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EFFECTS OF ANTHROPOMORPHISM IN CHATBOTS ON CUSTOMER ENGAGEMENT

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Abstract
This study investigates the influence of chatbot anthropomorphism on customer engagement (CE) in a B2C context, with a particular focus on the mediating role of customer comfort (CC) and the moderating roles of Uncertainty Avoidance (UA) and Negative Attitudes Toward Chatbots (NACs). Using structural equation modeling, four out of five proposed hypotheses were supported. While the moderating effect of UA was not significant and thus excluded from the final model, NACs demonstrated a complex moderation pattern: diminishing the indirect effect of anthropomorphism (AP) on CE via CC, but enhancing it in the serial mediation pathway involving Social Presence (SP) and CC. These findings challenge prior assumptions and highlight the dualistic impact of NACs. Furthermore, SP emerged as a significant antecedent to CC, reinforcing and extending previous research (e.g., Becker et al., 2022), which initially rejected a positive link between SP and CC. The study confirms that higher levels of AP in chatbot design increase SP, which in turn boosts CC and ultimately CE. However, when users harbor negative predispositions toward chatbots, high AP and SP may paradoxically reduce CC and CE. Practical implications suggest that chatbot interfaces should aim for high anthropomorphism to mimic human interaction and enhance

engagement, but user attitudes must be considered for effective implementation.

Keywords: Chatbot Anthropomorphism, Customer Engagement, Customer Comfort, Social Presence, Uncertainty Avoidance, Negative Attitudes Toward Chatbots.

Introduction

In the current era, organizations value online communication at any time and from any location with their customers, as the current generation is spending more time in digital environments (Maroengsit et al., 2019). Customers in this digital age have the option of selecting from a variety of companies that provide the same service or product. As a result of this, consumers can afford to be picky (Suwono & Sihombing, 2016). Companies are continuously challenged to draw in new customers and keep existing ones, which helps to enhance customer satisfaction (McLean & Wilson, 2016). Online services play an essential part in customers' lives (McLean & Wilson, 2016). According to Siswi & Wahyono (2020), when you provide and fulfil the needs of customers, it helps you in gaining customer satisfaction. It has been observed for decades that customer satisfaction enhances customer loyalty and customer retention. (Brandtzaeg & Følstad, 2017).

Due to digital development and growing competition, companies are constantly challenged to retain and attract customers (Maroengsit et al., 2019). Nowadays, new customers are not ready to waste their time and therefore expect to reach the company or product physically at their local stores or markets. (Suwono & Sihombing, 2016). The purpose of the study is to provide insight into the role of chatbots by increasing customer engagement. The topic of the study is to know the "Effects of anthropomorphism in chatbots on customer engagement". For all these purposes, bots are introduced for the customers in this digital era (Ameen et al., 2021), to answer the queries and complaints of the customer proactively, resulting in the customer feeling confident and satisfied (Hallowell, 1996). By getting help and the right support on time from the chatbot, the customer's reliability on an organisation increases, which enhances customer loyalty (Research priorities 2020-2022 - MSI). Customers are the key players in increasing any business/market shares

(Innis & La Londe, 1994). While in the past, interaction was made between customer and organisation only through face-to-face contact or mass media, in the current digital era, technology has made it easier to reach your customers online all day long. This is the reason companies focus on being digitalized to meet their customer needs anytime and anywhere and keep in touch with their customers to provide them proper and complete guidance by satisfying online facility and experience (Crolic et al., 2021).

This study is conducted to investigate the psychological phenomenon of customers when they interact with anthropomorphic chatbots. This investigation focused on the social presence and customer comfort, which have a positive impact on customer engagement when a customer comes into contact with a chatbot and increases the level of anthropomorphism in the chatbot. Also, this study gauges the uncertainty avoidance and NARS to find the impact of these as moderators.

The antecedents to Customer Engagement in the context of Human-Chatbot Interaction will be discussed in detail in the next chapters. However, many studies have previously tried to understand the relation between the levels of Anthropomorphism in Chatbots and the levels of customer comfort during said interactions. In our study, in the light of these interactions, we attempt to comprehend the moderating impact of NACS & uncertainty avoidance, such that the role of the predispositions of the Customers plays in scenarios where chatbot interaction is underway. Thus, we try to understand one cultural aspect of the consumer and one personal aspect. Furthermore, we try to understand if Customer Comfort has an impact on enhancing the degree of Customer Engagement in the same context. Similarly, we gauge if the level of Anthropomorphism in Chatbots increases Customer Comfort during interactions. We also check if Social Presence plays any part in raising the level of Customer Comfort.

Thus, we can say that we try to establish new mediators & moderators to understand the relation between the Anthropomorphism in Chatbots & Customer Engagement.

Research Objectives

The main objective behind our research study is to analyze the effect of Anthropomorphism in chatbots on Customer Engagement, how people/customers feel when they interact with a chatbot during their online interaction, and how it gives meaningful social interaction to people. Our goal was to estimate the extent to which Anthropomorphism in chatbots and their interaction affected customer Engagement. The following are the objectives of our research:

•To illustrate how Anthropomorphism has a positive effect on social presence.

•To explain how Anthropomorphism affects customer comfort.

•To find out if Social Presence has a positive effect on the relation between Anthropomorphism & Customer comfort during a chatbot interaction.

•To analyze if NARS has a significant effect on the Customer Comfort during the chatbot interaction

•To explain the relation between Uncertainty Avoidance & higher Customer Engagement

The main purpose of our study is to examine the influence of anthropomorphism in chatbots on customer engagement, how people feel when they communicate with a chatbot, and how it will impact social contact. The organization employs innovative technologies, for example, chatbots, to collaborate and interface with customers/clients. Companies use technological innovations such as websites, mobile applications, chatbots, and social media to engage customers with their brand, creating a compelling customer experience. The working professional has embraced these technological breakthroughs to transfer and fulfil customer needs for growth in their business revenue. Banks use chatbots to interact with customers in auditory or textual format and for communication, for taking out slips, and for announcements at cash counters, etc. Students can take advantage of these technologies in their projects.

