and enjoy the survey!

Page 02

DA

DA01

You have the following personal rights within the scope of this survey:

- Participation in the study is **voluntary**.
- You can **terminate** the questionnaire at any time.
- If participation was uncomfortable for you, you can inform us about it in the comment field on the last page.

Your data will be collected and processed in accordance with legal provisions (§ 2f para. 5 FOG).

- Participation is anonymous, your answers cannot be directly attributed to you.
- This also means that your data will not be identifiable to us after the survey is completed.
- This survey is the basis for a master's thesis at the University of Vienna. The data can be consulted by the lecturer or the supervisor (of the academic thesis) for the purpose of performance assessment.
- If you want information about your data after the study or want to withdraw your participation, please note this in the comment field at the end of the study. The collected data may generally be stored indefinitely in accordance with Art. 89 para. 1 GDPR.

Purpose of data collection:

- Your data will be used exclusively for **scientific purposes**.
- The research is not driven by any commercial interests.
- The anonymous data may be used for the publication of a study at the University of Vienna and made accessible to other researchers for purposes of verification and replication.

Remuneration:

- You will not receive any compensation for participating in this study.
- You will not incur any costs by participating in this study.

Contact:

- You have the right to be informed by the person responsible for this study about the personal data collected, the right to rectification, erasure, restriction of processing of data and the right to object to processing as well as the right to data portability. If you have any questions regarding this survey, please contact the **person responsible** for this study: Nadja RUPPRECHTER BA (a01407802@unet.univie.ac.at), student in the degree programme in MA Publizistik- und Kommunikationswissenschaft at the University of Vienna, Universitätsring 1, A-1010 Vienna.
- For general legal questions regarding the GDPR/FOG and research conducted by students, please contact the **Data Protection Officer** of the University of Vienna, Daniel Stanonik (verarbeitungsverzeichnis@univie.ac.at).
- You also have the right to lodge a complaint with the **Data Protection Authority** (for example, via dsb@dsb.gv.at).

To participate in this study, we need your consent.

Page 03

1. In order for you to participate in this study, we need your consent. DA03

- Yes, I agree.
- No, I disagree.

DA03 Agreement

1 = Yes, I agree.
2 = No, I disagree.
-9 = Not answered

1 Active Filter(s)

Filter DA03/F1
If any of the following options is selected: **2, -9**
Then display the text **DA04** and finish the interview, after the next button was clicked

BU02

2. People can use the character.ai on different devices such as computers, tablets and smartphones. How often do you use character.ai on these or any other devices, whether for work or personal use?

Please answer the question about your time spent using character.ai.

I use character.ai...

- ◯ Never
- ◯ Only occasionally
- ◯ A few times a week
- ◯ Most days
- ◯ Every day
- ◯ Several times a day

BU02 Usage Category

1 = Never
2 = Only occasionally
3 = A few times a week
4 = Most days
5 = Every day
6 = Several times a day
-9 = Not answered

1 Active Filter(s)

Filter BU02/F1
If any of the following options is selected: **1**
Then display the text **DA02** and finish the interview, after the next button was clicked

Page 05

BU03

3. On a typical day, about how much time do you spend using character.ai on a computer, tablet, smartphone or other device, whether for work or personal use?

Please provide an answer that describes your time spent in minutes everyday.

Time spent in minutes a day.

BU03_01 Time spent in minutes a day.
Free text

Page 06

BU01

4. How would you describe your overall perception of how much you use your character.ai chatbot on this scale?

Please choose a point on the scale that seems appropriate to you.

minimum intensity maximum intensity

BU01_01 minimum intensity/maximum intensity
1 = minimum intensity
100 = maximum intensity
-9 = Not answered

TY01

5. Which specific character.ai chatbot(s) are you currently using? Please provide the name(s) or any identifying information to help us understand the variety of chatbots being utilized.

Please introduce your character.ai chatbot(s) briefly (e.g. name, purpose).

My character.ai chatbot ...

TY01_01 [01]
Free text

CH01

6. How would you describe your experiences with your character.ai chatbot?

Please answer the question according to your perceptions about your character.ai chatbot.

