# Impact of Human-Like Empathy of AI Chatbots and Privacy Concerns on Consumer Complaint Behavior in E-Commerce

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***Abstract***

*This research examines the influence of AI chatbots' human-like empathy (HLE) on consumers' complaint behaviour (CCB) and its implications on brand trust (BT) and privacy concerns (PC). From prior literature, we review the shifts in the role of AI chatbots in customer service concerning the ability to mimic human feelings and improve brand-consumer interaction. Choosing the quantitative approach to the research, the online questionnaire survey was carried out with 400 respondents who had recently used AI chatbots. Our analysis revealed that AI chatbots HLE help ease consumers' anxiety (CA), build trust in the brand, and prompt a positive complaint attitude. Further, the results establish the moderating effect of privacy concerns on the relationships of AI chatbots HLE with consumers' complaint behaviour and attitudes. The findings of this study stress the relevance of creating empathetic AI systems to improve customer satisfaction and retention while considering possible privacy concerns. This investigation of AI chatbots in the customer service context may provide valuable insights for the business world regarding strategies based on empathy and security concerns for consumer data. It is, therefore, suggested that future studies should investigate in more depth the relationships between HLE, PC, and CCB to improve the creation of efficient AI-powered customer service solutions.*

**Keywords:** AI Chatbots, Human-Like Empathy, Privacy Concerns, Consumer Complaints Behavior, Consumer Anxiety, E-Commerce.

## Introduction

Customer service is a rapidly evolving field, and the AI chatbot has revolutionized customer care and organizational interaction (Bulchand-Gidumal et al., 2023). The potential of AI chatbots to express empathy similar to that of humans has attracted the interest of professionals and scholars (Fu et al., 2023). Over the years, AI chatbots have become increasingly prevalent, especially in customer service job documentation in several businesses (Adam et al., 2021). The main application and motivation behind using artificial intelligence in customer experience improvements worldwide is the identification of consumer demand trends (Dencheva, 2023). Out of the targeted interviewees, 47% of respondents said that their marketing company used AI to pinpoint everyday customer scenarios (Dencheva, 2023). According to the research conducted by

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Dencheva (2023), 23% of marketing executives utilized chatbots or artificial intelligence to enhance the marketing qualified leads MQLs.

Organizations have attempted to make AI chatbots have emotions and intelligence to understand as they know the importance of HLE in meaningful conversations and BT (Jiang et al., 2023). Changing the nature of the conversation to a more empathetic chatbot interaction is an attempt to respond to another grand challenge of endowing technology with human qualities and narrowing the gap between humans and computers (de Sá Siqueira et al., 2023). Widener & Lim (2020) state that caring acts protect the sanctity of the business-consumer relationship, prevent the occurrence of the undesirable, and end complaints. By considering consumers' concerns, it is possible to develop a technique of using AI chatbots to address the concerns before they arise so that consumers have a positive attitude toward them (Hardi et al., 2020). Knowing the moderating effect of users' empathy on their probability of making complaints and the outcomes of the complaints is of significant constructive value for the theory and practice. The current study aims to investigate the following research questions:

1. Do chatbots display HLE and affect CCB?
2. Does PC impact the relationship between the chatbot's HLE and CCB?
3. Does CA affect the relationship between the chatbot's HLE and CCB?
4. Does PC moderate the relationship between the chatbot's HLE and their actions?

## Literature Review

This literature establishes a relationship between consumers' attitudes and choices regarding a brand or a product through appraisal factors like BT, HLE, PC, CCB, and CA.

### Brand Trust and AI Chatbots

According to Chaudhuri and Holbrook (2001), brand trust refers to clients' average reliance on the brand's ability to deliver on the brand promise. Morgan and Hunt (1994) have defined trust as a complex idea encompassing reliability, belief, and a positive attitude toward a brand's reliability and authenticity. Strong and long-term customer business relationships, which are critical for marketing success, require it (Moorman et al., 1992).