The research focuses on professionals (engineers, doctors, businesspersons, teachers, accountants, etc.) who are using chatbots on online platforms. The fact that chatbots offer rapid responses and instant responses is one of the reasons why clients favor them. There isn't a line of people waiting to get help, and there aren't any lengthy articles with images for customers to go through. Chat bots can solve customer concerns and queries in multiple languages. Their 24/7 access enables customers to use them regardless of time or time zone. Use of chat bots for is becoming an incredibly powerful tool for businesses to improve customer engagement and qualify leads with dynamic conversational capabilities. Our main purpose is to study the behaviour of such professionals in using chatbot services and find out the relation between anthropomorphism and customer engagement.

Literature Review

Customer Engagement

The strong competitiveness and the huge number of Products and brand availability with AI transformations have led marketers to understand that customers contribute more than just purchasing the products. (Brodie et al., 2011; Gupta et al., 2018; Kumar and Pansari, 2016). In today's world of technology transformation through different Media (Kumar and Pansari, 2016), organizations have an opportunity to connect with their customer outside the purchasing context with the help of different social media platforms (So et al., 2016). Online customer contribution has now been considered in the research. (Hollebeek et al., 2016; Malthouse, Calder, Kim, & Vanden Bosch, 2016). Due to this, customers not only contribute to any organization in the form of purchase but also from the views about their final product to others through communication on social media. (Gupta et al., 2018). It will be the start of a new era where customer engagement plays a vital role in any firm. (Kumar and Pansari, 2016).

Customer Engagement

Customer engagement has been widely studied as a dependent variable in the field of marketing and customer experience. According to a review by Kim and Ko (2012), customer engagement is defined as "a psychological state in which customers are emotionally, cognitively, and behaviorally involved in a product or service" (p. 3). This state of involvement is thought to lead to positive outcomes for both the customer and the company, including increased loyalty and good recommendations (Kumar et al., 2018).

The current era's study on consumer brand engagement observed many relations between CBE and consumer attachment in connection with brand loyalty (Hollebeek et al. 2014). The engagement of consumer and brands is found to be a predictor of customer brand engagement with social media sites. Consumer involvement is also found to be a predictor of CBE with tourism social media sites as more usage of social media sites have created an impact on different dimensions positively related to cognitive, affective, and human behavioral engagement. (Bowden, 2009; Hollebeek, 2011). The outcomes confirm past research that highly recommends customers are more likely to think, feel and act in favor of their favorite brands. (Bowden 2009; Hollebeek 2011)

Overall, the literature suggests that customer engagement is an important factor to consider in the marketing and customer experience of a business. Companies that are able to effectively engage their customers are likely to see positive outcomes, including increased loyalty, positive word-of-mouth, and increased sales and profitability.

Anthropomorphism

Instead of how closely companies design robots to resemble people, the word anthropomorphism relates to how much customers perceive service robots to be like humans. Anthropomorphism, or the activity of attributing human traits to non-human beings, has been widely studied in the context of chat bots and other artificial intelligence (AI) systems. According to a review by Epley et al. (2007), anthropomorphism can increase users' feelings of social presence and perceived intelligence of a chat bot, leading to more positive evaluations of the system. Multiple studies concluding that when used in a virtual environment, chatbots' imitation of human behaviour can frequently lead clients to believe they are speaking with a real person (Wünderlich and Paluch 2017)

As a result of a growing agreement in psychology and marketing, anthropomorphism is essential for understanding how people engage with nonhuman products. (MacInnis and Folkes 2017; Waytz et al. 2014). When used in a virtual environment, chatbots' imitation of human behaviour can frequently lead clients to believe they are speaking with a real person (Wünderlich and Paluch 2017)

As per one of the studies, marketing managers frequently support human-like service robots to boost consumers' impressions of social presence to facilitate customer-robot interactions (Niemelä et al. 2017). Another study suggests these robots resemble humans in terms of shape, behaviour, or appearance. (Bartneck et al. 2009).

In previous research, anthropomorphism as an Independent Variable has been thoroughly examined with customer comfort. (Duffy 2003, p. 181) analysis shows the employment of service robots makes it easier to deal with consumers since they reflect the guiding principles and expectations individuals have in social situations. Although researchers have regularly looked at how anthropomorphism affects customers' willingness to utilize service robots, the results have been conflicting, exhibiting favorable (Stroessner & Benitez 2019), unfavorable (Goudey and Bonnin 2016), and unfavorable (Broadbent et al. 2011) impacts. Thus there aren't any defined management guidelines to judiciously evaluate how to use AI [artificial intelligence] to approach consumer engagement in a more methodical and planned manner (Huang and Rust 2020, p. 3).

Anthropomorphism of chat bots has also been found to have practical implications for their effectiveness in certain contexts. For example, a study by Bickmore and Cassell (2005) found that users were more likely to engage in interpersonal communication and share personal information with a chat bot that they perceived as more human-like. This increased social presence and perceived intelligence of the chat bot was associated with higher levels of user satisfaction and willingness to use the system again in the future.

Overall, the literature suggests that anthropomorphism of chat bots can have a positive impact on user evaluations and engagement with the system. Companies designing chat bots may want to consider incorporating human-like characteristics, such as names and personality traits, in order to increase users' feelings of social presence and perceived intelligence of the chat bot.

Customer Comfort

Customer comfort is a multifaceted concept that has been studied by researchers in a variety of fields, including marketing, psychology, and human-computer interaction. Customer comfort has been defined as a state of physical, mental, and emotional ease or well-being experienced by customers (Hsu & Lu, 2010). It is a subjective and complex construct that is influenced by both individual and situational factors (Oh & Parks, 2001).Social factors such as interactions with staff and other customers can also affect a customer's comfort level (Ngai, Lam, & Chan, 2007).

Customer Comfort as a Mediator

There is a growing body of research on the concept of customer comfort as a mediator in various contexts.In a study conducted by Kang and Bailey (2011), the authors found that high levels of anthropomorphism in chatbots were only related to increased customer engagement when the chatbot was perceived as comfortable by the customer. When the chatbot was perceived as uncomfortable, there was no relationship between anthropomorphism and customer engagement. These results imply that consumer comfort mediates the relationship between chatbot anthropomorphism and customer engagement.