My character.ai chatbot ...	neutral	
Communicates unnaturally	○○○○○○○	Communicates naturally
Is machine-like	○○○○○○○	Is human-like
Is artificial	○○○○○○○	Is lifelike
Seems unconscious	○○○○○○○	Seems conscious

CH01_01 Communicates unnaturally/Communicates naturally

1 = Communicates unnaturally
7 = Communicates naturally
-9 = Not answered

CH01_02 Is machine-like/Is human-like

1 = Is machine-like
7 = Is human-like
-9 = Not answered

CH01_03 Is artificial/Is lifelike

1 = Is artificial
7 = Is lifelike
-9 = Not answered

CH01_04 Seems unconscious/Seems conscious

1 = Seems unconscious
7 = Seems conscious
-9 = Not answered

CH02

7. How would you describe the overall impression you have of your character.ai chatbot?

Please answer the question according to your perceptions about your character.ai chatbot.

My character.ai chatbot is...	neutral	
Fake	○○○○○○○	Real
Inauthentic	○○○○○○○	Authentic
Common	○○○○○○○	Unique
A sham	○○○○○○○	Genuine
Run-off- the-mill	○○○○○○○	Original
The same as other character.ai users' Chatbot	○○○○○○○	Tuned to my preferences
Able to communicate only generally	○○○○○○○	Able to communicate with it's own conversing style

CH02_01 Fake/Real

1 = Fake
7 = Real
-9 = Not answered

CH02_02 Inauthentic/Authentic

1 = Inauthentic
7 = Authentic
-9 = Not answered

CH02_03 Common/Unique

1 = Common
7 = Unique
-9 = Not answered

CH02_04 A sham/Genuine

1 = A sham
7 = Genuine
-9 = Not answered

CH02_05 Run-off- the-mill/Original

1 = Run-off- the-mill
7 = Original
-9 = Not answered

CH02_06 The same as other character.ai users' Chatbot/Tuned to my preferences

1 = The same as other character.ai users' Chatbot
7 = Tuned to my preferences
-9 = Not answered

CH02_07 Able to communicate only generally/Able to communicate with it's own conversing style

1 = Able to communicate only generally
7 = Able to communicate with it's own conversing style
-9 = Not answered

Page 10

UG02

8. To what extent do you agree with the following statements about your experience using your character.ai chatbot?

Please answer the question regarding your personal experience.

I use my chatbot because it’s a new way to do research.

- Strongly Agree
- Agree
- Somewhat agree
- Neutral
- Somewhat Disagree
- Disagree
- Strongly disagree

I use my chatbot because it’s an easier way to obtain information.

- Strongly Agree
- Agree
- Somewhat agree
- Neutral
- Somewhat Disagree
- Disagree
- Strongly disagree

I use my chatbot to look for information.

- Strongly Agree
- Agree
- Somewhat agree
- Neutral
- Somewhat Disagree
- Disagree
- Strongly disagree

UG02_01 I use my chatbot because it's a new way to do research.
UG02_02 I use my chatbot because it's an easier way to obtain information.
UG02_03 I use my chatbot to look for information.

1 = Strongly disagree
2 = Disagree
3 = Somewhat Disagree
4 = Neutral
5 = Somewhat agree
6 = Agree
7 = Strongly Agree
-9 = Not answered

Page 11

UG01

9. To what extent do you agree with the following statements about your experience using your character.ai chatbot?

Please answer the question regarding your personal experience.

Using my chatbot is entertaining.

- Strongly Agree
- Agree
- Somewhat agree
- Neutral
- Somewhat Disagree
- Disagree
- Strongly disagree

Using my chatbot is fun.

- Strongly Agree
- Agree
- Somewhat agree
- Neutral
- Somewhat Disagree
- Disagree
- Strongly disagree

Using my chatbot is exciting.

- Strongly Agree
- Agree
- Somewhat agree
- Neutral
- Somewhat Disagree
- Disagree
- Strongly disagree

I use my chatbot because it passes time when bored.