Huang et al. (2020) reported that chatbots can attempt human-like conversation and deliver accurate, immediate answers to customers' inquiries, resulting in a good customer experience. By providing user-specific responses to specific queries or likes, chatbots achieve relevant objectives and create substantial customer emotionally instrumental relationships with the business entities (Go & Sundar, 2019). According to Mayer et al. (1995), this personalized communication enables the construction of ideas of competency and compassion, which supports BT. The ability to converse and build trust through cloud chatbots is limited by concerns over bias in decision-making, data privacy and security, and other related problems (Vergaray et al., 2023). Acknowledging that chatbots are automated in their responses and addressing data use issues increases assurance and preserves brand reputation.

### AI Conversations and the Pursuit of Human-Like Empathy

Human-like empathy is the capacity of artificial intelligence chatbots to mimic actual human emotions and talk to clients (Fu et al., 2023). It even anticipates users' feelings and acts on them in a way that reflects more than positing the correct information or answering questions (Naous et al., 2020). Yim (2023) stated that in the literature, empathy is defined as a concept that entails recognizing other people's feelings and protecting those feelings in every possible manner. As a result, consumers can be affected by human-like empathy from chatbots (Fu et al., 2023). Consumers have an initial positive reaction towards the engagement with the chatbots if they expect the chatbots to treat them friendly, kindly, and empathetically (Chew, 2022).

According to Mitchell et al. (2021), consumers who thought they were empathized by the chatbot in the conversation noted higher user satisfaction and an improved general experience. Furthermore, human-like empathy shapes customers' behaviour over the long term due to the trust established with the client-company relationship (Janson, 2023). Implementing empathy in chatbots comes with understanding the principles of emotional intelligence, though there is a potential to be insensitive or misunderstood. The balance between using programmed interfaces and showing concern about not becoming a source of negative user response is vital (Brown & Halpern, 2021).

**Privacy Concerns about Chatbots**

A privacy concern in the context of AI chatbot engagements is the apprehensions and doubts that users have over the safety and protection of their information while interacting with businesses digitally (Widener & Lim, 2020). Such issues range from the security of data, cases of wrong persons accessing the information, and the owners' use of information in the wrong way (Fichter & Anguelov, 2024). Chatbots powered by artificial intelligence (AI) have become a regular part of consumer-brand engagement. However, these have also been enhanced with the general progress; some privacy problems are appearing. Privacy issues in AI Chatbot interactions greatly influence consumers' actions.

Personalized interactions through the chatbot are somewhat less efficient since the user will likely decline to provide any information regarding their identity (Sebastian, 2023). Encryption and safe storage are two security features that must be implemented to ensure that users' data will not be compromised. While it is necessary to solve the problems considered, achieving satisfactory data security and AI chatbot efficiency can be difficult. Companies are expected to provide support and services tailored to the individual, but at the same time, consumers do not want their data stolen by companies (Sebastian, 2023). Laws such as the General Data Protection Regulation (GDPR), which also mandates business organizations to have open data policies, complicate handling privacy issues.

**Complaint Behaviour of the Consumer with Chatbots**

Consumer complaint behaviour relates to actions taken, relationships, and disposition that a consumer demonstrates anytime they wish to convey their concerns, complaints, or grievances over products or services they have used (Calin, 2012). It includes complaints sent to the company using an official email or to a consumer care service or 'rants' posted on the company's social media page or any other public forum (Marx & Zimmermann, 2018). Hardi et al. (2020) posit that since chatbots can attend to customer issues quickly and efficiently, handling such concerns may positively correlate with the consumer inclination towards using such platforms for grievances reportage. Still, consumers can become even more angered and frustrated if they feel that chatbots do not comprehend or respond adequately to their concerns, and that causes them to switch to another channel to share their discontent (di Castri et al., 2020).

Customers' satisfaction can be enhanced by applying natural language processing and problem-solving strategies used in chatbots, which reduces the time required to solve complaints (Larasati et al., 2022). Furthermore, sentiment analysis algorithms have enabled chatbots to track consumers' emotions in their messages, thus responding to their complaints more compassionately and personally (Larasati et al., 2022). Due to such improvements, the customers consider it more accessible and enjoyable to express their concerns. This means dissatisfaction progresses if misinterpretations or inadequate responses originate from poor perception of complex issues or feelings (Sari & Adinda, 2023).