Anthropomorphism, the attribution of human-like characteristics to non-human entities, has been found to increase customer engagement with chatbots (Reeves & Nass, 1996). This is because anthropomorphism can make chatbots more relatable and easier to understand for customers (Yee & Bailenson, 2007). However, the positive relation between anthropomorphism in chatbots and customer engagement may be moderated by customer comfort (Kang & Bailey, 2011). Another research has also found that customer comfort with chatbots is related to increased customer engagement (Li et al., 2016). Li and colleagues (2016) found that chatbots that were perceived as comfortable and likeable by customers led to increased customer satisfaction and purchase intentions.

In conclusion, the literature suggests that the positive relation between anthropomorphism in chatbots and customer engagement is mediated by customer comfort. This means that in order for anthropomorphism to be effective in increasing customer engagement, chatbots must be perceived as comfortable by customers.

H1: Customer Comfort Mediates the Positive Relation between Anthropomorphism in Chatbots & Customer Engagement

Social Presence

According to Garrison et al. (1999), the concept of social presence refers to the projection of one's personal characteristics into an online community in order to be perceived as a real entity. Additionally, research by Heerink et al. (2008) suggests that it is not unrealistic for individuals to treat devices and systems as social entities, often referred to as embodied agents. As reported by Biocca et al. (2003), in communication involving both humans and bots, the construct of "Social Presence" has been identified as a crucial factor. Research by Kim et al. (2020) suggests that a high level of social presence in a medium is associated with perceptions of warmth, as it conveys the sense of interacting with a human, being socially approachable, and having a responsive nature. Studies have also shown that when consumers engage with digital agents such as chatbots and web virtual assistants during virtual shopping, it leads to an increase in social presence among shoppers (Moon et al., 2013).

Social Presence as Mediator

Interacting with others through technology can provide a sense of human warmth and friendliness, as shown by Hassanein and Head (2007). This can be achieved through various forms of digital communication, such as email-based customer support (Gefen and Straub, 2003), online communities (Kumar and Benbasat, 2002), chat (Kumar and Benbasat, 2002), and human online assistants (Aberg and Shahmehri, 2001; Hostler et al., 2005), which all use the internet as a means to connect people. According to T. Kim et al (2020), when consumers perceive their interactions with an anthropomorphized agent to be more personalized, friendly, sociable and responsive, they tend to develop a more positive attitude towards the agent, thus increasing a sense of social presence. Additionally, the choice of dialect used for communication can also play a role in this, as natural and informal language can contribute to a feeling of psychological closeness and warmth (Wiener and Mehrabian, 1968) and ultimately impact the perceived social presence (Nass and Steuer, 1993).

Prior research on the role of social presence in virtual worlds in common is scarce. Social presence has been found to directly reinforce loyalty in e-service context (Cyr 2007). In other words, when users perceive a social presence in the environment, they naturally and efficiently communicate with the service agent and feel more comfortable (Kang et al.,2018)

H2: Social Presence serially mediates with Customer Comfort; the positive relation between Anthropomorphism in Chatbots & Customer Engagement

Uncertainty Avoidance

Uncertainty Avoidance may be defined as the phenomenon which dictates how people from different cultures react to different levels of uncertainty. In other words, Uncertainty Avoidance measures the uncertainty & unpredictability tolerance of people belonging to different cultures or ethnicities (Hofstede, 2001). According to Hofstede (2001), any culture may fall into one of the three levels of uncertainty avoidance: high, low or moderate. Pakistan is reported to have an uncertainty avoidance index of 70, falling into the category of high uncertainty avoidance (Hofstede Insights, 2017). Uncertainty Avoidance has been explored by many studies, which link its relation to different constructs. In their study about the relation between Uncertainty Avoidance & Creativity, Adair and Xiong (2018) found that the motivation to reduce uncertainty predicted higher levels of implicit bias against novelty. This implies that Uncertainty avoidance inhibits creative behavior (Adair & Xiong, 2018). This, in turn, implies that the consumer may not engage in exploring new brands, and continue to consume & engage with the same service or product which the consumer is satisfied with. Similarly, one study found that uncertainty avoidance is much more useful in predicting behaviour in gain-framed situations than in loss-framed situations, further strengthening the fact that consumers tend to make decisions which predict the most probable gain rather than loss (Ladbury & Hinsz, 2009). Another study details the effects of Uncertainty avoidance on the product perceptions of the consumers (Anne Lee et al., 2007). They found that consumers from high UA countries perceive products with high PU (Perceived Uncertainty) to be of lower quality than do consumers from low UA countries.

Uncertainty Avoidance as Moderator

The role of UA as a moderator for Customer engagement has been explored extensively in prior studies. A study by Wang, Li, and Wang (2018) found that the relationship between anthropomorphism and customer engagement in chatbots was moderated by uncertainty avoidance. Specifically, they found that the effect of anthropomorphism on customer engagement was stronger for individuals with high levels of uncertainty avoidance compared to those with low levels of uncertainty avoidance. This suggests that the impact of anthropomorphism on customer engagement may be more pronounced for individuals who are less comfortable with uncertainty.

Other research has also explored the role of uncertainty avoidance as a moderator in the context of chatbots. For example, a study by Lu and Hsu

(2009) found that the relationship between anthropomorphism and customer satisfaction with chatbots was moderated by uncertainty avoidance. They found that the effect of anthropomorphism on customer satisfaction was stronger for individuals with high levels of uncertainty avoidance compared to those with low levels of uncertainty avoidance.

In summary, the research on uncertainty avoidance as a moderator suggests that that it can improve the anthropomorphism-mediated indirect effect of chatbots on consumer engagement. Further research is needed to fully understand the role of uncertainty avoidance in moderating the effects of anthropomorphism on customer engagement in chatbots.

Thus, we may infer the following:

H3: Uncertainty Avoidance enhances the indirect effect of Anthropomorphism in Chatbots on Customer Engagement mediated by Customer Comfort.