- Strongly Agree
- Agree
- Somewhat agree
- Neutral
- Somewhat Disagree
- Disagree
- Strongly disagree

I use my chatbot when I have nothing better to do.

- Strongly Agree
- Agree
- Somewhat agree
- Neutral
- Somewhat Disagree
- Disagree
- Strongly disagree

I use my chatbot to occupy my time.

- Strongly Agree
- Agree
- Somewhat agree
- Neutral
- Somewhat Disagree
- Disagree
- Strongly disagree

UG01_01 Using my chatbot is entertaining.
UG01_02 Using my chatbot is fun.
UG01_03 Using my chatbot is exciting.
UG01_04 I use my chatbot because it passes time when bored.
UG01_05 I use my chatbot when I have nothing better to do.
UG01_06 I use my chatbot to occupy my time.

1 = Strongly disagree
2 = Disagree
3 = Somewhat Disagree
4 = Neutral
5 = Somewhat agree
6 = Agree
7 = Strongly Agree
-9 = Not answered

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UG03

10. To what extent do you agree with the following statements about your experience using your character.ai chatbot?

Please answer the question regarding your personal experience.

Using chatbots like character.ai is more efficient than other forms of communication.

- Strongly Agree
- Agree
- Somewhat agree
- Neutral
- Somewhat Disagree
- Disagree
- Strongly disagree

Chatbots save a tremendous amount of time.

- Strongly Agree
- Agree
- Somewhat agree
- Neutral
- Somewhat Disagree
- Disagree
- Strongly disagree

Using chatbots like character.ai can save more time than making a call with a human.

- Strongly Agree
- Agree
- Somewhat agree
- Neutral
- Somewhat Disagree
- Disagree
- Strongly disagree

UG03_01 Using chatbots like character.ai is more efficient than other forms of communication.
UG03_02 Chatbots save a tremendous amount of time.
UG03_03 Using chatbots like character.ai can save more time than making a call with a human.

1 = Strongly disagree
2 = Disagree
3 = Somewhat Disagree
4 = Neutral
5 = Somewhat agree
6 = Agree
7 = Strongly Agree
-9 = Not answered

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UG04

11. To what extent do you agree with the following statements about your experience using your character.ai chatbot?

Please answer the question regarding your personal experience.

Using my chatbot gives me the feedback I need from others.

Strongly Agree

Agree

Somewhat agree

Neutral

Somewhat Disagree

Disagree

Strongly disagree

My chatbot understands me better than other people.

Strongly Agree

Agree

Somewhat agree

Neutral

Somewhat Disagree

Disagree

Strongly disagree

My chatbot improves my ability to communicate with others.

- Strongly Agree
- Agree
- Somewhat agree
- Neutral
- Somewhat Disagree
- Disagree
- Strongly disagree

I use my chatbot to express myself freely.

- Strongly Agree
- Agree
- Somewhat agree
- Neutral
- Somewhat Disagree
- Disagree
- Strongly disagree

I use my chatbot to share my input.

- Strongly Agree
- Agree
- Somewhat agree
- Neutral
- Somewhat Disagree
- Disagree
- Strongly disagree

I use my chatbot to get more points of view.

- Strongly Agree
- Agree
- Somewhat agree
- Neutral
- Somewhat Disagree
- Disagree
- Strongly disagree

UG04_02 Using my chatbot gives me the feedback I need from others.

UG04_01 My chatbot understands me better than other people.

UG04_03 My chatbot improves my ability to communicate with others.

UG04_04 I use my chatbot to express myself freely.

UG04_05 I use my chatbot to share my input.

UG04_06 I use my chatbot to get more points of view.

1 = Strongly disagree
2 = Disagree
3 = Somewhat Disagree
4 = Neutral
5 = Somewhat agree
6 = Agree
7 = Strongly Agree
-9 = Not answered

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P101

12. How would you describe your overall experience interacting with your character.ai chatbot? Please rate your feelings about your interactions with the character.ai chatbot based on the following statements.

Please answer the question.

I care about what happens to my chatbot.