### AI Chatbots and Their Effect on Consumer Anxiety

Addressing consumer anxiety in AI chatbot interactions is of utmost importance. Spielberger (1966) stated that people suffering from anxiety can feel tense and dreadful with their awareness. It involves a spectrum of emotional effects caused by factors like concerns about the quality of the products, risk related to investment, concern when making a decision, or discomfort while dealing with the customers (Rook, 1987). In the study by Cheng and Jiang (2022), the authors note that chatbots are helpful and inspirational agents between clients and firms. However, how well and consistently these interactions occur does impact how anxious the customers are. If chatbots fail to respond to customers or offer wrong information while handling a critical concern or making a crucial decision, it increases people's anxiety levels (Xu et al., 2022). This highlights the urgency of improving AI chatbot capabilities to address consumer anxiety.

According to Vanasombut et al. (2008), chatbot developments assert that efficient chatbot interactions, which offer the correct information and correspond rapidly enough to the problems, can reduce customers' concerns. However, if the case is that chatbots are regarded as being incompetent or as unable to solve customer issues adequately. Then there is this, which increases anxiety and results in more stress or dissatisfaction with the interactions between customers and brands. This aligns with a study by Sidaoui et al. (2020) that established that chatbot interviews influenced customer experience assessment.

Despite these possibilities, client anxiety management remains challenging for artificial intelligence chatbots. For them, it may be more difficult to ease anxiety if they cannot answer kindly, identify subtle feelings, or answer questions. Lack of technical proficiency, language differences, or unequal response increases consumer anxiety, resulting in frustration and an adverse impression of the product or service (Phillips et al., 2023). Examining consumer anxiety reduction and trust, perceived reliability, and quality of information as factors that enhance/repair digital customer experiences also helps increase customers' experiences in interactions with chatbots (Zhu et al., 2022).

## Theoretical Review

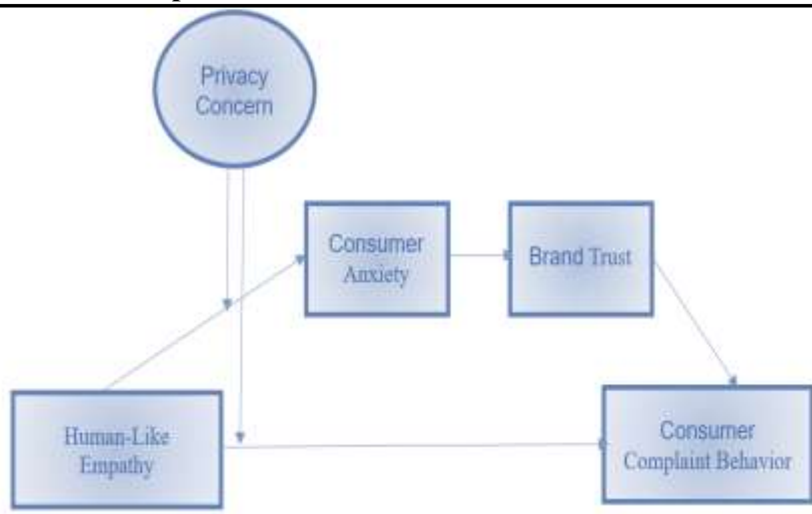
Several theories, including the Technology Adoption Model (TAM), offer valuable insights into the impact of AI chatbots on consumer behaviour. TAM, a widely known theory, posits that a client's perceived usefulness and ease of use of new technologies influence their adoption decision (Davis, 1989). If consumers find an AI chatbot valuable and easy to use, they are more likely to accept it. This theory helps explain why consumers are more inclined to engage with a chatbot that exhibits empathy similar to a human, as it enhances the perceived value of the technology (Fornell et al., 1996). In addition, by utilizing the Social Presence Theory, the users notice that the platforms appear more social when there are signs of mimicking face-to-face interactions (Short et al., 1976). If chatbots exhibit human-like emotional concerns, users are more inclined to perceive them as social entities, increasing their interaction with the program (Go & Sundar, 2019). The Privacy Calculus Theory (Malhotra et al., 2004) states that people should assess the advantages and disadvantages of exposing data before applying technology.

