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It's a Match! The effects of chatbot anthropomorphization and chatbot gender on consumer behavior☆

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ABSTRACT

Chatbots are increasingly used as substitutes for human service agents in online shops. This has led researchers to analyze how chatbot characteristics influence consumer responses. However, while the relevance of chatbot characteristics has been examined, to date, consumers' personalities have remained unattended in the research on this innovative mode of online support. Therefore, this study aims to understand how the interaction of consumer characteristics and chatbot characteristics influences consumer behavior. In doing so, we focus on how chatbots' visual cues (i.e., anthropomorphization, gender) influence consumer behavior while also considering consumers' self-concept. To answer the research question, we first conceptually discuss why consumer behavior depends on perceived self-congruence between consumers and a chatbot, which can be reached by anthropomorphizing chatbots and giving them the "right" gender. Subsequently, based on multiple studies, we empirically test the hypotheses considering male, female, and non-binary consumers. Our results demonstrate the relevance of both chatbot anthropomorphization and chatbot gender.

1. Introduction

The ongoing progress of information and communication technology has led to a shift in consumption from traditional brick-and-mortar retailing to online retailing (Massey et al., 2007; Nguyen et al., 2018). Companies have reacted to this shift by expanding their online retailing activities (e.g., expanding their online shopping platforms) (Karray & Sigué, 2018). However, despite the efforts that have been invested in the expansion of online activities, online retailing, unlike brick-and-mortar retailing, cannot provide the direct face-to-face customer service that can be provided by human service agents. Direct customer service (e.g., providing product information, answering customer questions) is nevertheless crucial because service agents influence the overall success of a brand (Balmer & Greyser, 2006; Fionda & Moore, 2009; Kim & Ko, 2012). In addition, direct customer service plays a particularly important role in an online environment, as consumers expect to receive information quickly and easily in an on-demand and real-time environment where everything seems just a click away. If they do not receive the information they seek, consumers will become frustrated and move to a competitor that offers them the online experience they are looking for. For this reason, brands have begun to implement digital technologies, particularly those based on artificial intelligence, to substitute human service agents on their online retailing platforms (Looney et al., 2008).

More precisely, digital service chatbots that aim to provide customer services and substitute human service agents have gained particular popularity and are already used by many companies in various industries (Go & Sundar, 2019). These chatbots are mainly based on artificial intelligence and tend to be voice-driven or text-based dialog systems that enable consumer interactions by using natural language (Sheehan et al., 2020). In sum, human service agents aim to meet customer requirements in face-to-face brick-and-mortar retailing, while on online retailing platforms, chatbots act as virtual service agents to support customers with their concerns and carry out specific and complex tasks autonomously (Pantano & Pizzi, 2020).

Therefore, chatbots can play a dominant role in the online shopping experience not only by helping customers find their way around a company's website or complete a purchase but also by accompanying them in various ways throughout the different stages of the customer journey. In the pre-purchase phase, for example, chatbots can use

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predictive modeling to check the availability of products that match consumers' predicted preferences. In the purchase phase, chatbots can introduce customers to certain special offers, while in the post-purchase phase, they can inform customers about the delivery process (Selamat & Windasari, 2021). Studies that have investigated the influence of chatbots on consumer behavior have shown that their use strengthens the customer-brand relationship (Trivedi, 2019). Furthermore, the results of Lo Presti et al. (2021) show that interaction with a chatbot positively influences consumer purchase intention, which is why they recommend that retailers integrate chatbots into their websites to stimulate consumers' purchase intention.

Despite the positive effects of chatbots on consumer behavior and their other advantages (e.g., 24/7 availability, low-cost service, customer-tailored assistance) (Pantano & Pizzi, 2020; Yoon et al., 2013), many consumers are skeptical about the use of chatbots because they often do not meet consumers' expectations (Araujo, 2018; Diederich et al., 2020; Sheehan et al., 2020). For example, customers often perceive digital service chatbots as too artificial (Sheehan et al., 2020). Consequently, to understand how chatbots and their characteristics influence consumer behavior, the research has begun to analyze the effects of chatbot characteristics on consumer responses. This work has obtained empirical support for the positive effects of anthropomorphic chatbot design cues (i.e., chatbot anthropomorphization) on consumer behavior outcomes (De Cicco et al., 2020; Go & Sundar, 2019; Roy & Naidoo, 2021; Sheehan et al., 2020; Yen & Chiang, 2020). For example, anthropomorphism can be manipulated by designing chatbots with human figures (i.e., visual cues) or naming them with human-associated names (i.e., identity cues). Furthermore, conversational cues (e.g., language style) can also be manipulated to increase perceived anthropomorphization (see, e.g., Go & Sundar, 2019). Examples of how chatbots can be designed and anthropomorphized are shown in Fig. 1.

In general, the previous research has indicated that the positive effect of chatbot anthropomorphization on consumer behavior can be explained by consumers' increased perceptions of social presence, which means that with chatbot anthropomorphization, consumers perceive a higher presence of another person in their chatbot interaction, which in turn positively influences consumer behavior (De Cicco et al., 2020; Go & Sundar, 2019). Our study thus aims to provide new relevant knowledge, as previous studies have not taken consumers' personality (i.e., self-concept) into account, and we know from an impressive stream of research that consumer behavior is strongly dependent on consumers' self-concept and the perceived congruence of their own self-concept and another entity's self-concept (Bekk et al., 2016; Malär et al., 2018; Malär et al., 2011), which leads to the question of whether chatbots' visual cues (i.e., anthropomorphization and gender) should match consumers' self-concept.

In this regard, Feine, Gnewuch, Morana, and Maedche (2019) revealed that most of the chatbots available in customer service are in some way designed according to the female gender (e.g., female names, female looking avatars), which is in line with a recent UNESCO report (West et al., 2019). However, to the best of our knowledge, there is no comprehensive study to date that confirms that consumers prefer chatbots designed with female gender cues to chatbots with male gender cues or chatbots without gender-related design cues. Ultimately, due to the ongoing progress in information and communication technology, it can be expected that this question will become increasingly relevant, as the relevance of artificial agents will increase and thus will have a sustaining impact on consumers' shopping habits, which is why human-chatbot interactions should be given further attention in research.

To shed light on this gap in the research, this study seeks to answer the following questions. First, do consumers compare themselves with online store chatbots, which are based on artificial intelligence? Second, do brands create self-congruence between consumers and chatbots through chatbot anthropomorphization? The previous research has supported the positive effect of chatbot anthropomorphization on consumer behavior due to social presence, while this article aims to show that chatbot anthropomorphization increases the perceived similarity between human beings and chatbots, which in turn is supposed to positively affect consumer behavior. Third, do consumers' have a preferred chatbot gender? By considering the gender with which consumers identify, we obtain new evidence on this question. Based on the development of the fundamental understandings and various treatments of gender and gender identity in recent years, we provide evidence based on samples with male, female, and non-binary consumers. We first provide the theoretical underpinnings of the hypotheses by addressing these issues and identifying the influence of congruence theory in the context of chatbots. Then, we empirically test our hypotheses based on multiple studies (one cross-sectional study and three experiments). We conclude the study by discussing the academic implications for ongoing research and practical implications for online retailers.

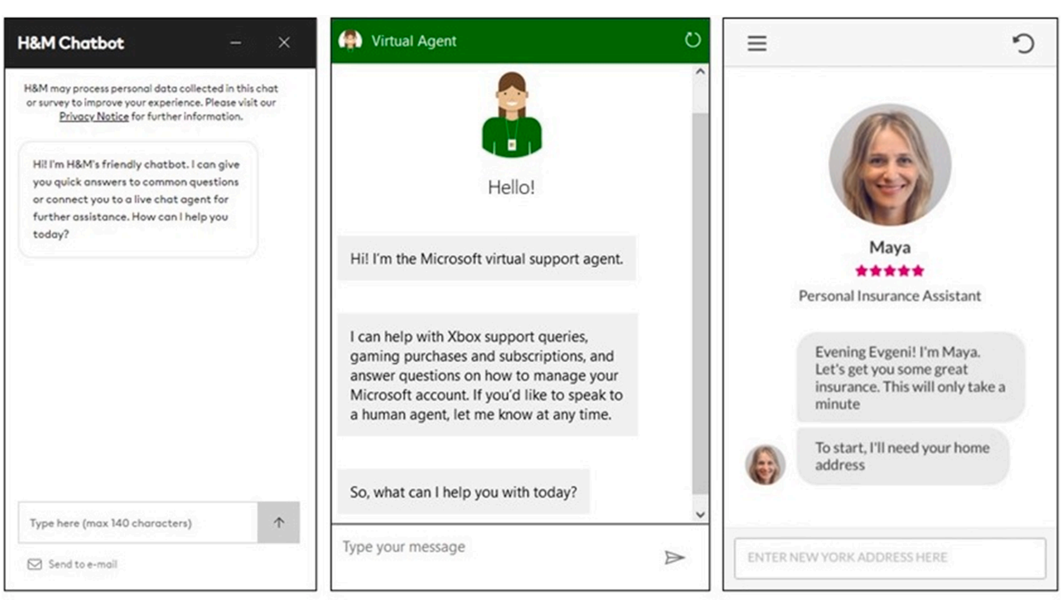

Fig. 1. Screenshot examples of real-world chatbot designs from different companies (Hennes & Mauritz AB; Microsoft Corporation; Lemonade Inc.).