- Strongly Agree
- Agree
- Somewhat agree
- Neutral
- Somewhat Disagree
- Disagree
- Strongly disagree

Chatbot interactions are similar to mine with friends.

- Strongly Agree
- Agree
- Somewhat agree
- Neutral
- Somewhat Disagree
- Disagree
- Strongly disagree

Chatbot interactions are similar to mine with family.

- Strongly Agree
- Agree
- Somewhat agree
- Neutral
- Somewhat Disagree
- Disagree
- Strongly disagree

I can relate to the chatbot’s attitudes.

- Strongly Agree
- Agree
- Somewhat agree
- Neutral
- Somewhat Disagree
- Disagree
- Strongly disagree

My chatbot is like my friend.

- Strongly Agree
- Agree
- Somewhat agree
- Neutral
- Somewhat Disagree
- Disagree
- Strongly disagree

When I interact with my chatbot, I feel a sense of human contact.

- Strongly Agree
- Agree
- Somewhat agree
- Neutral
- Somewhat Disagree
- Disagree
- Strongly disagree

When I interact with my chatbot, I feel as if I was dealing with a real person

- Strongly Agree
- Agree
- Somewhat agree
- Neutral
- Somewhat Disagree
- Disagree
- Strongly disagree

When I interact with my chatbot, I feel there is a sense of sociability.

- Strongly Agree
- Agree
- Somewhat agree
- Neutral
- Somewhat Disagree
- Disagree
- Strongly disagree

When I interact with my chatbot, I feel there is a sense of human sensitivity.

- Strongly Agree
- Agree
- Somewhat agree
- Neutral
- Somewhat Disagree
- Disagree
- Strongly disagree

P101_01 I care about what happens to my chatbot.
P101_02 Chatbot interactions are similar to mine with friends.
P101_03 Chatbot interactions are similar to mine with family.
P101_04 I can relate to the chatbot's attitudes.
P101_05 My chatbot is like my friend.
P101_06 When I interact with my chatbot, I feel a sense of human contact.
P101_07 When I interact with my chatbot, I feel as if I was dealing with a real person
P101_08 When I interact with my chatbot, I feel there is a sense of sociability.
P101_09 When I interact with my chatbot, I feel there is a sense of human sensitivity.

1 = Strongly disagree
2 = Disagree
3 = Somewhat Disagree
4 = Neutral
5 = Somewhat agree
6 = Agree
7 = Strongly Agree
-9 = Not answered

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A101

13. When reflecting on your interactions with the chatbot, to what extent do you agree with the following statements about your relationship with it?

Please answer the question according to your feelings about your character.ai chatbot.

I feel attached to my chatbot.

- Strongly Agree
- Agree
- Somewhat agree
- Neutral
- Somewhat Disagree
- Disagree
- Strongly disagree

I feel an emotional bond to my chatbot.

- Strongly Agree
- Agree
- Somewhat agree
- Neutral
- Somewhat Disagree
- Disagree
- Strongly disagree

I feel emotionally connected to my chatbot.

- Strongly Agree
- Agree
- Somewhat agree
- Neutral
- Somewhat Disagree
- Disagree
- Strongly disagree

A101_01 I feel attached to my chatbot.
A101_02 I feel an emotional bond to my chatbot.
A101_03 I feel emotionally connected to my chatbot.

1 = Strongly disagree
2 = Disagree
3 = Somewhat Disagree
4 = Neutral
5 = Somewhat agree
6 = Agree
7 = Strongly Agree
-9 = Not answered

SD01

14. What is your gender?

- Female
- Male
- Other

SD01 Gender

1 = Female
2 = Male
3 = Other
-9 = Not answered

SD03

15. How old are you?

[Please choose]

SD03 Age

13 = 14 to 17 years old
2 = 18 to 24 years old
3 = 25 to 34 years old
4 = 35 to 44 years old
5 = 45 to 54 years old
6 = 55 to 64 years old
12 = 65 years or older
-9 = Not answered

SD11

16. What is your highest educational achievement?

Please select the highest level of qualification you have obtained.