Furthermore, the Elaboration Likelihood Model (ELM) provides a comprehensive understanding of how individuals process information through two routes. The model suggests that human-like, empathetic chatbots could positively influence customers because the emotions infused by the chatbot into the conversation could optimistically shape customer attitudes and subsequently influence customer behaviours. This impact is expressed through the peripheral route (Janson, 2023). Lastly, the Social Exchange Theory points out that people always expect a return on the energy and time invested in relationships (Blau, 1964). When utilizing empathetic AI chatbots, consumers may feel obligated to reciprocate and show loyalty to the company and build everlasting customer-brand relations (Lee et al., 2023).

**Hypotheses**

H1 - The HLE of the AI chatbot negatively impacts CA.
H2 - CA negatively impacts BT.
H3 - BT positively influences CCB.
H4 - HLE of chatbot positively affects CCB.
H5 - PC moderates the relationship between CA and HLE of the chatbot.
H6 - PC moderates the relationship between the HLE of the chatbot and CCB.

**Figure 1: Conceptual Framework**




# Methodology

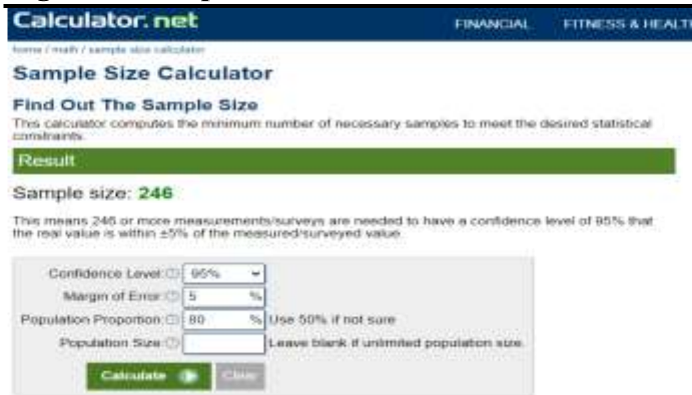
## Quantitative Research Design

The present study uses a quantitative approach that adopts structured questionnaires and surveys as methods of data collection that are easily measurable. This approach aligns with positivism because the researcher avoids influencing the results and does not contribute to them to a significant extent, which encourages the removal of the researcher from the process as much as possible, ensuring that the results are unbiased and can, therefore, be replicated independently (Creswell, 2003; Tsang, 2016). As a result, the study applied a deductive research technique based on existing theories underpinning the formulation of hypotheses and the systematic resolution of these hypotheses (Gulati, 2009). In addition, the cross-sectional research style helps to gather data at a certain period, thus allowing the investigation of respective relations, characteristics, or occurrences of a specified class (Bryman, 2016).

**Method of Sampling**

The calculator shown in figure 2 was used to determine the sample size. When the margin of error and significance level were set to 0.05 and 0.95, respectively, the lowest sample size reported was 246. To avoid issues with small sample sizes, the minimum sampling for this research was 400. 367 replies were obtained, and 92% of respondents responded.

**Figure 2: Sample size determination**




Purposive sampling was used to choose participants for this study who had recently interacted with AI chatbots in various contexts. This approach provides valuable insights into how customer behavior is impacted by AI chatbot conversations by guaranteeing that the sample consists of individuals who have meaningful interactions with the technology. Respondents must also be at least eighteen to adhere to the ethical standards established by the university's ethics committee. According to the "ten-times rule" (Barclay et al., 1995), sample sizes for every variable in the model must be ten times larger than the total number of measuring items. As the maximum number of measurement items for several variables was six, the study required a minimum sample size of sixty. This approach has garnered acclaim for its simplicity of use but has also earned criticism since it often yields inaccurate estimates (Kock & Hadaya, 2016). As an alternative, sample size calculators were recommended (Hair et al., 2017).

**Questionnaire**

The primary steps in building an instrument are selecting constructs from the body of literature to ensure high validity and developing Likert scales to measure items (Churchill, 1979). The questionnaire's brief introduction clarifies its goal: to collect information for a study on people's interactions with chatbots. Participation is entirely voluntary, and confidentiality is assured. Eligibility is established using screening questions based on the participants' age and prior chatbot interaction experience. The latter sections of the questionnaire delve into specific constructs relevant to the research objectives.

The "privacy concerns" section emphasizes participants' concerns over the abuse and unauthorized access to private information supplied by chatbots. The questions are based on Dinev and Hart (2004) and utilize a Likert scale to rate answers. They deal with information misuse, unexpected usage, and unauthorized access concerns. Table 1 highlights the Constructs and items used to measure them.