2. Theoretical and conceptual background

The recent research examining the influence of chatbot anthropomorphization on consumer behavior has indicated that the theoretical foundation of chatbot anthropomorphization can be found in the concept of animism (Araujo, 2018; Go & Sundar, 2019; Melián-González et al., 2021; Sheehan et al., 2020). According to the animism concept, people tend to humanize inanimate objects and fill them with life. This human need serves the purpose of interacting with the inanimate object since the presence of human characteristics facilitates interaction with this entity. (Epley et al., 2007; Gilmore, 1919). In this process, the degree of anthropomorphization varies from the transfer of single human character traits to the transfer of a complete human personality (Eichen, 2010).

Epley et al. (2007) state that this tendency is based on multiple psychological processes that include both cognitive and motivational aspects. Furthermore, they find three key determinants (elicited agent knowledge, effectance motivation, and sociality motivation) that explain why individuals anthropomorphize objects. Elicited agent knowledge as a primary determinant of anthropomorphism focuses on the accessibility and applicability of anthropocentric knowledge and justifies anthropomorphic tendencies by the fact that knowledge of humans is generally more abundant than knowledge of nonhuman agents. For this reason, elicited agent knowledge is applied by humans to understand the behavior of nonhuman agents. The second determinant, effectance motivation, is the motive to explain and understand the behavior of the nonhuman agent and is motivated by the desire to effectively interact with one's environment. The attribution of human characteristics improves the understanding of nonhuman agents and thereby reduces uncertainty in the interaction and enables better anticipation of future behavior. Finally, the third determinant, sociality motivation, is the desire to establish social connections and social affiliation, whereby the humanization of nonhuman agents enables the development of social connections.

In general, the characteristics (i.e., features) that contribute to the perceived humanization of nonhuman entities can be very versatile. In the case of a robot, its physical appearance, i.e., the presence of human features such as a head, body, or legs, already increases the perceived anthropomorphization. In addition, nonphysical features such as the gaze, gestures, speech flow, or facial expressions of a robot can also lead to higher perceived anthropomorphization (Blut et al., 2021). In the context of chatbots, various studies emphasize the importance of anthropomorphism in consumer behavior and provide empirical evidence for the positive effect of chatbot anthropomorphization on behavioral outcomes (De Cicco et al., 2020; Go & Sundar, 2019; Roy & Naidoo, 2021; Sheehan et al., 2020). However, the design elements of a nonhuman entity (i.e., chatbot) that could trigger consumers' perceived anthropomorphism are more limited in number for text-based chatbots than, for example, a robot that can be equipped with arms, legs, a face, and a human voice, since the design elements must be integrated into the small chat window. To investigate the effect of chatbot anthropomorphization, the authors created chatbots with various anthropomorphic design cues (e.g., visual cues, identity cues, and conversational cues) (see, e.g., De Cicco et al., 2020; Go & Sundar, 2019; Roy & Naidoo, 2021). For example, De Cicco et al. (2020) used conversational cues to anthropomorphize chatbots and showed that a social-oriented interaction style leads to a more favorable attitude toward chatbots than a task-oriented interaction style. Furthermore, Roy and Naidoo (2021) showed that the anthropomorphic design cues perceived by consumers in response to a chatbot's interaction style (i.e., warm vs competent) influence their attitude and product purchase intention.

In support of and in addition to Epley et al.'s (2007) theory of why human beings anthropomorphize inanimate objects, it has been found that the positive influence of chatbot anthropomorphization on consumer behavior can be explained by the perception of social presence (De Cicco et al., 2020; Go & Sundar, 2019), which describes consumers' perceptions of the conspicuousness of another entity during an interaction (Short et al., 1976). That is, anthropomorphic design cues increase the perception of the conspicuousness of another entity in an interaction and thereby strengthen the perception of social presence (Go & Sundar, 2019).

This behavior of humanizing chatbots and perceiving them as social entities should eventually drive consumers' need to compare themselves with a chatbot because human beings tend to humanize entities such as brands or digital services and then compare their own self-concept with the entity's self-concept (Karjaluoto et al., 2019; Sirgy et al., 1991). Such comparison underlies the concept of self-congruence, which is described as the perceived similarity between one's own self-concept and the self-concept of another individual or object (Sirgy et al., 1991; Zogaj, Tscheulin, & Olk, 2021). Thus, considering that humans generally feel closer to personified objects (e.g., brands) (Malär et al., 2011), and given that they have greater knowledge of other humans (Epley et al., 2007), the anthropomorphization of chatbots should positively influence perceived self-congruence between consumers and chatbots.

This idea is also supported by construal-level theory, which explains that the psychological distance to an entity influences one's perceptions and behaviors (Trope et al., 2007). That is, a smaller psychological distance is positively related to one's own and present self (Malär et al., 2011; Tan et al., 2019). Thus, considering that consumers are human beings, chatbot anthropomorphization should increase the psychological closeness between consumers and chatbots, which is why it can be expected that perceived chatbot anthropomorphization positively influences the perceived similarity (i.e., self-congruence) between consumers and chatbots. Therefore, hypothesis H1 is postulated as follows:

H1: Perceived chatbot anthropomorphization positively affects perceived self-congruence between consumers and chatbots.

The importance of self-congruence and its positive effects on behavioral outcomes in several contexts (e.g., brands and products, tourism, retailing, donating) has been demonstrated in a plethora of studies (Zhu et al., 2019; Luna-Cortés et al., 2019; Hedhli, Zourrig, & Park, 2017; Zogaj et al., 2021). Moreover, Karjaluoto et al. (2019) extended the congruence research in the digital context of mobile financial service apps and confirmed that self-congruence positively influences users' perceived values of mobile financial service apps. Summarizing the above considerations on the relationship between chatbot anthropomorphization, self-congruence, and consumer behavior, we hypothesize the following:

H2: Self-congruence mediates the effect of perceived chatbot anthropomorphization on purchase intentions.

When implementing a chatbot, companies can combine their brand logo with their brand name to embed the chatbot on their online platforms (see, e.g., https://www.tesla.com/de_de/modely), which would ultimately have a neutral appearance. However, if brands subsequently seek to anthropomorphize their chatbots, they can, for example, replace their brand logo and their brand name with a combination of an image of a human service agent (i.e., visual cue) and a human-associated name (i.e., identity cue). This approach not only results in an increased perception of a more human-like chatbot (see, e.g., Go & Sundar, 2019), but it also provides consumers with an indication of the chatbot's gender. However, although recent research has provided evidence for the positive influence of chatbot anthropomorphization on consumer behavior (see, e.g., De Cicco et al., 2020; Go & Sundar, 2019; Roy & Naidoo, 2021; Sheehan et al., 2020), there is a lack of comprehensive research results regarding consumers' gender preference in the context of (anthropomorphized) chatbots.

In this regard, some studies have shown that the gender of the chatbot can influence consumer behavior (Beldad et al., 2016; Brahnam & De Angeli, 2012; Hone, 2006; McDonnell & Baxter, 2019). For example, Brahnam and De Angeli (2012) show that the gender of the chatbot can influence how consumers interact and communicate with the chatbot. Furthermore, the results of Beldad et al. (2016) reveal that matching chatbot gender with product gender influences consumer behavior. More specifically, matching the gender of the chatbot and that of the product (e.g., male chatbot advice on a male-associated product) has a positive influence on consumers' belief in the credibility of the product-related advice and their purchase intention. However, to the best of the authors' knowledge, there has been no evidence for consumers' gender preference in conjunction with consumers' gender in the context of chatbots.

Thus, to close this gap in the research, we draw on self-congruence theory. As explained above, to evaluate perceived self-congruence with a chatbot, consumers compare their self-concept with the perceived self-concept of the chatbot. For this, consumers need cues that give them information about the chatbot's self-concept. When companies design their chatbots and present the chatbot with an avatar of a human service agent and a human-associated name, they provide consumers with different cues. Subsequently, consumers rely on their evaluations of the perceived similarity between their own self-concept and the perceived self-concept of the chatbot based on these cues. However, since gender is a central part of consumers' self-concept (Grohmann, 2009) and only a few visual cues about the chatbot's self-concept are available (i.e., an image of a human service agent and a human-associated name), it seems plausible that the indication of the chatbot's gender will become a salient cue for evaluating consumers' perceived similarity with the chatbot.