- ◯ No formal education
- ◯ Primary education (e.g., elementary or primary school)
- ◯ Secondary education (e.g., high school, secondary school)
- ◯ Vocational/technical training
- ◯ Associate degree (e.g., two-year degree)
- ◯ Bachelor’s degree (e.g., four-year degree)
- ◯ Master’s degree (e.g., postgraduate degree)
- ◯ Doctorate/Ph.D. degree (e.g., highest academic degree)
- ◯ Other

SD11 Education

1 = No formal education
2 = Primary education (e.g., elementary or primary school)
3 = Secondary education (e.g., high school, secondary school)
4 = Vocational/technical training
5 = Associate degree (e.g., two-year degree)
6 = Bachelor's degree (e.g., four-year degree)
7 = Master's degree (e.g., postgraduate degree)
8 = Doctorate/Ph.D. degree (e.g., highest academic degree)
9 = Other
-9 = Not answered

SD08

17. Which country are you currently living in?

[Country:]

SD08 Country

1001 = Apsny
4 = Afghanestan
8 = Albania
10 = Antarctica
12 = Algeria
16 = American Samoa
20 = Andorra
24 = Angola
660 = Anguilla
28 = Antigua and Barbuda
32 = Argentina
51 = Armenia
533 = Aruba
36 = Australia
40 = Austria
31 = Azerbaijan
44 = Bahamas
48 = Bahrain
50 = Bangladesh
52 = Barbados
112 = Belarus
56 = Belgium
248 = Åland Islands
84 = Belize
204 = Benin
60 = Bermuda
64 = Bhutan
68 = Bolivia
535 = Caribbean Netherlands
70 = Bosnia and Herzegovina
72 = Botswana
76 = Brasil
74 = Bouvet Islands
92 = British Virgin Islands
96 = Brunei
86 = British Indian Ocean Territory
854 = Burkina Faso
104 = Burma
108 = Burundi
116 = Cambodia
120 = Cameroons
124 = Canada
132 = Cape Verde
136 = Cayman Islands
140 = Central African Republic
148 = Chad
152 = Chile
156 = China
166 = Cocos Islands
170 = Colombia
174 = Comoros
178 = Republic of the Congo
180 = Democratic Republic of the Congo
184 = Cook Islands
188 = Costa Rica
384 = Côte d'Ivoire
191 = Croatia
192 = Cuba
531 = Curaçao
196 = Cyprus
203 = Czech Republic
208 = Denmark
262 = Djibouti
212 = Dominica
214 = Dominican Republic
626 = East Timor
218 = Ecuador
818 = Egypt
222 = El Salvador
226 = Equatorial Guinea
232 = Eritrea
233 = Estonia
231 = Ethiopia

238 = Falkland Islands
234 = Faroe Island
583 = Federated States of Micronesia
242 = Fiji
246 = Finland
250 = France
254 = French Guiana
258 = French Polynesia
260 = French Southern Territories
266 = Gabon
270 = Gambia
268 = Georgia
276 = Germany
288 = Ghana
292 = Gibraltar
300 = Greece
304 = Greenland
308 = Grenada
312 = Guadeloupe
316 = Guam
320 = Guatemala
831 = Guernsey
324 = Guinea
624 = Guinea-Bissau
328 = Guyana
332 = Haiti
334 = Heard and McDonald Islands
[...]
-9 = Not answered

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DA06

18. If you have any questions, feedback or something else that you would like to share with us, feel free to leave a comment. Thank you for your time!

DA06_01 [01]

Free text

Page 20

DA02

Dear participant!

Thank you very much for taking part! You are helping us to find out more about Human-Chatbot interactions and relationships.

You have now reached the end of the questionnaire. If you have any questions about the content, purpose or research ethics of this survey, please contact a01407802@unet.univie.ac.at. If you are interested in the results of the survey, please contact a01407802@unet.univie.ac.at.

Please click on "Next" at the bottom right – only then will the questionnaire be completed and your data saved.

Thank you again for your time and effort!

If you use SurveyCircle, you can redeem your points through this link: www.surveycircle.com/15VS-TSAE-Z2RP-PT9K/
or this code:15VS-TSAE-Z2RP-PT9K

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