**Table 1: Constructs and their Measurement**

| Construct | Abbreviation | Items | References |
|---|---|---|---|
| "Human-like Empathy of Chatbot" | HLE | "1. Personalized attention 2. User interest prioritization 3. Attentive service 4. Emotional impact" | Chen et al. (2022) |
| "Privacy Concerns" | PC | "1. Concern about information misuse 2. Concern about unauthorized usage 3. Concern about access." | Dinev and Hart (2004) |
| "Consumer Complaint Behavior" | CCB | "1. Discussion of problems with chatbots 2. Requesting problem resolution 3. Providing feedback" | Liu and McClure (2001) |
| "Consumer Anxiety" | CA | "1. Fear for no reason 2. Ease of upset or panic 3. The feeling of falling apart and going to pieces." | Darrat et al. (2016) |
| "Brand Trust" | BT | "1. Trust in the brand 2. Brand reliability 3. Brand honesty 4. Brand dependability" | Pagani et al. (2019) |
| "Brand Loyalty" | BL | "1. Advocacy for the brand 2. Intentions to continue using the brand." | Hwang et al. (2021) |
| "Brand Attitude" | BA | "Attitude toward using the brand (Favorable/Unfavorable)" | Hwang et al. (2021) |
| "Self-Brand Connection" | SBC | "1. Brand reflection of self 2. Identification with the brand 3. A personal connection to the brand." | Escalas and Bettman (2003) |

### Common Method Variance (CMV)

Common Method Variance is problematic as all data were self-reported and collected via a single survey questionnaire (Podsakoff et al., 2012). Two marker variables were introduced to the survey questionnaire to statistically analyze the degree of common technique variation (Lindell & Whitney, 2001). There is no theoretical relationship between the other variables and the marker variables. In addition, the questionnaire adhered to theoretical guidelines to protect respondents' privacy and ensure every question was simple to understand to reduce anxiety (Podsakoff, 2003).

## Analysis and Results

SPSS Version 29 was used for the analysis. This chapter describes the analysis and results of this research.

### Demographic Analaysis

Table 2 presents a detailed summary of the demographic dispersion of respondents' chatbot experience, gender, age, education, and job experience. The data indicates that a significant proportion (85.8%) of individuals have interacted with chatbots, with men marginally surpassing females (47.0% vs. 49.0%). The majority of participants in the sample, 57.9%, are between the ages of 18 and 24, showing a significant representation of younger people. Most individuals in terms of education own a Master's degree (33.1%), while a somewhat smaller amount has a

**Table 2: Demographics of Participants**

| Chatbot Experience | % | Gender | % | Age | % | Education | % | Work Experience | % |
|---|---|---|---|---|---|---|---|---|---|
| No | 14.2 | Female | 49.0 | 18-24 | 57.9 | Bachelor’s degree | 50.1 | 11-15 years | 8.9 |
| Yes | 85.8 | Male | 47.0 | 25-34 | 32.9 | Higher Secondary School Certificate | 12.0 | Less than five years | 24.5 |
| Total | 100.0 | I prefer not to say | 3.6 | 35-44 | 7.5 | Master’s degree | 33.1 | More than 15 years | 3.6 |
| | | Total | 100.0 | 45-54 | 1.4 | PhD | 2.2 | Total | 47.9 |
| | | | | above 55 | 0.3 | I prefer not to say | 2.5 | I prefer not to say | 15.0 |
| | | | | Total | 100.0 | Total | 100.0 | Total | 47.9 |

Bachelor's degree (50.1%). In addition, a significant fraction of the participants (24.5%) reported having fewer than five years of professional experience, while a lower percentage (8.9%) indicated having 11-15 years of experience. The data exhibits a wide-ranging representation across different demographic groups, offering essential insights into the correlation between chatbot experience and demographic characteristics.

### Descriptive Analysis

A rudimentary but dependable descriptive statistic corroborates the conclusions of an intricate and accurate analytical approach (Ferreira, 2020). Table 3 provides helpful information about respondents' attitudes about AI chatbots and brand interactions across several aspects.