Negative Attitudes towards Chatbots Scale (NACS)

The NACS Scale has been adapted from NARS (Negative Attitudes towards Robots Scale); a scale originally developed by Nomura et al. (2005). This scale captures the predisposed negative attitudes of humans towards robots (Nomura et al., 2005). Although the perception of any human for a machine may not include any instances of anthropomorphic value, in the case of robots, humans tend to perceive them differently from machines. Falling broadly in the category of robots, this predisposed negative attitude of humans towards robots may persist in the case of chatbots as well. Thus, the NARS scale is adapted to NACS in the context of the study to reflect the constructs closely.

NACS as a Moderator

Multiple studies have been conducted to further investigate NARS deeply in relation to different constructs. One study unveiled that prior experience with robots & frequent exposure may lead to a higher NARS score (Bartneck et al., 2019). Another study found that there are different attitudes of users toward robots, which depend upon the assumptions which the user makes prior to use about the said robots; further, the gender of the user may also make a difference in the NARS score of the user (Nomura et al., 2006). Robert (2021) in his study linked the Attitudes towards Working with Robots (AWRO) with the NARS scale to establish a model which may predict who is more or less likely to work with robots (Robert, 2021).

It has been suggested that chatbots can be more effective when they are designed to be anthropomorphic, as this can increase customer engagement (Ha & Stoel, 2014). This is due to the fact that anthropomorphic chatbots are seen as being more human-like and can so promote a sense of social presence, which is the perception of co-presence with another being (Ha & Stoel, 2014). Social presence has been found to be positively related to customer engagement (Javalgi, White, & Ali, 2016).

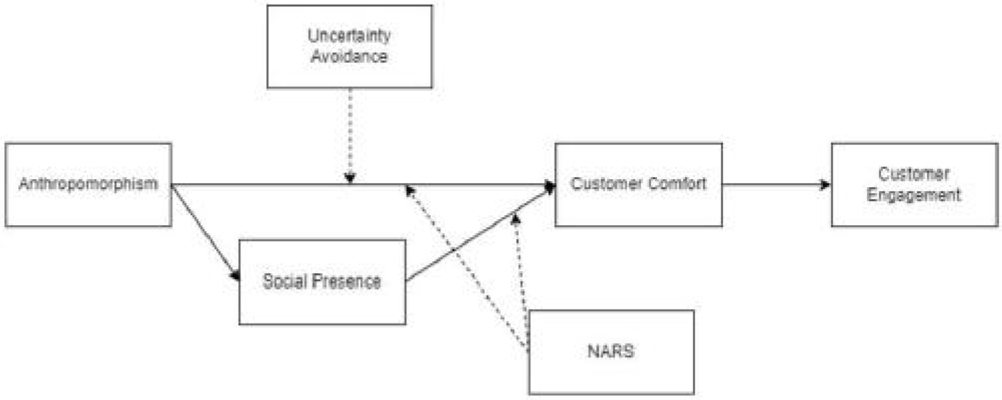
However, research has also shown that the effectiveness of anthropomorphism in chatbots can be moderated by the customer's attitude towards chatbots (Ha & Stoel, 2014). In particular, a negative attitude towards chatbots as moderators can lessen the indirect impact of anthropomorphism, as mediated through consumer comfort, on customer engagement (Ha & Stoel, 2014).

This negative attitude towards chatbots as moderators may be due to a lack of trust in the competence and reliability of chatbots (Khawaja, 2016). It has been found that customers are more likely to trust and engage with chatbots when they are perceived as competent and reliable (Khawaja, 2016). Thus, in the backdrop of the studies above, we may establish that the role of NACS may diminish the user experience based on the user’s predispositions about the chatbots in use. Hence, it is only logical that NACS may be characterized as a moderator of the user experience. Thus, we may hypothesize that:

H4: Negative Attitude towards Chatbots diminishes Anthropomorphism’s indirect effect in Chatbots on Customer Engagement through Customer Comfort mediation.

H5: Negative Attitude towards Chatbots diminishes the Anthropomorphism’s indirect effect in Chatbots on Customer Engagement serially through Social Presence & Customer Comfort mediation.

Theoretical Framework



Methodology

Adhering to the Philosophy of Positivism, the research was conducted so as to minimize the penetration of bias in the data collected. This was done to make sure that the data gathered does not skew or overstate any results. With the dawn of automation and the fifth industrial revolution, human intervention in even the smallest of tasks is being eliminated. Thus, the concept of an employee to engage in meeting the demands and requirements of the consumers is somewhat outdated. This is reflected in the adoption of the automated self-service kiosks in famous fast-food chains, the integration of automated chatbots in customer feedback departments & self-driving cars, etc. It is a well-known fact that customer engagement drives customer loyalty. It is of utmost importance in the corporate world to broaden the horizon of a brand's customer base through customer loyalty. Therefore, in such Human-Computer Interactive settings, the level of customer comfort dictates the probability of gaining or losing potential clients. An investigation into the relation between the antecedents which affect customer comfort in the scenarios above is only reasonable. In the wake of the above context, a deductive research approach was adopted as the nature of the problem called for the adoption of the deductive research methodology. As discussed earlier, the relation between anthropomorphism & customer comfort has not yet been fully understood. Furthermore, the moderating effects of NARS and UA in such a context have yet to be explored. In addition, the mediating effect of the social presence of any non-social anthropomorphic entity also needs to be explored.

A causal & exploratory research design was opted to investigate the in-depth relation between all the constructs of interest according to the conceptual framework discussed in the earlier chapter. Since data is not available and is being collected with the help of a questionnaire, non-probability sampling is being used in our research. Our research is purposive as our questionnaire includes qualifying questions which allow us to differentiate between chatbot users and non-users.

The use of chatbots, which are machine agents that act as interfaces for data and service providers, is gaining popularity. However, there is a lack of research that examines why people use chatbots. To address this, an online questionnaire was administered to chatbot users aged between 16 and 40 in order to understand their motivations for using chatbots. This study aims to identify the key driving factors behind the use of chatbots.