Thus, considering that humans generally feel more similar to other humans of the same gender because they are naturally more similar to them (i.e., psychological closeness), it can be expected that gender congruence has a positive influence on consumer behavior. This is in line with the findings of van den Hende and Mugge (2014), which show that gender-schema congruity has a positive effect on consumers' product evaluations. Therefore, in the context of anthropomorphized chatbots, female and male consumers are supposed to perceive greater congruence with chatbots that represent their gender compared to chatbots that represent another gender or are designed to be gender-neutral. In turn, again, as demonstrated above, it can be expected that perceived self-congruence positively affects consumer behavior, which is why we hypothesize the following:

H3: The effect of a female-designed chatbot on purchase intentions via self-congruence is stronger than the effect of a **a)** neutral-designed or **b)** male-designed chatbot on female consumers' purchase intentions via self-congruence.

H4: The effect of a male-designed chatbot on purchase intentions via self-congruence is stronger than the effect of a **a)** neutral-designed or **b)** female-designed chatbot on for male consumers' purchase intentions via self-congruence.

In recent years, criticism of the binary gender system has emerged that has led to a fundamental development of the understanding and treatment of gender and gender identity. The reason for this criticism lies in the "lived experience of people who perceive themselves as not fitting into either the female or the male gender role, and on the observation that most cultures and historical eras have been and are aware of individuals who by body, behavior, and/or identity do not conform to the binary sex/gender system" (Meyer-Bahlburg, 2019, p. 2028). As a result, many people have chosen to avoid conventional binary gender expression (i.e., male and female) and have opted for an expression that better reflects their true identity (i.e., non-binary). Consequently, several nations have started to offer not only the binary categories male and female for official state documents but also a non-binary gender option (Elias & Colvin, 2020).

More specifically, "non-binary" is an umbrella term that is used to describe a variety of gender identities, thereby expanding the exclusively binary understanding of gender (Chew et al., 2020). According to Matsuno and Budge (2017, p. 2-3), the term non-binary refers to "(a) an individual whose gender identity falls between or outside male and female identities, (b) an individual who can experience being a man or woman at separate times, or (c) an individual who does not experience having a gender identity or rejects having a gender identity". Furthermore, consumers who identify as non-binary and thus do not exclusively identify as male or female prefer to use gender-neutral pronouns (e.g., they/them/their or zie/hir/hirs) rather than exclusive binary (i.e., male or female) gender pronouns (i.e., him or her) (Budge et al., 2013; Matsuno & Budge, 2017).

Following this, consumer behavior research is not excluded from this fundamental development of the understanding and treatment of gender and gender identity as an increasing number of consumers identify as neither male nor female. Furthermore, "researchers in the social sciences are rarely interested in the physiological/bodily aspects (i.e., genitalia, chromosomes, bodily attributes) or legal gender but are more often interested in how individuals identify or express themselves from a social perspective" (Lindqvist et al., 2020, p. 10). Consequently, the consumer behavior research should consider the developments with regard to the understanding and treatment of gender. Therefore, the present study aims to investigate consumers' gender preference for chatbots for non-binary consumers. In doing so, we draw on self-congruence theory and further suggest operationalizing gender as a two-dimensional construct, which can be divided into the gender assigned at birth (i.e., sex) and the gender with which the consumer identifies.

Thus, when considering consumers who identify as non-binary; prefer not to be categorized into exclusively binary gender groups (i.e., male or female) and use gender-neutral pronouns, it can be expected that these consumers will perceive a greater closeness with a chatbot designed with neither male nor female gender characteristics but a neutral one. Therefore, non-binary consumers are expected to perceive a higher similarity with chatbots that are neutral than with male-designed or female-designed chatbots. However, the gender assigned at birth should not be disregarded here because one is not only born with one's gender assigned at birth, but one is also raised with it. In this regard, empirical studies show that the gender assigned at birth has an influence on people's behavior as perceived gender equality has a positive effect on an individual's evaluations of people and objects (Hende and Mugge, 2014; Karjaluoto et al., 2019). Furthermore, considering the positive effect of self-congruence on consumer behavior, we hypothesize the following:

H5: The effect of a neutral chatbot on purchase intentions via self-congruence is stronger than the effect of a female-designed chatbot on purchase intentions via self-congruence for consumers with an assigned female gender at birth who identify as non-binary.

H6: The effect of a neutral chatbot on purchase intentions via self-congruence is stronger than the effect of a male-designed chatbot on purchase intentions via self-congruence for consumers with an assigned male gender at birth who identify as non-binary.

3. Study 1

3.1. Methodology

To test hypotheses H1 and H2, we first conducted a cross-sectional study based on chatbot-consumer conversation scenarios among online shoppers. We began the study by asking the respondents whether they had previously shopped online. We excluded 70 respondents who had not shopped online before to ensure that we had online respondents with online shopping experience. Next, we described a short online shopping situation and asked the respondents to imagine that they had just opened the website of the online shop ABC to buy summer trousers. We used a fictitious brand (i.e., ABC) to eliminate confounding preexisting brand associations. Trousers were used as the product category because fashion has become the largest e-commerce segment (Rotar, 2020). Next, the respondents were instructed to imagine that a so-called service chatbot, i.e., a virtual sales assistant, appeared to answer any of their questions. Afterward, we showed the respondents a customer-chatbot conversation on a product consultation (see web appendix Figures A and B) and asked them to imagine that they had just had the conversation with the chatbot. To eliminate effects that could occur due to chatbot name or chatbot sex, we used a neutral chatbot image without an apparent gender or name. This procedure reflects common practice as many companies (see, e.g., Tesla) use their brand name as a chatbot name and their brand logo as a chatbot avatar. After the respondents read the conversation, we first asked them whether they understood what a chatbot was. If a respondent's answer was no, he or she was removed from the study. Overall, 58 respondents said no. Next, an attention check followed. We asked the respondents to report the price of the trousers they had chosen. A total of 249 gave an incorrect answer and were excluded from the study. This was not a surprise as panel participants – we collected data via Qualtrics – very often have low attention when filling out questionnaires, which is why it is usually recommended to use such attention checks. Finally, 210 respondents remained in the sample and answered the questionnaire completely.

The data were collected in summer 2020 via the online panel provider Qualtrics (https://www.qualtrics.com). Since we aimed to examine the effects for online shoppers, we collected data according to the age and sex distribution of German online shoppers from 18 to 64 years. The sample was structured as follows: 18–24 years: 6.2 % female and 6.2 % male; 25–34 years: 11.0 % female and 10.5 % male; 35–44 years: 10.0 % female and 10.0 % male; 45–54 years: 12.9 % female and 12.9 % male; and 55–64 years: 10.5 % female and 10.0 % male. Overall, the average age was 41.7 years (median = 41.5 years), and 50.5 % of the respondents were female.

The constructs used were previously validated by other studies (see Table 1); nonetheless, we estimated psychometric properties to ensure validity (see Table 2). In addition, the participants reported their sex, age, and attitudes toward online shopping (control variables).

Table 1
Constructs used in Studies 1–4.

Construct	Items
Anthropomorphization (Study 1 & Study 2) Based on Bartneck, Croft, Kulic and Zoghbi (2009)	Please indicate your impression of the service chatbot based on the following characteristics. 1 = machinelike to 7 = manlike 1 = artificial to 7 = lifelike
Self-congruence (Study 1 to Study 4) Based on Malär et al. (2018) and Malär et al. (2011)	Please take a moment to think about the service chatbot. Think about the personality of the service chatbot. Imagine the service chatbot in your thoughts and describe it with personality characteristics (e.g., character traits, personality traits, appearance). Now please think about how you see yourself (your actual self) . What kind of person are you? How would you describe your personality? Then, indicate your agreement or disagreement with the following statements. (1 = strongly disagree to 7 = strongly agree). The personality of the service chatbot is consistent with how I see myself (my actual self) .The personality of the service chatbot is a mirror image of me (my actual self)
Purchase intentions (Study 1 to Study 4) Based on Collier and Bienstock (2006)	To what extent do the following statements apply to your behavioral intentions? (1 = strongly disagree to 7 = strongly agree). I intend to continue to visit this e-retailer's site in the future. I intent to purchase from this e-retailer in the future.
Attitudes toward online shopping (Study 1 to Study 4) Based on Jarvenpaa et al. (1999)	To what extent do the following statements apply to your online shopping attitudes? (1 strongly disagree to 7 = strongly agree). The idea of using the internet to shop is appealing. I like the idea of using the internet to shop.