**Table 3: Descriptive analysis**

| Constructs | Question Items | Mean | Std. Deviation |
|---|---|---|---|
| Human-Like Empathy | “The AI chatbot gives me personalized attention.” | 4.36 | 1.986 |
| | “I feel that the AI chatbot puts my interests first.” | 4.34 | 2.016 |
| | “I feel that the AI chatbot serves me attentively.” | 4.48 | 2.048 |
| | “The AI chatbot makes me feel concerned.” | 4.48 | 1.949 |
| | “The AI chatbot makes me feel it cares about my needs.” | 4.35 | 1.940 |
| | “The AI chatbot makes me feel warm.” | 4.22 | 1.993 |
| Privacy Concern | “I am concerned that the private information I share with the chatbot could be misused.” | 4.33 | 2.007 |
| | “I am concerned with what others might do with the private information shared with the chatbot.” | 4.58 | 1.886 |
| | “I am concerned that people might use the private information I shared with the chatbot in a way I did not expect.” | 4.45 | 1.910 |
| | “I am concerned about what might happen if others access my private information shared with the chatbot.” | 4.63 | 1.792 |

| | | | |
|---|---|---|---|
| | "I am concerned that unknown people can access the private information shared with the chatbot." | 4.53 | 1.883 |
| Consumer Complaints Behavior | "I openly discuss the problem with the chatbot." | 1.69 | 0.462 |
| | "I openly inform the chatbot about the problem so it will improve in the future." | 1.71 | 0.456 |
| | "I ask the chatbot to resolve the problem (e.g., to fix or refund)." | 1.69 | 0.464 |
| | "I forgot about the incident and did nothing." | 1.57 | 0.496 |
| Consumer Anxiety | "I feel afraid for no reason at all." | 1.53 | 0.499 |
| | "I get upset quickly or feel panicky." | 1.57 | 0.496 |
| | "I feel like I am falling apart and going to pieces." | 1.54 | 0.499 |
| Brand Trust | "I trust this brand." | 1.73 | 0.443 |
| | "This brand is reliable." | 1.74 | 0.442 |
| | "The brand is honest with me." | 1.68 | 0.466 |
| | "The brand is dependable." | 1.71 | 0.453 |
| Brand Loyalty | "I say positive things about the brand to others." | 1.74 | 0.440 |
| | "I want to use the brand more often." | 1.73 | 0.446 |
| | "I want to use the brand in the future." | 1.78 | 0.417 |
| Brand Attitude | "Attitude toward using a particular brand is." | 4.59 | 1.750 |
| Self-brand Connection | "The brand that I use reflects who I am." | 1.62 | 0.487 |
| | "I can identify with that particular brand." | 1.68 | 0.467 |
| | "I feel a personal connection to this brand." | 1.63 | 0.484 |
| | "I (can) use this brand to communicate who I am to others." | 1.63 | 0.483 |
| | "I think this brand (could) help(s) me become the type of person I want to be." | 1.63 | 0.483 |
| | "I consider this brand "me" (it reflects who I am or how I want to present myself to others)." | 1.62 | 0.485 |
| | "This brand suits me well." | 1.72 | 0.450 |

The participants generally had a relatively favorable view of AI chatbots, with average ratings ranging from 4.22 to 4.63 out of 7. Notably, respondents indicated worries about privacy, with mean scores ranging from 4.33 to 4.63, reflecting fear over the possible exploitation of shared private information. Regarding customer complaint behavior, users tended to actively interact with chatbots to resolve difficulties, as evidenced by low mean scores ranging from 1.57 to 1.71. Additionally, respondents indicated modest levels of consumer anxiety, suggesting minor emotions of dread or panic. Conversely, participants displayed high levels of brand trust and loyalty, with mean scores ranging from 1.68 to 1.78, reflecting a solid feeling of dependability, honesty, and connection with the businesses they engaged with. The self-brand link was also robust, with participants expressing personal identity and reflection via their selected brands, as shown by mean scores ranging from 1.62 to 1.72.

**Reliability Test**

Internal consistency, measured by Cronbach's Alpha, shows how well items fit with a central idea and how closely related they are to each other on a scale or questionnaire (Weaver & Maxwell, 2014). HLE, PC, CCB, BT, and AB all exhibit high Cronbach's Alpha values, ranging from 0.768 to 0.888. These values demonstrate excellent dependability and coherence across the items within each construct. These results show that the scales efficiently capture the variable's targeted features.