This research uses scale development best practices to create a marker variable—attitude toward the color blue—that can be applied in a wide variety of social science research. The collected data was analyzed through PLS-SEM (Partial Least Squares-Structuring Equation Modelling) on the basis of the fact that researchers believe PLS-SEM data analysis is more accurate for researchers. (F. Hair Jr et al., 2014)

Measures

The conceptual model involves six constructs. Items to measure each construct have been adopted from the extant literature. Eight items for the construct of customer comfort have been adopted from Spake et al. (2011); five items for the construct of anthropomorphism have been adopted from Sheehan et al. (2020); 14 items for Negative Attitudes towards Chat-bots have been adopted from Nomura et al. (2006); four items for Social Presence have been adopted from the study of Heerink et al. (2008); five items were adopted from the study of Hari et al. (2022) for the construct of customer engagement; seven items for the construct of uncertainty avoidance have been adopted from the study of Jung and Kellaris (2004); and seven items for the construct of attitude toward color blue were adopted from the study of Brian & Marcia, (2022).

Results and Discussion

After gathering a total number of 540 responses via the questionnaire developed, as described in the preceding sections, the Un-coded data file was extracted and coded for use in Smart PLS. Smart PLS was opted as the platform for analysis as it is a variance-based software optimized for PLS-SEM analysis. Out of the total 540 responses, no missing values were reported, 81 responses were discarded on the basis of the qualifying questions, and 92 responses were discarded on the basis of cross-loadings, which affected the Discriminant Validity of the constructs. After the deductions in responses, 367 valid responses were left, which were used to perform PLS-SEM analysis. The following tests were performed, and the results are briefly discussed in the following sub-sections.

Multivariate Normality via Mardia's Test

This test is carried out to evaluate the prevalent skewness & kurtosis in the data. The test was performed via an online calculator website, which yielded the following results for the test:

Table 1: Mardia's Test

Mardia's multivariate skewness and kurtosis			
	b	z	p-value
skewness	677.6648	41450.4959	0
kurtosis	2629.5423	106.9415	0

As we can observe from the above table, the P-values for both skewness & kurtosis are less than 0.05. This indicates that the data is indeed skewed & kurtotic. Thus, we have to proceed with non-parametric testing (bootstrapping) for successfully obtaining a normally distributed dataset for our regression analysis.

Demographic Profile

The collected data exhibits the following demographic profile properties:

Gender

The following is the demographic distribution of the respondents based on gender:

Table 2.1: Gender Based Demographics

Gender				
	Frequency	Percent	Valid Percent	Cumulative Percent
Male	199	54.2	54.2	54.2
Female	168	45.8	45.8	100.0
Total	367	100.0	100.0	

As we can see, out of the total 367 responses, 54.2% of the sample size consisted of Male respondents, while the remaining 45.8% of the respondents were Females.

Age Group

The following is the demographic distribution of the respondents based on Age Groups:

Table 2.2: Age-Based Demographics

Age Group				
	Frequency	Percent	Valid Percent	Cumulative Percent
16 - 20	82	22.3	22.3	22.3
21 - 25	86	23.4	23.4	45.8
26 - 35	113	30.8	30.8	76.6
>35	86	23.4	23.4	100.0
Total	367	100.0	100.0	

As we can observe from the above table, 22.3% of the respondents belonged to the "16 – 20 Years" age group, 23.4% belonged to the "21 – 25 Years", 30.8% belonged to the "26 – 35 Years" and the remaining 23.4% of respondents belonged to the ">35 Years" age group.

Usage Frequency

The following is the demographic distribution of the respondents based on the usage frequency.

Table 2.3 Usage Frequency

Usage Frequency				
	Frequency	Percent	Valid Percent	Cumulative Percent
Daily	85	23.2	23.2	23.2
Weekly	93	25.3	25.3	48.5
Monthly	101	27.5	27.5	76.0

Yearly	88	24.0	24.0	100.0
Total	367	100.0	100.0	

As we can see, the distribution of the respondents in terms of the usage frequency is quite uniform, with the highest usage being monthly, followed by weekly usage, yearly usage and then finally by the daily usage.

Usage Media

The following is the demographic distribution of the respondents based on the usage of media:

Table 2.4 Usage Media

Usage Media				
	Frequency	Percent	Valid Percent	Cumulative Percent
Workplace	79	21.5	21.5	21.5
On the mobile	92	25.1	25.1	46.6
Marketplace	82	22.3	22.3	68.9
Online via computer browser	114	31.1	31.1	100
Total	367	100.0	100.0	

As we can see, the greatest proportion of responses use the chatbots of various industries online via the computer browser, i.e., 31.1%, followed by usage on the mobile phone, i.e. 25.1%, followed by usage in the marketplace, i.e. 22.3% and lastly via workplace, i.e. 21.5%.

Chatbot Industry

Table 2.5: Chatbot Industry

The following is the demographic distribution of the respondents based on the Chatbot Industry,

Chatbot Industry				
	Frequency	Percent	Valid Percent	Cumulative Percent
Ecommerce	105	28.6	28.6	28.6
Healthcare	82	22.3	22.3	51.0
Banking	93	25.3	25.3	76.3
Other	87	23.7	23.7	100.0
Total	367	100.0	100.0	

As we can see, the most popular usage industry for chatbot interactions is the Ecommerce industry, with a percentage of 28.6%, followed by the Banking sector, securing a percentage of 25.3%. Other sectors make up 23.7% of the chatbot usage demographics, while the healthcare industry comes last with only 22.3% to its name.

Chatbot Brand

The following is the demographic distribution of the respondents based on the Brand of the Chatbot Used.

Table 2.6 Chatbot Brand

Chatbot Brand				
	Frequency	Percent	Valid Percent	Cumulative Percent
Siri	127	34.6	34.6	34.6
Google Assistant	74	20.2	20.2	54.8
Alexa	62	16.9	16.9	71.7
Other	104	28.3	28.3	100.0
Total	367	100.0	100.0	

From the above table, it is evident that the most popular brand in Chatbots is Siri with a percentage of 34.6%, followed by the other category, which includes other brands which were not included in the list. Thirdly, we have Google Assistant with a percentage of 20.2% and finally, we have Alexa with a percentage of 16.9%.