3.2. Results

Before assessing the hypotheses, we conducted a reliability analysis in SPSS 27 and a confirmatory factor analysis in AMOS 27 to test construct validity and the model's goodness of fit. Both the Cronbach's alpha values and composite reliability (CR) values were greater than 0.800 (anthropomorphization: α = 0.906 and CR = 0.906; self-congruence: α = 0.894 and CR = 0.897; purchase intentions: α = 0.932 and CR = 0.932; attitudes toward online shopping: α = 0.863 and CR = 0.868), indicating internal consistency (Cortina, 1993). Furthermore, as presented in Table 2, the AVE values were greater than 0.50 and greater than the MSV values. Furthermore, the Fornell-Larcker criterion was met as the square root of the AVE values was greater than the correlations among the constructs. Thus, there were no discriminant validity concerns (Hair et al., 2010). Moreover, the HTMT analysis indicated that there were no discriminant validity concerns as all values were smaller than 0.85 (Franke & Sarstedt, 2019; Henseler et al., 2015).

Next, we assessed the model's goodness of fit based on statistics recommended by Byrne (2016). The chi-square/degrees of freedom ratio value was 1.833 ($\chi 2$ = 25.667; df = 14) and thus lower than the threshold of 3.0. The standardized root mean-square residual (SRMR) value was 0.019 ($<$0.05). The comparative fit index (CFI) value (0.990), the incremental fit index (IFI) value (0.990), and the Tucker-Lewis index (TLI) value (0.981) were greater than the threshold of 0.95. Finally, the root mean-square error of approximation (RMSEA) was 0.063 ($<$0.08), and the p of close fit was 0.258 (greater than0.05), also indicating an appropriate model fit.

To test H1 and H2, we estimated the effect of perceived anthropomorphization (independent variable) on purchase intentions (dependent variable) via self-congruence (mediator) using PROCESS model 6 (Version 3.5) based on 10,000 bootstrap samples and a 95 % confidence interval (CI) (see Hayes, 2018). Sex, age, and attitudes toward online shopping were considered control variables. The results indicated that perceived chatbot anthropomorphization positively influences self-congruence between human beings and chatbots (c = 0.646; 95 % CI [0.521, 0.771]). Thus, hypothesis H1 is supported. Self-congruence, in turn, had a positive direct effect on purchase intentions (c = 0.275; 95 % CI [0.166, 0.384]). Consequently, the indirect effect of perceived chatbot anthropomorphization on purchase intentions via self-congruence was significant and positive (c' = 0.178; 95 % CI [0.095, 0.269]), supporting hypothesis H2. Moreover, with respect to the control variables, sex (c = -0.028; 95 % CI [-0.304, 0.249]) and age (c = -0.008; 95 % CI [-0.018, 0.003]) did not affect purchase intentions, while attitudes toward online shopping had a positive effect on purchase intentions (c = 0.363; 95 % CI [0.250, 0.478]). Overall, the variables explained 52.27 % of the variance in purchase intentions.

4. Study 2

4.1. Methodology

The second study was conducted to verify the causality of H1 and H2, as we solely assumed causality in Study 1 but did not test for causality. Thus, in this study, we tested the model using an experimental between-subject design instead of a cross-sectional survey design. Moreover, we collected the data in China instead of Germany to extend the generality of Study 1. In accordance with Study 1, we again questioned respondents who had previously shopped online. Overall, we excluded 15 respondents who answered that they had not previously shopped online. However, to extend generality, the respondents were asked to imagine that they were buying headphones (instead of trousers). Headphones were used as the product category because electronics and media have

Table 2
Construct validity.

Construct	Mean	SD	AVE	MSV	F1	F2	F3	F4
Anthropomorphization (F1)	4.471	1.460	0.828	0.450	**0.910**	(0.665)	(0.660)	(0.323)
Self-congruence (F2)	3.841	1.571	0.814	0.450	*0.671****	**0.902**	(0.604)	(0.175)
Purchase intentions (F3)	4.781	1.435	0.873	0.437	*0.661****	*0.600****	**0.934**	(0.515)
Att. tow. Online shopping (F4)	5.495	1.265	0.768	0.259	*0.337****	*0.188**	*0.509****	**0.876**

Note: SD = standard deviation; AVE = average variance extracted; MSV = maximum shared variance; in bold: square root of the AVE; in italics: correlations between constructs; in brackets: HTMT Analysis; significance: *p <.05, **p <.01, ***p <.001.

become one of the largest e-commerce segments (Rotar, 2020). Furthermore, we again used the fictitious brand ABC to eliminate confounding preexisting brand associations.

The experimental design was based on three service conversation scenarios instead of one conversation scenario to be able to manipulate chatbot anthropomorphization. The content of the three conversation scenarios was identical and corresponded to the conversation scenario of Study 1. That is, the three scenarios differed only in the appearance (visual cue and identity cue) of the chatbot. In the first scenario (control group), the chatbot was not anthropomorphized (i.e., it was the same neutral chatbot as in Study 1; see web appendix Figures C and D). In the second scenario, the chatbot was anthropomorphized using a female name and a female image (see web appendix Figures E and F). In the third scenario, the chatbot was again anthropomorphized, however, using a male name and a male image (see web appendix Figures G and H). Women were shown the neutral scenario or the anthropomorphized female scenario, and men were shown the neutral scenario or the anthropomorphized male scenario. We decided to show women (men) the female (male) chatbot to eliminate sex effects, as we were (at least in Study 2) not interested in interaction effects but in the main effects of anthropomorphization on consumer behavior. In doing so, we randomly set the order of the scenarios (neutral vs anthropomorphized female or neutral vs anthropomorphized male) for each respondent.

Next, the respondents were instructed to imagine that a service chatbot appeared to answer any questions they had. Afterward, we showed the respondents the respective customer-chatbot conversation on a product consultation and asked them to imagine that they just had the conversation with the chatbot. After the respondents read the respective conversation, we first asked them whether they understood what a chatbot was. If a respondent's answer was no, he or she was removed from the study. Overall, two respondents said no. Next, an attention check followed. We asked the respondents to answer how expensive the headphones they had chosen were. A total of 164 respondents gave an incorrect answer and were excluded from the study. Finally, 226 respondents remained in the final sample and answered the questionnaire.

The data were collected in summer 2020 (convenience sample) via the messaging and social media app WeChat (https://www.wechat.com). The sample was structured as follows: 18–24 years: 17.7 % female and 4.0 % male; 25–34 years: 19.9 % female and 18.1 % male; 35–44 years: 9.7 % female and 11.5 % male; 45–54 years: 7.1 % female and 9.7 % male; 55–64 years: 0.4 % female and 1.8 % male. Overall, the average age was 33.5 years (median = 30.0 years), and 54.9 % of the respondents were female.

The constructs used were the same as in Study 1 and are thus presented in Table 1. However, nonetheless, we again estimated both a reliability analysis and a confirmatory factor analysis to verify construct validity and model fit. Finally, the participants reported their age and attitudes toward online shopping (control variables). As women and men saw different conversation scenarios, we decided to run two separate analyses.

4.2. Results

Before assessing the hypotheses, we ran a reliability analysis in SPSS 27 and a confirmatory factor analysis in AMOS 27 to test construct validity and the model's goodness of fit. Both the Cronbach's alpha values and CR values for all constructs were greater than 0.8 (perceived anthropomorphization $\alpha = 0.917$ and CR = 0.918; self-congruence: $\alpha = 0.927$ and CR = 0.930; purchase intentions: $\alpha = 0.964$ and CR = 0.964; attitudes toward online shopping: $\alpha = 0.932$ and CR = 0.936), indicating internal consistency (Cortina, 1993). Furthermore, as presented in Table 3, the AVE values were greater than 0.50 and greater than the MSV values. The Fornell-Larcker criterion was met as the square root of the AVE values was greater than the correlations among the constructs. Thus, there were no discriminant validity concerns (Hair et al., 2010). Moreover, the HTMT analysis also indicated that there were no discriminant validity concerns as all values were smaller than 0.85 (Franke & Sarstedt, 2019; Henseler et al., 2015).

Next, we assessed the model's goodness of fit based on statistics recommended by Byrne (2016). The chi-square/degrees of freedom ratio value was 1.409 ($\chi2 = 19.729$; df = 14) and thus lower than the threshold of 3.0. The SRMR value was 0.015 (<0.05). The CFI value (0.997), IFI value (0.997), and TLI value (0.993) were greater than the threshold of 0.95. Finally, the RMSEA was 0.043 (<0.08), and the p of close fit was 0.570 (greater than0.05), also indicating an appropriate model fit.