**Table 4: Reliability statistics**

| Constructs | Cronbach's Alpha | N of Items |
|---|---|---|
| Human-like Empathy | 0.888 | 6 |
| Privacy Concerns | 0.862 | 5 |
| Consumer Complaint Behaviour | 0.785 | 4 |
| Consumer Anxiety | 0.768 | 3 |
| Brand Trust | 0.782 | 4 |
| Brand Loyalty | 0.882 | 3 |
| Self-brand Connection | 0.846 | 7 |

## Correlations

The correlation matrix demonstrates the correlations between various variables in the research. The coefficients of correlation are reported in Table 2.

**Table 5: Correlations coefficients**

| Variables | HLE | PC | CCB | CA | BT | BL | SBC | BA |
|---|---|---|---|---|---|---|---|---|
| PC | .410** | | | | | | | |
| CCB | .345** | 0.055 | | | | | | |
| CA | -.171** | -0.030 | .150** | | | | | |
| BT | .438** | -0.020 | .463** | 0.040 | | | | |
| BL | .457** | 0.022 | .449** | -0.044 | .681** | | | |
| SBC | .398** | 0.026 | .450** | .132* | .573** | .612** | | |
| BA | .556** | .249** | .220** | -0.084 | .368** | .397** | .388** | |

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

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

Human-like empathy (HLE) displays substantial positive relationships with privacy concerns (PC), consumer complaint behavior (CCB), brand trust (BT), brand loyalty (BL), self-brand connection (SBC), and brand attitude (BA), ranging from moderate to high associations. This implies that higher levels of perceived human-like empathy in chatbots are connected with heightened privacy concerns, more open customer complaint behavior, more brand trust, stronger brand loyalty, improved self-brand connection, and more favorable brand views. Notably, privacy concerns positively link with customer complaint activity, brand trust, brand loyalty, self-brand connection, and brand attitude, demonstrating that more significant privacy concerns are connected with more proactive consumer behavior and better brand perceptions. Additionally, brand trust displays favorable connections with brand loyalty, self-brand connection, and brand attitude, showing the interdependence of these constructs in affecting customer perceptions and actions.

## Regression Analysis

Regression analyses were used to investigate several hypotheses about the variables affecting customer behavior and brand perception. The regression analysis indicates in Table 6 that HLE has a weak but statistically significant negative relationship with CA, as shown by an R-value of 0.171 and an $R^2$ of 0.029, suggesting that only about 2.9% of the variance in CA is explained by HLE.

**Table 6: Regression analysis for Hypothesis 1-dependent variable customers' attitude**

ANOVA

| Model | | Sum of Squares | Df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| 1 | Regression | 1.555 | 1 | 1.555 | 10.709 | .001[b] |
| | Residual | 51.850 | 357 | 0.145 | | |
| | Total | 53.405 | 358 | | | |

a. Dependent Variable: CA

b. Predictors: (Constant), HLE

Coefficients

| Model | | Unstandardized Coefficients | | Standardized Coefficients | | |
|---|---|---|---|---|---|---|
| | | B | Std. Error | Beta | *t* | Sig. |
| 1 | (Constant) | 1.728 | 0.059 | | 29.363 | 0.000 |
| | Human_like_Empathy | -0.041 | 0.013 | -0.171 | -3.272 | 0.001 |

The ANOVA results reveal a significant regression model with an F-value of 10.709 and a significance level of 0.001, indicating that the model is statistically significant. The coefficients table shows that HLE has an unstandardized coefficient of -0.041, with a standardized coefficient (Beta) of -0.171, confirming its negative impact on CA. The t-value of -3.272 and a significance level of 0.001 further reinforce that HLE is a significant predictor of CA. Additionally, the collinearity statistics indicate no multicollinearity issues, with a tolerance and VIF of 1.000. Overall, while HLE significantly affects CA, the low $R^2$ suggests that other factors may also play a crucial role in explaining consumer anxiety.