Outer-Loadings, Composite Reliability & AVE

Outer loadings of the items are evaluated to assess the convergent reliability of the Constructs. This shows that all the items converge successfully onto the latent variable. Similarly, Composite Reliability assesses the reliability of the constructs & the Average Variance Extracted (AVE) checks for the Convergent Validity of the Constructs. The values for the parameters, as mentioned earlier, are given as follows:

Table 3: Outer-Loadings, Composite Reliability & AVE of Constructs

Constructs	Items	Outer-Loadings	Composite Reliability (rho_c)	Average Variance Extracted (AVE)
Anthropomorphism	AP01	0.798	0.883	0.654
	AP02	0.838		
	AP03	0.752		
	AP04	0.834		
Customer Comfort	CC01	0.734	0.879	0.593
	CC02	0.775		
	CC03	0.818		
	CC06	0.705		
	CC08	0.798		
Customer Engagement	CE01	0.814	0.858	0.603
	CE02	0.81		
	CE03	0.744		
	CE04	0.72		
Negative Attitudes Towards Chatbots (NACS)	NA02	0.82	0.92	0.589
	NA04	0.711		
	NA05	0.744		
	NA06	0.771		
	NA07	0.77		
	NA08	0.793		
	NA10	0.707		
	NA14	0.795		
Social Presence	SP01	0.86	0.922	0.748
	SP02	0.873		
	SP03	0.875		
	SP04	0.843		
Uncertainty Avoidance	UA03	0.777	0.832	0.623
	UA04	0.799		
	UA05	0.782		

All the items for which the outer-loadings yielded values of less than 0.5 were dropped to enhance the Construct reliability. As we can observe from the given table, all the outer-loading & Composite reliability values are greater than 0.7. Similarly, the values for AVE also exceed the lower limit of 0.5.

Thus, it is not wrong to deduce that all the remaining items in the model successfully converge upon the constructs. Similarly, since the composite reliability is also well above the threshold, we can say that construct reliability is established. Furthermore, the values of AVE also establish the convergent validity of all the constructs in the model. Hence, we can move onto assessing the Discriminant Validity of the Constructs.

HTMT Ratio

The Heterotrait-Monotrait (HTMT) Ratio is used to evaluate the Discriminant validity of the Constructs. This shows that the constructs are indeed distinct variables. The HTMT ratio for the latent variables in our framework is evaluated as follows:

Table 4: HTMT Ratio

	AP	**CC**	**CE**	**NA**	**SP**	**UA**
AP						
CC	0.9					
CE	0.808	0.816				
NA	0.861	0.754	0.775			
SP	0.9	0.743	0.809	0.863		
UA	0.936	0.819	0.865	0.868	0.871	

Since all the values for the Discriminant Validity, i.e., the HTMT ratio for all the constructs, are less than the retention criteria of 0.9, we can say that discriminant validity is established. However, only the value for UA is greater than the retention criteria, but since it is not significantly greater, we may neglect its effect on the model, and the discriminant validity of the constructs holds. Thus, all the constructs are distinct and differ from each other. Therefore, the Discriminant Validity of all the Constructs is established.

Hence, we may move towards establishing the Collinearity Statistics of the Model in the next step.

VIF Values

The Variance Inflation Factor (VIF) Values represent the Collinearity Statistics and are used to evaluate that no construct overlaps another. The VIF values for the sample size are given as:

Table 5: VIF Values Matrix

	CC	CE	SP
AP	4.553		1
CC		1	
NA	3.721		
SP	5.031		
UA	2.943		

As we can see, the relation between UA & CC does not overlap as the VIF value for the relation is less than 3.3. However, all values for other relations exceed the threshold, but do meet the retention criteria of <5. Only value for SP & CC exceeds the retention criteria. This can be solved by adding more samples to the sample size; however, due to the limitations of the study, the collected sample size was evaluated and analyzed. Now that we have evaluated the Measurement Model of our study, we may proceed to evaluate the Structural Model in the next steps.

Statistical Significance of Path Model

The most important aspect of the regression analysis is evaluating the Structural Model of the Theoretical Framework. The following Path Coefficients are evaluated.

Table 6: Statistical Significance of Path Model

	β Coefficient	Standard Error	T statistics	P values	Decision
Indirect Effect					
AP -> CC -> CE	0.157	0.051	3.097	0.001	S
AP -> SP -> CC -> CE	0.146	0.052	2.839	0.002	S
Moderation Effect					
UA x AP -> CC	0.003	0.036	0.077	0.469	NS
NA x AP -> CC	-0.169	0.054	3.129	0.001	S

NA x SP -> CC	0.146	0.044	3.331	0.000	NS

Indirect Effect (Mediation)

H1: Customer Comfort Mediates the Positive Relation between Anthropomorphism in Chatbots & Customer Engagement

As we can observe from Table 6, the P-value for the path AP -> CC -> CE is returned as 0.001, which shows a significant relation and therefore supports H1. The beta coefficient for H1 is returned as 0.157, which portrays a net positive impact of CC on the relation between AP & CE.

H2: Social Presence serially mediates with Customer Comfort; the positive relation between Anthropomorphism in Chatbots & Customer Engagement

As we can observe from Table 6, the P-value for the path AP -> SP -> CC -> CE is returned as 0.002, which shows a significant relation and therefore supports H2. The beta coefficient for H2 is returned as 0.146, which portrays a net positive impact of the serial mediation of SP & CC on the relation between AP & CE.

Moderation Effect

H3: Uncertainty Avoidance enhances Anthropomorphism's effect in Chatbots on Customer Engagement.

As we can observe from Table 6, the P-value for the path UA x AP -> CC is returned as 0.469, which shows an insignificant relation and therefore H3 is Not Supported.

H4: Negative Attitude towards Chatbots diminishes Anthropomorphism's effect in Chatbots on Customer Engagement.

As we can observe from Table 6, the P-value for the path NA x AP -> CC is returned as 0.002, which shows a significant relation and therefore supports H4. The beta coefficient for H4 is returned as -0.169, which portrays a net negative impact of the Moderating effect of NA on the indirect effect between AP & CE mediated by CC.

H5: Negative Attitude towards Chatbots diminishes the relationship between Social Presence & Customer Comfort.

As we can observe from Table 6, the P-value for the path NA x SP -> CC is returned as 0, which shows a significant relation. But the beta coefficient for this relationship is positive. Thus, we can say that the hypothesis H5 is also not supported.