With respect to testing the hypotheses, we estimated the results separately for women and men, as we showed women the anthropomorphized female and neutral chatbots and men the anthropomorphized male and neutral chatbots (the aim was to eliminate sex effects that might occur due to the different sexes of the chatbot and the respondent, which, in turn, will be analyzed in Studies 3 and 4). Before assessing the hypotheses, we conducted two ANOVAs (anthropomorphized female chatbot vs neutral chatbot and anthropomorphized male chatbot vs neutral chatbot) to assess whether female (male) respondents perceived the anthropomorphized female (anthropomorphized male) chatbot to be more anthropomorphized than the neutral chatbot. As shown in Table 4, ANOVA results indicated that the female respondents perceived the anthropomorphized female chatbot (5 % significance level) as more anthropomorphic than the neutral chatbot, and the male respondents perceived the anthropomorphized male chatbot (10 % significance level) as more anthropomorphic than the neutral chatbot.

4.2.1. Female group

To test hypotheses H1 and H2, we considered the type of chatbot (binomial variable) as an independent variable and coded the neutral chatbot as "0″ and the anthropomorphized female chatbot as "1", as we expected the anthropomorphized female chatbot to have positive effects on the respective factors. Then, we estimated the effect on purchase intentions (dependent variable) via perceived anthropomorphization (mediator 1) and self-congruence (mediator 2) using PROCESS model 6 (Version 3.5) based on 10,000 bootstrap samples and a 95 % CI (see Hayes, 2018). Age and attitudes toward online shopping were considered control variables. The results indicated that anthropomorphizing the chatbot positively influenced perceived anthropomorphization (c =

Table 3
Construct validity.

Construct	Mean	SD	AVE	MSV	F1	F2	F3	F4
Anthropomorphization (F1)	5.058	1.612	0.849	0.474	0.921	(0.694)	(0.617)	(0.336)
Self-congruence (F2)	4.385	1.724	0.869	0.474	0.689***	**0.932**	(0.670)	(0.245)
Purchase intentions (F3)	5.270	1.419	0.930	0.453	*0.621****	**0.673****	**0.964**	(0.560)
Att. tow. Online shopping (F4)	6.000	1.188	0.879	0.307	0.346***	0.248***	0.554***	**0.938**

Note: SD = standard deviation; AVE = average variance extracted; MSV = maximum shared variance; in bold: square root of the AVE; in italics: correlations between constructs; in brackets: HTMT Analysis; significance: ***p <.001.

Table 4
Manipulation check.

Scenario	N	Mean	df	F	Mean square	Sig.
Female respondents	124					
Neutral chatbot	66	4.364	1	39.611	70.919	0.000
Female chatbot	58	5.879				
Male respondents	102					
Neutral chatbot	46	4.696	1	3.465	9.890	0.066
Male chatbot	56	5.321				

1.451; 95 % CI [1.012, 1.889]). Furthermore, perceived anthropomorphization has a positive effect on self-congruence (c = 0.576; 95 % CI [0.384, 0.769]). Thus, hypothesis H1 was supported. Self-congruence, in turn, had a positive direct effect on purchase intentions (c = 0.387; 95 % CI [0.265, 0.509]). Consequently, the indirect effect of anthropomorphizing the chatbot on purchase intentions via perceived anthropomorphization (mediator 1) and self-congruence (mediator 2) was significant and positive (c' = 0.323; 95 % CI [0.150, 0.573]), supporting hypothesis H2. Moreover, with respect to the control variables, age (c = -0.018; 95 % CI [-0.036, 0.001]) had no effect on purchase intentions, while attitudes toward online shopping had a positive effect on purchase intentions (c = 0.554; 95 % CI [0.414, 0.694]). Overall, the variables explained 62.13 % of the variance in purchase intentions. Finally, similar to Study 1, Study 2 (female group) confirmed our hypotheses.

4.2.2. Male group

To test hypotheses H1 and H2, we considered the type of chatbot (binomial variable) as an independent variable and coded the neutral chatbot as "0″ and the anthropomorphized male chatbot as "1". Then, we estimated the effect on purchase intentions (dependent variable) via perceived anthropomorphization (mediator 1) and self-congruence (mediator 2) using PROCESS model 6 (Version 3.5) based on 10,000 bootstrap samples and a 95 % CI (see Hayes, 2018). Age and attitudes toward online shopping were considered control variables. The results indicated that anthropomorphizing the chatbot positively influences perceived anthropomorphization (c = 0.824; 95 % CI [0.233, 1.414]). Furthermore, perceived anthropomorphization has a positive effect on self-congruence between human beings and chatbots (c = 0.645; 95 % CI [0.470, 0.820]).

Thus, hypothesis H1 was supported. Self-congruence, in turn, had a positive direct effect on purchase intentions (c = 0.358; 95 % CI [0.207, 0.509]). Consequently, the indirect effect of anthropomorphizing the chatbot on purchase intentions via perceived anthropomorphization and self-congruence was significant and positive (c' = 0.190; 95 % CI [0.028, 0.372]), supporting hypothesis H2. Moreover, with respect to the control variables, age (c = 0.004; 95 % CI [-0.017, 0.025]) had no effect on purchase intentions, while attitudes toward online shopping had a positive effect on purchase intentions (c = 0.341; 95 % CI [0.166, 0.516]). Overall, the variables explained 57,04 % of the variance in purchase intentions. Finally, similar to Study 2 (female group) and Study 1, Study 2 (male group) confirmed our hypotheses.

5. Study 3

5.1. Methodology

The third study was conducted to test hypotheses H3 and H4. To this end, we carried out an experiment (between-subject design) with data from Germany. Again, we questioned only respondents who had previously shopped online. Overall, we excluded 60 respondents who had never shopped online. As in Study 1, we opted for trousers as the purchase item because fashion is the largest e-commerce segment (Rotar, 2020). As before, we again used the fictitious brand ABC to eliminate confounding preexisting brand associations.

The experimental design was based on three service conversation scenarios in which we manipulated chatbot gender. The content of the three conversation scenarios was identical. That is, the three scenarios differed only in the appearance (i.e., visual cue and identity cue) of the chatbot. In the first scenario, the chatbot was neutral (i.e., no gender) (see web appendix Figures I and J). In the second scenario, we used a female chatbot, that is, the chatbot had a female name and a female avatar (see web appendix Figures K and L). In the third scenario, a male name and a male avatar were used (see web appendix Figures M and N). Unlike in Study 2, both women and men were shown in all scenarios (i.e., neutral chatbot, female chatbot, and male chatbot). This procedure enabled us to examine the relevance of chatbot gender. In doing so, we randomly set the order of the scenarios (neutral vs female vs male) for both men and women for each respondent. Next, the respondents were instructed to imagine that a service chatbot appeared to answer any questions they may have. Afterward, we showed the respondents the respective customer-chatbot conversation on a product consultation and asked them to imagine that they just had the conversation with the chatbot. After the respondents read the respective conversation, we first asked them whether they understood what a chatbot was. If a respondent's answer was no, he or she was removed from the study. Overall, 31 respondents said no. Next, an attention check was conducted. Unlike in Study 2, we were interested in gender effects, which is why we asked the respondents to identify the chatbot's gender. A total of 49 respondents responded incorrectly and were excluded from the study. Finally, 420 respondents remained in the final sample and answered the questionnaire.

The data were collected at the beginning of 2021 via the online panel provider Qualtrics. Since we aimed to examine the effects for online shoppers, we collected the data according to the age and sex distribution of German online shoppers from 18 to 64 years. The sample was structured as follows: 18–24 years: 6.7 % female and 6.4 % male; 25–34 years: 11.2 % female and 10.2 % male; 35–44 years: 10.2 % female and 9.8 % male; 45–54 years: 12.4 % female and 12.1 % male; and 55–64 years: 11.2 % female and 9.8 % male. Overall, the average age was 41.1 years (median = 41.0 years), and 51.7 % of the respondents were female.

Specifically, the female group (N = 217) consisted of 74 respondents who saw the female chatbot, 74 respondents who saw the male chatbot, and 69 respondents who saw the neutral chatbot. The male group (N = 203) consisted of 66 respondents who saw the male chatbot, 70 who saw the female chatbot, and 67 respondents who saw the neutral chatbot.

The constructs used were the same as in the previous study and are thus presented in Table 1. Again, we estimated a reliability analysis and a confirmatory factor analysis to verify construct validity and model fit. Finally, the participants reported their age and attitudes toward online shopping (control variables).