Coefficient of Determination (R^2) and Adjusted R^2

R Square value explains how much of the endogenous variable is explained by the exogenous variable. The values of R-squared and adjusted R-squared are given in Table 7.

Table 7: R-squared & Adjusted R-squared Matrix

	R-square	R-square adjusted
CC	0.643	0.636
CE	0.447	0.446
SP	0.595	0.594

As we can see in the above table, a 63.6% change in CC is explained by the preceding constructs. Similarly, 44.6% change in CE is explained by its preceding constructs & 59.4% change in SP is explained by its preceding constructs. Thus, all the explained variance of all the dependent variables lies within the Moderate category.

Effect Size (F2)

The F-square value explains the strength of the relation between the endogenous variable & the exogenous variable. In other words, it quantifies the effect on the R-squared value of the exogenous variable if the endogenous variable were to be removed. The F-square values are given as under:

Table 8: f-Squared Matrix

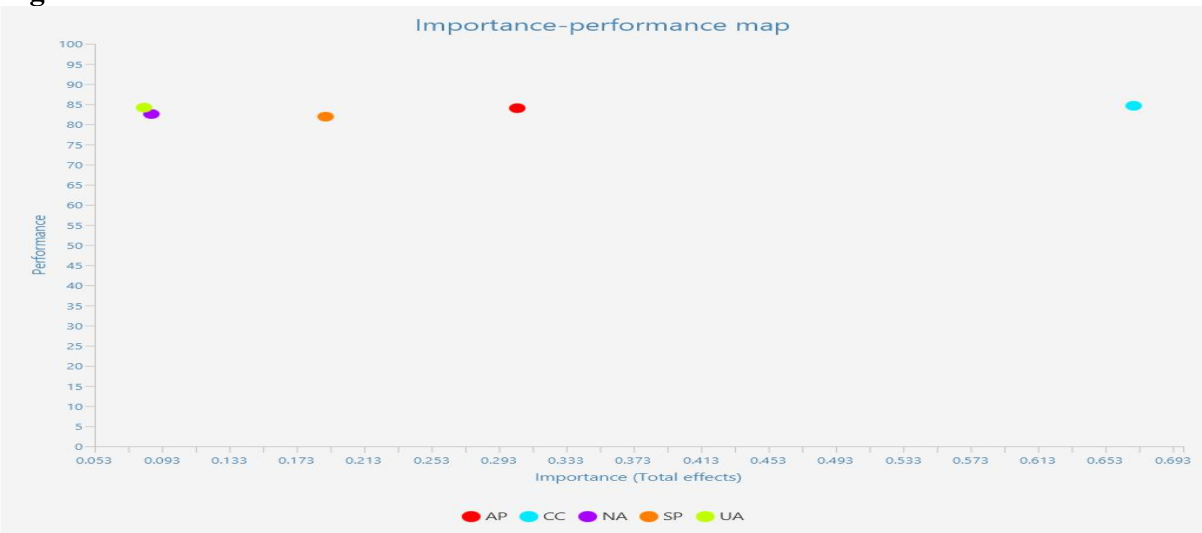
	CC	CE	SP
AP	0.034		1.472
CC		0.81	
CE			
NA	0.013		
SP	0.045		
UA	0.014		
NA x AP	0.092		
UA x AP	0		
NA x SP	0.1		

As we can see, most values fall into the category of small effect size, i.e., 0.2 & medium effect size, i.e., 0.15. However, the effect size of CC for CE falls in the large category as it exceeds 0.35.

IPMA Matrix (Importance Performance Map Analysis)

The IPMA Matrix plots the performance of all the variables against their importance and evaluates the most important variables in the framework, which need to be maintained in order to yield favorable results. According to the IPMA matrix below, we can see that the most important and top-performing variable is Customer Comfort, followed by anthropomorphism. This may be due to the fact that Anthropomorphism in Chatbots enhances Customer Comfort during human-machine interaction and, in turn, enhances Customer Engagement. Furthermore, Uncertainty Avoidance & Negative Attitudes towards Chatbots remain the least important variables.

Figure 9: IPMA Matrix



MICOM Analysis

MICOM (Measurement Invariance of Composite Models) Analysis is required to establish the invariance of the measures. This is a three-step procedure, which, when analyzed, establishes the invariance of the measure. In this study, the MICOM analysis is carried out on the demographic groups categorized by gender.

Configural Invariance

Since the entire questionnaire was developed and the methodology adopted for the research was consistent for all the samples of the population, we can say that configural invariance is established.

Compositional Invariance

Compositional Invariance gauges if the confidence interval of a composite is significantly lower than 1. If this is not the case, then compositional invariance is established.

Table 10.2 Compositional Invariance

	Original correlation	Correlation permutation mean	5.00%	Permutation p-value
AP	0.999	0.999	0.999	0.227
CC	0.999	0.999	0.997	0.583
CE	0.996	0.997	0.993	0.255
NA	0.998	0.998	0.995	0.423
SP	0.999	0.999	0.998	0.409
UA	0.996	0.995	0.986	0.379

As we can see, the confidence interval (5%) is not significantly lower than 1, therefore, there is compositional invariance in the model. Additionally, all Permutation P-values are greater than 0.05.

Equality of Composite Mean Values

Table 10.3 Equality of Composite Mean Values

	Original difference	Permutation mean difference	2.50%	97.50%	Permutation p-value
AP	-0.397	0	-0.207	0.201	0
CC	-0.339	0.001	-0.201	0.202	0.001
CE	-0.245	0	-0.204	0.207	0.017
NA	-0.409	0.001	-0.199	0.207	0
SP	-0.423	0	-0.202	0.206	0
UA	-0.328	0	-0.206	0.214	0.002

We can observe in the above table that no equality of composite means occurs in the measures, as all the Permutation P-values are less than 0.05.