5.2. Results

Before assessing the hypotheses, we ran a reliability analysis in SPSS 27 and a confirmatory factor analysis in AMOS 27 to test construct validity and the model's goodness of fit. Both the Cronbach's alpha values and CR values for all constructs were greater than 0.8 (self-congruence: $\alpha = 0.886$ and CR = 0.888; purchase intentions: $\alpha = 0.938$ and CR = 0.938; attitudes toward online shopping: $\alpha = 0.820$ and CR = 0.821), indicating internal consistency (Cortina, 1993). Furthermore, as presented in Table 5, the AVE values were greater than 0.50 and greater than the MSV values. The Fornell-Larcker criterion was met as the square root of the AVE values was greater than the correlations among the constructs. Thus, there were no discriminant validity concerns (Hair et al., 2010). Moreover, the HTMT analysis also indicated that there were no discriminant validity concerns, as all values were smaller than 0.85 (Franke & Sarstedt, 2019; Henseler et al., 2015).

Next, we assessed the model's goodness of fit based on statistics recommended by Byrne (2016). The chi-square/degrees of freedom ratio value was 2.211 ($\chi2 = 13.266$; df = 6) and thus lower than the threshold of 3.0. The SRMR value was 0.013 (<0.05). The CFI value (0.995), IFI value (0.995), and TLI value (0.988) were greater than the threshold of 0.95. Finally, the RMSEA was 0.054 (<0.08), and the p of close fit was 0.381 (greater than0.05), also indicating an appropriate model fit.

With respect to testing the hypotheses, we estimated the results separately for women and men, as we were interested in whether women perceive greater self-congruence between themselves and a female chatbot than with a neutral or male chatbot and whether men perceive greater self-congruence between themselves and a male chatbot than with a neutral or female chatbot. A manipulation check to test whether the respondents perceived, for example, the male chatbot as more male than the female chatbot was not needed, as we had asked the respondents (see attention check above) whether the chatbot was male, female, or neutral (no gender).

5.2.1. Female group

To test H3a and H3b, we considered the type of chatbot (multi-categorial indicator variable) as an independent variable and coded the female chatbot (here: control group) as "0″, the male chatbot (here: experimental group) as "1", and the neutral chatbot (here: experimental group) as "2". This procedure is recommended by Hayes (2018), who shows that a multicategorial group with "*g*" categories (here: 3 groups) can be used as an independent indicator in a regression model if it is represented by "*g-1*" variables coding the control group (here: female chatbot) as "0" and coding each other group as a distinct indicator. Next, these "*g-1*" variables are treated as the causal independent variable in a mediation model, and the results are given as relative effects. More information regarding mediation analysis with a multicategorial independent variable is given in Hayes and Preacher (2014). As this analysis requires coding the control group as "0" (here, female chatbot for female consumers), the coefficients will be negative if a match regarding gender has positive effects. Then, we estimated the effect on purchase intentions (dependent variable) via self-congruence (mediator variable) using PROCESS model 4 (Version 3.5) based on 10,000 bootstrap samples and a 95 % CI (see Hayes, 2018). Age and attitudes toward online shopping were considered control variables.

The results indicated that both the male chatbot (c = -0.701; 95 % CI [-1.182, -0.220]) and the neutral chatbot (c = -0.833; 95 % CI [-1.332, -0.333]) had a significantly lower effect than the female chatbot on self-congruence between female subjects and the respective chatbot. Self-congruence, in turn, had a positive direct effect on purchase intentions (c = 0.460; 95 % CI [0.342, 0.577]). Consequently, the relative indirect effects of the male chatbot (c = -0.322; 95 % CI [-0.574, -0.108]) and the neutral chatbot (c = -0.383; 95 % CI [-0.650, -0.146]) on purchase intentions via self-congruence were significant and negative. Thus, both hypotheses H3a and H3b can be supported so that it can be stated that the effect of a female chatbot on purchase intentions via self-congruence is stronger than the effect of a male or a neutral chatbot on purchase intentions via self-congruence for female consumers. Moreover, with respect to the control variables, age (c = -0.002; 95 % CI [-0.015, 0.011]) had no effect on purchase intentions, while attitudes toward online shopping had a positive effect on purchase intentions (c = 0.538; 95 % CI [0.397, 0.680]), as in previous studies. Overall, the variables explained 35,92 % of the variance in purchase intentions. For the sake of completeness, we also ran a mediation analysis to test whether the male chatbot had a different effect on purchase intentions via self-congruence than the neutral chatbot. The results showed no significant difference.

5.2.2. Male group

To test H4a and H4b, we considered the type of chatbot to be an independent variable and coded the male chatbot (here: control group) as "0″, the female chatbot (here: experimental group) as "1", and the neutral chatbot (here experimental group) as "2". Then, we estimated the effect on purchase intentions (dependent variable) via self-congruence (mediator variable) using PROCESS model 4 (Version 3.5) based on 10,000 bootstrap samples and a 95 % CI (see Hayes, 2018). Age and attitudes toward online shopping were considered control variables.

The results indicated that both the female (c = -0.660; 95 % CI [-1.119, -0.201]) and the neutral (c = -0.581; 95 % CI [-1.044, -0.117]) chatbots had a significantly lower effect than the male chatbot on self-congruence between male subjects and the respective chatbot. Self-congruence, in turn, had a positive direct effect on purchase intentions (c = 0.487; 95 % CI [0.365, 0.608]). Consequently, the relative indirect effects of the female chatbot (c = -0.321; 95 % CI [-0.584, -0.099]) and the neutral chatbot (c = -0.283; 95 % CI [-0.537, -0.067]) on purchase intentions via self-congruence were significant and negative. Thus, hypotheses H4a and H4b can be supported so that it can be stated that the effect of a male chatbot on purchase intentions via self-congruence is stronger than the effect of a female or a neutral chatbot on purchase intentions via self-congruence for male consumers. Moreover, with respect to the control variables, again, age (c = -0.010; 95 % CI [-0.023, 0.002]) had no effect on purchase intentions, while attitudes toward online shopping had a positive effect on purchase intentions (c = 0.400; 95 % CI [0.252, 0.548]). Overall, the variables explained 34,42 % of the variance in purchase intentions. For the sake of completeness, we again ran a mediation analysis to test whether the female chatbot had a

Table 5
Construct validity.

Construct	Mean	SD	AVE	MSV	F1	F2	F3
Self-congruence (F1)	3.663	1.470	0.799	0.250	**0.894**	(0.501)	(0.014)
Purchase intentions (F2)	4.780	1.516	0.938	0.250	*0.500****	**0.940**	(0.410)
Att. tow. online shopping (F3)	5.770	1.167	0.697	0.167	*-0.019*	*0.409****	**0.835**

Note: SD = standard deviation; AVE = average variance extracted; MSV = maximum shared variance; in bold: square root of the AVE; in italics: correlations between constructs; in brackets: HTMT Analysis; significance: ***p <.001.

different effect on purchase intentions via self-congruence than the neutral chatbot. The results showed no significant difference.

6. Study 4

6.1. Methodology

The fourth study was conducted to test hypotheses H5 and H6 and is thus based on non-binary respondents. To this end, we carried out an experiment (between-subject design) with data from the USA, Australia and the UK, as it was difficult to collect data across non-binary consumers. Basically, this experiment was very similar to Study 3 – that is, trousers were the buying item, and "ABC" the brand used. However, in contrast to the previous experiment, we aimed to collect data from non-binary consumers, which is why we additionally had to determine whether those individuals were born as female or male (i.e., sensitive data). Thus, we first asked the respondents with which gender they identify (i.e., female, male, or non-binary). If they answered "female" or "male", they were excluded from the study. If they answered "non-binary", we went on to ask them to identify their sex at birth. Here, the respondents were able to opt not to answer the question.

At the start of the data collection, we asked Qualtrics to collect 420 questionnaires (210 female-born respondents: 70 neutral chatbot, 70 male chatbot, and 70 female chatbot; 210 male-born respondents: analog). Qualtrics responded that this demographic is not easily accessible. Thus, we decided to show female-born respondents only the neutral and female chatbots and the male-born respondents only the neutral and male chatbots. The main research aim was to understand whether non-binary consumers prefer a chatbot that matches their sex at birth or the gender with which they identify. The content of the three conversation scenarios was identical and corresponded to the conversation scenario of Study 3. That is, as in Study 3, the scenarios differed only in the appearance (i.e., visual cues and identity cues) of the chatbot (see web appendix Figures I to N). This procedure enabled us to examine whether chatbot gender matters. In doing so, we randomly set the order of the scenarios (neutral vs female and neutral vs male).

As in previous studies, we only questioned respondents who had previously shopped online. Overall, we excluded 84 respondents who had never shopped online. Next, the respondents were instructed to imagine that a service chatbot appeared to answer any of their questions. Afterward, we showed the respondents the respective customer-chatbot conversation on a product consultation and asked them to imagine that they just had the conversation with the chatbot. After the respondent read the respective conversation, we first asked them whether they understood what a chatbot was. If a respondent's answer was no, he or she was removed from the study. Overall, seven respondents said no. Next, an attention check followed. As in Study 3, we asked the respondents to identify the perceived gender of the chatbot. A total of 80 respondents gave an incorrect answer and were excluded from the study.

Finally, 165 respondents remained in the final sample and answered the questionnaire; only 32 of those respondents were born as male. With this small number of non-binary subjects with a male gender assigned at birth, no reliable model can be estimated, which is why we made the decision to not include male-born subjects in our further study. At this point, we sought to collect more data (several boosts in different countries); however, our cooperation partner (market research institute) informed us that further data could not be collected because they had already tried in three relevant countries (USA, Australia, the UK), and they had reached the limits of the data. In the future, however, it can be expected that the number of persons with a male gender assigned at birth but who identify as non-binary will grow, which is why future research can focus even more on this group. Thus, we were able to test H5 but not H6. Therefore, 133 respondents remained in the final sample, of which 66 saw the female and 67 the neutral chatbot scenario. The data were collected at the beginning of 2021 via the online panel provider Qualtrics. Since the data collection was restricted, we opted for a convenience sample. The sample was structured as follows: 13–17 years: 26.3 %; 18–24 years: 48.1 %; 25–34 years: 20.3 %; and 35–44 years: 5.3 %. Overall, the average age was 21.7 years (median = 20.0 years).

The constructs used were the same as in the previous study and are thus presented in Table 1. Again, we estimated a reliability analysis and a confirmatory factor analysis to verify construct validity and model fit. Finally, the participants reported their age and attitudes toward online shopping (control variables).

6.2. Results

Before assessing the hypotheses, we ran a reliability analysis in SPSS 27 and a confirmatory factor analysis in AMOS 27 to test construct validity and the model's goodness of fit. Both the Cronbach's alpha values and CR values for all constructs were greater than 0.8 (self-congruence: $\alpha = 0.828$ and CR = 0.876; purchase intentions: $\alpha = 0.917$ and CR = 0.927; attitudes toward online shopping: $\alpha = 0.902$ and CR = 0.969), indicating internal consistency (Cortina, 1993). Furthermore, as presented in Table 6, the AVE values were greater than 0.50 and greater than the MSV values. The Fornell-Larcker criterion was met as the square root of the AVE values was greater than the correlations among the constructs. Thus, there were no discriminant validity concerns (Hair et al., 2010). Moreover, the HTMT analysis also indicated that there were no discriminant validity concerns, as all values were smaller than 0.85 (Franke & Sarstedt, 2019; Henseler et al., 2015).

Next, we assessed the model's goodness of fit based on statistics recommended by Byrne (2016). The chi-square/degrees of freedom ratio value was 1.369 ($\chi2 = 8.214$; df = 6) and thus lower than the threshold of 3.0. The SRMR value was 0.035 (<0.05). The CFI value (0.995), IFI value (0.995), and TLI value (0.987) were greater than the threshold of 0.95. Finally, the RMSEA was 0.053 (<0.08), and the p of close fit was 0.408 (greater than0.05), also indicating an appropriate model fit.

A manipulation check to test whether the respondents perceived the female chatbot as more female than the neutral chatbot was not needed, as we had asked the respondents (see attention check above) whether the chatbot was female or neutral (no gender). To test H5, we considered the type of chatbot (binomial variable) as an independent variable and coded the female chatbot as "0″ and the neutral chatbot as "1", as we expected the neutral chatbot to have positive effects on the respective factors. Then, we estimated the effect on purchase intentions (dependent variable) via self-congruence using PROCESS model 4 (Version 3.5) based on 10,000 bootstrap samples and a 95 % CI (see Hayes, 2018). Age and attitudes toward online shopping were considered control variables.

The results indicated that the neutral chatbot had a significantly stronger effect than the female chatbot on self-congruence between female-born subjects who identified as non-binary and the respective chatbot based on only a 90 % CI. Thus, we decided to run the model based on a 90 % CI (c = 0.415; 95 % CI [-0.060, 0.889]). The new estimation indicated that the neutral chatbot had a significantly stronger effect than the female chatbot on self-congruence between female-born subjects and the respective chatbot (c = 0.415; 90 % CI [0.017, 0.812]). Self-congruence, in turn, had a positive direct effect on purchase intentions (c = 0.209; 90 % CI [0.079, 0.338]). Surprisingly, the indirect effect of the neutral chatbot on purchase intentions via self-congruence was not significant (c = 0.087; 90 % CI [-0.001, 0.234]). However, this is a very close miss and can be explained based on the "borderline effect" of the neutral chatbot vs female chatbot on self-congruence, which was only significant based on a 90 % CI. Thus, H5 can be supported only partially, so it can be stated that the effect of a neutral chatbot on purchase intentions via self-congruence is highly likely stronger than the effect of a female chatbot on purchase intentions via self-congruence for female-born consumers who do not identify with the male or female gender but that there is still a need for further research. Moreover, with

Table 6
Construct validity.

Construct	Mean	SD	AVE	MSV	F1	F2	F3
Self-congruence (F1)	3.737	1.384	0.788	0.077	**0.888**	(0.252)	(0.039)
Purchase intentions (F2)	4.910	1.294	0.864	0.077	*0.277**	**0.929**	(0.284)
Att. tow. online shopping (F3)	5.786	1.108	0.943	0.059	*0.000*	*0.242***	**0.971**

Note: SD = standard deviation; AVE = average variance extracted; MSV = maximum shared variance; in bold: square root of the AVE; in italics: correlations between constructs; in brackets: HTMT Analysis; significance: *p <.05; **p <.01.

respect to the control variables, age (c = -0.008; 90 % CI [-0.036, 0.021]) had no effect on purchase intentions, while attitudes toward online shopping had a positive effect on purchase intentions (c = 0.307; 90 % CI [0.147, 0.467]), consistent with previous studies. These effects (i.e., control variable effects) were also supported based on a 95 % CI. Overall, the variables explained 12.52 % of the variance in purchase intentions.

7. Discussion

Before discussing contributions, implications and limitations and future research ideas, an overview of the results can be found in Table 7.

7.1. Theoretical contribution

Previous studies have analyzed the effect of chatbot characteristics on consumer responses. This article extends this knowledge by considering not only chatbot characteristics but also consumer characteristics in terms of congruence between consumers and chatbots to present a more accurate picture of the relationships in the context of innovative online support. Specifically, the research on chatbot anthropomorphization has indicated that chatbot anthropomorphization positively influences consumer behavior (De Cicco et al., 2020; Go & Sundar, 2019; Sheehan et al., 2020), which is in line with the results of the present article. With our results, we extend the understanding by showing that the anthropomorphization of chatbots leads to an increased perception of similarity between consumers and chatbots (i.e., self-congruence), which positively affects consumer behavior. Thus, anthropomorphic design elements that increase perceived chatbot anthropomorphization (i.e., visual cues and identity cues) also increase consumer-chatbot self-congruence, which is why there is a positive effect of anthropomorphization on consumer behavior.

Table 7
Overview of results.

Hypotheses	Study	Effect
H1: Direct effect: chatbot anthropomorphization → self-congruence	Study 1 Study 2	Confirmed Confirmed
H2: Indirect effect: Chatbot anthropomorphization → self-congruence → purchase intentions	Study 1 Study 2	Confirmed Confirmed
H3a: Indirect effect female born consumers: Female-designed chatbot > neutral chatbot → self-congruence → purchase intentions	Study 3	Confirmed
H3b: Indirect effect female born consumers: Female-designed chatbot > male-designed chatbot → self-congruence → purchase intentions	Study 3	Confirmed
H4a: Indirect effect male born consumers: Male-designed chatbot > neutral chatbot → self-congruence → purchase intentions	Study 3	Confirmed
H4b: Indirect effect male born consumers: Male-designed chatbot > female-designed chatbot → self-congruence → purchase intentions	Study 3	Confirmed
H5: Indirect effect non-binary consumers born as female: Neutral chatbot > female-designed chatbot → self-congruence → purchase intentions	Study 4	Partially confirmed
H6: Indirect effect non-binary consumers born as male: Neutral chatbot > male-designed chatbot → self-congruence → purchase intentions	Study 4	Not tested

In addition, although a number of studies have shown that the gender of the chatbot can influence consumer behavior (see, e.g., Beldad et al., 2016; Brahnam & De Angeli, 2012; Hone, 2006; McDonnell & Baxter, 2019), this article is the first to provide comprehensive evidence for consumers' gender preference in conjunction with consumers' gender in the context of anthropomorphized chatbots. That is, consistent with the previous research, we show that consumers take gender into account when subconsciously evaluating the interaction with chatbots and that gender influences consumers' responses to anthropomorphized chatbots. In addition, our results show that chatbot gender influences consumers' responses to chatbots, with consumers preferring a gender congruent chatbot. More precisely, by drawing on self-congruence theory, we provide theoretical contributions to the previous chatbot literature by showing that female consumers feel more similarity with chatbots of their own gender (i.e., female chatbots) compared to neutrally or male-designed chatbots. Similarly, male consumers feel more similar to chatbots of their own gender (i.e., male chatbots) than to neutral chatbots or female chatbots, which then positively influences consumer behavior.