Equality of Composite Variance

Table 10.3.2 Equality of Composite Variance

	Original difference	Permutation mean difference	2.50 %	97.50 %	Permutation p-value
AP	1.124	0.009	-0.56	0.619	0
CC	1.16	0.009	-0.62	0.674	0.001
CE	1.051	0.006	-0.63	0.639	0.001
NA	1.449	0.007	-0.64	0.665	0
SP	1.181	0.008	-0.59	0.616	0
UA	0.902	0.012	-0.61	0.634	0.003

We can observe in the above table that no equality of composite variance occurs in the measures, as all the Permutation P-values are less than 0.05.

Thus, we may establish that although configural & compositional invariance exists in the measures, there is no equality of the composite means or variances. Thus, there is no variance in the behavior pattern of both the gender groups. Furthermore, Multigroup Analysis (MGA) cannot be performed due to the absence of invariances.

Discussion

By assessing the measurement and structural model, we can see that 4 out of the 5 hypotheses are accepted. The moderating effect of Uncertainty Avoidance on the framework was not supported. Therefore, we can say that Uncertainty Avoidance does not play any role in enhancing or diminishing the indirect effect of AP on CE mediated by CC. Thus, we can remove it from the originally proposed model.

On the Contrary, the moderation effect of NAC's on both the paths is supported. The moderation of NAC's in the indirect effect of AP on CE mediated by CC diminishes the strength of the relation as portrayed by the beta-coefficient, whereas its moderation effect in the indirect relation between AP & CE serially mediated by SP & CC is enhanced. This is contrary to intuition, which may suggest that the moderating effect of NARS on Customer Comfort be negative. Therefore, the moderation effect of NAC's for the former relation is Supported and the moderation effect for the latter is Not Supported. In addition, the relation between Social Presence and Customer Comfort was proved as a net positive relation, which falls in line with the findings of Becker et al. (2022). However, Becker et al. (2022) tested the relation between Social Presence & Customer Comfort as negative, which was rejected. We can say that Social Presence also plays a vital role as the antecedent of Customer Comfort. Thus, by increasing the Anthropomorphism in a Chatbot, its Social Presence increases, which elevates the Customer Comfort level during the interaction & ultimately increases the overall Customer Engagement.

The proposed mediation effects of Customer Comfort on the relation between Anthropomorphism & Customer Engagement were also accepted. This shows that as the level of Anthropomorphism or Huma-likeness in the Chatbot's interactions increases, so does the Customer Comfort & therefore, Customer Engagement is increased.

Conclusion

Previously, NACS scale was not used in the study. Whereas NACS played a moderator role in our study which influenced a new attribute in the research. It was also observed that the uncertainty avoidance as a moderator in our study predicts no significant role. In previous studies, it was mentioned that customer comfort plays an important role in increasing the effect of anthropomorphism on customer engagement (Becker et al., 2022), but our study contributed that with the presence of attribute like Social Presence, the effect of customer comfort is enhanced.

It is evident to increase customer engagement in a B2C category, users want to have immediate answers to their queries on an online platform. Our study implies that one should design chatbot with high anthropomorphism. This will help the user to have more human like interference and they will not be able to identify whether there is chatbot or human representative on the other side. By this means Anthropomorphism will increase the impact on the social presence. The impact on customer comfort will be high that will lead to increase in the customer engagement. However, our study also predicts if one has predisposition towards the chatbots then rather increase in customer comfort, the NARS will decrease the customer comfort even though anthropomorphism and social presence is high this will negatively impact the customer engagement.

This study limits in terms that it doesn't uses probability Sampling rather a non-probability sampling approach has been used since we didn't have exhaustive list available. Therefore, a random population questionnaire was floated for gathering data.

Limitations and Recommendations for Further Research

Our recommendation concludes that one should use probability sampling in extension of this research. In this method cluster or quota sampling should be used to have known population, to better predict. In our study we haven't use previous experience as moderator, so we recommend using as extension to this research. Also, our study focused to use one dependent variable customer engagement, we recommend using other customer connected attributes such as customer satisfaction and customer loyalty.

Our study lacks to prove that uncertainty avoidance has an impact on customer engagement so one should consider this attribute in further study. There are some other moderation to be included such as brand image and brand loyalty impacts the customer engagement when one interacts with the chatbot.

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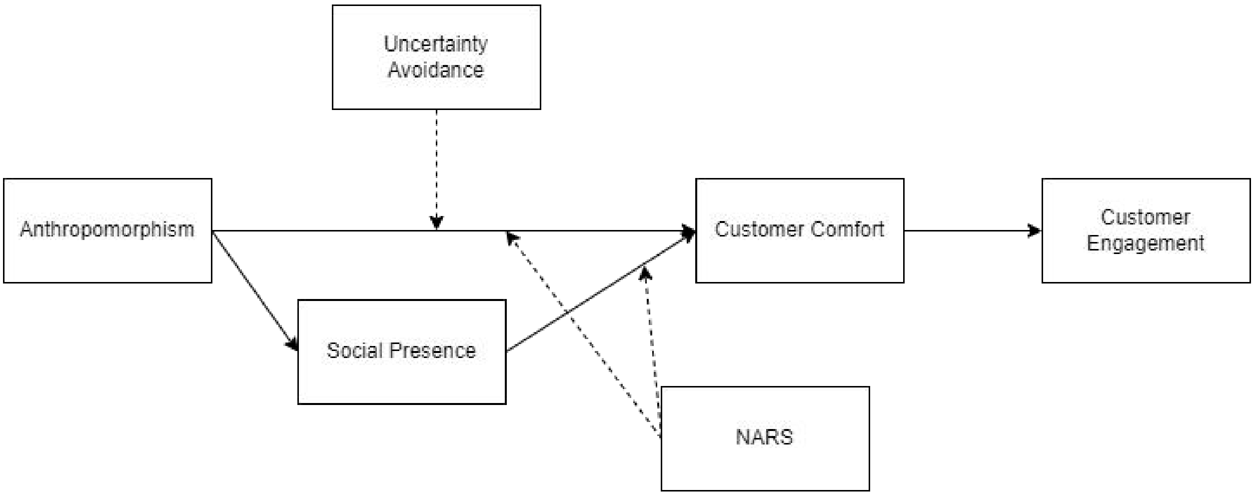
Appendix

I. Theoretical Framework



II. Questionnaire

* This section has removed for evaluation of plagiarism, as the all the question are adopted from previous papers