Furthermore, this study considers the development of the fundamental understandings and treatments of gender and gender identity in recent years, which have led people to avoid conventional binary gender expression (i.e., male and female) and opt for an expression that better reflects their true identity (e.g., non-binary). Following this development, we were the first study to provide insights concerning consumers' gender preference for anthropomorphized chatbots with a group of consumers who do not identify with the binary gender groups male and female (i.e., non-binary consumers). That is, we show that consumers with an assigned female gender at birth who identify as non-binary consumers perceive a higher perceived similarity with neutral chatbots compared to female chatbots, which then positively influences their consumer behavior.

7.2. Managerial implications

The first main contribution is related to chatbot anthropomorphization. That is, since chatbot anthropomorphization positively influences the perceived similarity between the consumer and the chatbot (i.e., self-congruence), which further positively affects consumers' purchase intentions, brands that intend to use chatbots on their online retailing platforms should design their chatbots with anthropomorphic design cues. Importantly, the present article presents customers' self-concepts as an important starting point for chatbot design cues. Thus, brands should use market research to examine the self-concept of their consumers and design the chatbot with anthropomorphic design cues that align with the target groups' self-concepts, as such a chatbot-consumer fit would positively influence consumers' purchase intentions.

The second main contribution is related to chatbot gender. Before jumping to practical conclusions, it should be considered that most chatbots available in customer service are designed based on female names and female avatars (Feine et al., 2019), even though there are also neutral chatbots, which are used by famous companies such as Tesla. A look at this study's results indicates that action is needed in this area, as our results show that a chatbot's gender should be chosen based on consumers' gender. Specifically, due to self-congruence reasons, male consumers prefer male chatbots, female consumers prefer female chatbots, and non-binary consumers prefer neutral chatbots. Consequently, we advocate that brands determine the respective gender of the customer who visits their online store. To accomplish this, brands have different options. For example, when a brand knows that the greatest share of its customers are female, then the brand should use a female chatbot. If a brand does not have this kind of information about how many of its customers are male, female, or non-binary, then the respective brand could ask for customers' gender when the consumer-chatbot conversation starts. Furthermore, customers' gender can also be predicted based on artificial intelligence. For example, Google (and most other large brands) collects plenty of individual data. To view one's collected data, users must simply go to https://www.google.com/dashboard in the URL line of their browser (they must be logged into their Gmail account). Based on these data, many brands can analyze what kind of person is using the respective device (e.g., smartphone, notebook). Finally, a consumer/chatbot gender match would increase the perception of self-congruence, which in turn would have a positive effect on purchase intentions.

7.3. Limitations and future research

At the outset, it should be noted that our study provides valuable implications both theoretically and practically; however, the results of our study should be interpreted considering the contrived nature of the data collection, which is typical for laboratory experiments. This results in the following limitations to our findings, which may serve as a starting point for future research efforts.

To humanize chatbots, in our experiments, we manipulated both the chatbot's image and the chatbot's name. That is why we could not assess whether the image or the name of the chatbot caused the effects on perceived anthropomorphization. Since we were interested in the effects of perceived anthropomorphization and not on the effect of different anthropomorphic design cues, this approach was suitable. However, to understand how individual humanization cues (e.g., visual cues vs identity cues) affect perceived anthropomorphization and self-congruence, future studies should change cues individually while keeping the others constant. Thus, it would be interesting for future research studies to compare the effect of various anthropomorphic cues, such as the chatbot's image, name, hair color, and writing style, on perceived overall chatbot anthropomorphization and on perceived self-congruence.

In our study, we aimed to investigate the influence of chatbot anthropomorphization on consumer behavior, which is why we compared, for example, a neutral chatbot with an anthropomorphized chatbot. However, it should be considered that as the degree of anthropomorphization increases, one runs the risk that while there might be a higher congruence due to the anthropomophization of the chatbot, at the same time there might be a reduction in congruence because the chatbot with its visual cues (e.g., hair color, skin color, assessors) no longer matches the consumer's self-concept. Future studies should therefore examine the extent to which pure anthropomorphization no longer plays a role, but rather congruence with visual cues becomes decisive in influencing consumer behavior.

Furthermore, while we have focused on consumer-chatbot congruence in this article, the question arises whether brand-chatbot congruence plays a role for consumer behavior. It is well known from other studies that congruence between brands and its representatives (e.g., service employees, influencer) can also have a positive impact on consumer behavior. Therefore, we recommend future studies to investigate the relevance of brand-chatbot congruence. More specifically, should a more female-perceived brand like Loreal use a female chatbot or a male chatbot (i.e., brand-chatbot congruence vs consumer-chatbot congruence) with its male customers?

The present study was able to confirm that the effect of a female chatbot on consumer behavior is stronger than the effect of a neutral or a male-anthropomorphized chatbot on consumer behavior for female consumers and vice versa for male consumers. However, a strict preference order (e.g., female chatbot > neutral chatbot > male chatbot for female consumers) could not be determined and may be the subject of future research. There are two possible arguments for the results: female (male) consumers did not perceive greater similarity with a male (female) chatbot than with a neutral chatbot.

On the one hand, female consumers may use the presented gender of the chatbot as a predominant reference point of their evaluation of perceived similarity. In this case, it could be assumed that female consumers feel the greatest perceived similarity with a female chatbot (as has been shown in this study). Subsequently, it could be assumed that the perceived similarity with the neutral chatbot is greater than the perceived similarity with the opposite gender (here: male chatbot), as a different gender could increase psychological distance.

On the other hand, female consumers may use the perceived humanity of the chatbot as the dominant reference point of their evaluation of perceived similarity. In this case, it could be assumed that female consumers still feel the highest perceived similarity with a female chatbot, since it has both a high perceived humanity and the same gender. Subsequently, it can be assumed that the perceived similarity with the male chatbot, as a human being, is higher than the perceived similarity with a neutral chatbot, which is perceived to be machine-like and thus less human-like. Future research could shed more light on this research question.

In the context of gender, this article provides the first insights into non-binary consumers' behavior regarding the perception of chatbots. However, although we tried (in cooperation with Qualtrics) to collect data from individuals born as male but who identify as non-binary in three countries (USA, Australia and the UK), it was not possible to collect a sufficient number of interviews, so we could not estimate a model and thus were not able to test H6. In the data collection process, we even undertook several boosts; however, we were told that this group of people is simply not yet sufficiently accessible. However, since it is a socially relevant topic and the gender identity debate is increasing, it is also relevant to examine this group. Therefore, in future research, we recommend focusing on this and being aware of the challenge of data collection. Otherwise, future research studies could first conduct qualitative studies in which a small sample is sufficient to determine how non-binary (male-born) persons perceive chatbots and to identify their preferences in this regard. Concerning non-binary individuals, another minor limitation should be discussed. In studies 1–3, we did not provide the option "non-binary" as gender option. However, in exchange with our data collection company, it turned out that this is negligible, since on the one hand, the general number of non-binary people in their panel is vanishingly small, while, on the other hand, people often simply drop out of a study when an option (e.g., a missing gender options such as non-binary) does not fit their characteristic.

Finally, it should be noted that depending on the entity with which one communicates, the expectations (and thus the fulfillment of expectations and the resulting satisfaction) can change. Therefore, it would be interesting to see if, for example, the expectations are significantly lower when communicating with a neutral chatbot than with an anthropomorphized chatbot. This can be assumed if one considers that self-congruence has a positive influence on perceptions and behaviors such as satisfaction (i.e., the stronger self-congruence, the higher the satisfaction), because if self-congruence generally has a positive effect due to perceived similarity, then, conversely, the expectation should be smaller if an entity such as a chatbot does not align with the individual (i.e., real self or ideal self). Therefore, if expectations are lower when communication with a neutral chatbot (e.g., because there is less self-congruence with a neutral chatbot and male/female individuals), then it should be easier to fulfill those expectations. If we next assume that the chatbot offers the same performance regardless of its appearance, it could be that a neutral chatbot is rated better due to lower expectations, which are related to less self-congruence and thus lead to greater consumer satisfaction.

CRediT authorship contribution statement

Adnan Zogaj: Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization, Writing – original draft, Writing – review & editing. **Philipp M. Mähner:** Methodology, Investigation, Conceptualization, Data curation, Visualization, Writing – original draft, Writing – review & editing. **Linyu Yang:** Data curation. **Dieter K. Tscheulin:** Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jbusres.2022.113412.

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