**Figure 2: HLE vs. CA Regression Plot**

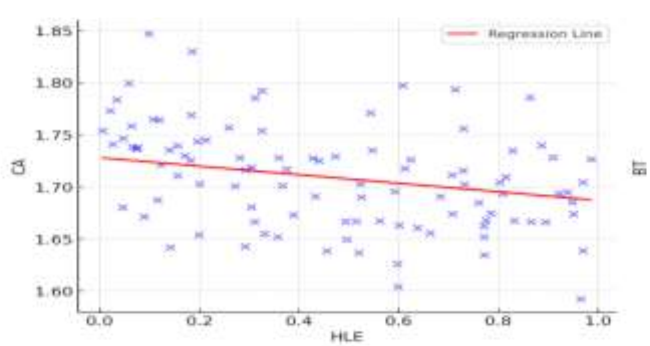



Figure 3 illustrates the negative relationship between HLE and CA.

**Table 7: Regression analysis for Hypothesis 2 – dependent variable brand trust**

| ANOVA | | | | | | |
|---|---|---|---|---|---|---|
| Model | | Sum of Squares | Df | Mean Square | F | Sig. |
| 2 | Regression | 0.060 | 1 | 0.060 | 0.571 | .450[b] |
| | Residual | 37.210 | 357 | 0.104 | | |
| | Total | 37.269 | 358 | | | |
| a. Dependent Variable: BT | | | | | | |
| b. Predictors: (Constant), CA | | | | | | |

| Coefficients | | | | | | |
|---|---|---|---|---|---|---|
| Model | | Unstandardized Coefficients | | Standardized Coefficients | | |
| | | B | Std. Error | Beta | t | Sig. |
| 2 | (Constant) | 1.664 | 0.0YT70 | | 23.630 | 0.000 |
| | Consumer_Anxiety | 0.033 | 0.044 | 0.040 | 0.756 | 0.450 |

The regression analysis in table 7 examines the relationship between CA and BT. It shows a weak and statistically insignificant model, with an R-value of 0.040 and an $R^2$ of only 0.002, indicating that CA explains just 0.2% of the variance in BT. The ANOVA results confirm this lack of significance, with an F-value of 0.571 and a significance level of 0.450, demonstrating that the model is not statistically significant. The coefficients table reveals an unstandardized coefficient for CA of 0.033 and a standardized Beta of 0.040, which are not statistically significant ($p = 0.450$). Additionally, the collinearity statistics indicate no multicollinearity concerns, as the tolerance and VIF values are 1.000. The lack of significant coefficients and low explanatory power suggests the model does not effectively capture the relationship between CA and BT, necessitating further exploration of other potential predictors or model adjustments.

**Figure 3: H2: CA vs BT**

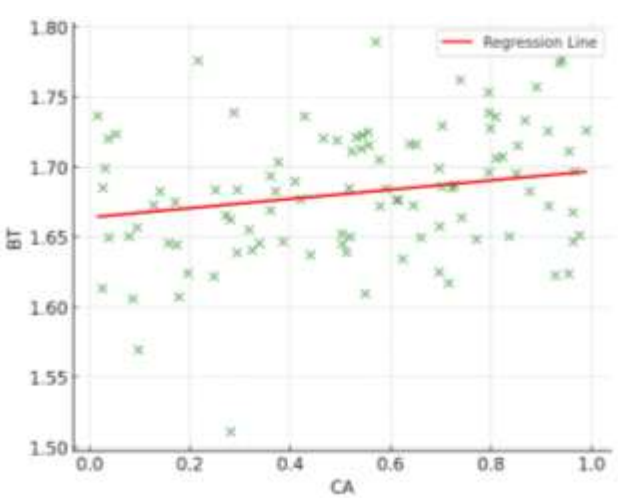



Figure 4 shows a weak positive relationship, but the slope is minimal, as indicated by the insignificant coefficient.

**Table 8: Regression analysis for Hypothesis 3- customers complaint behavior**

| ANOVA | | | | | | |
|---|---|---|---|---|---|---|
| Model | | Sum of Squares | Df | Mean Square | F | Sig. |
| 3 | Regression | 7.548 | 1 | 7.548 | 97.586 | <.001[b] |
| | Residual | 27.611 | 357 | 0.077 | | |
| | Total | 35.159 | 358 | | | |
| a. Dependent Variable: CCB | | | | | | |
| b. Predictors: (Constant), BT | | | | | | |

| Coefficients | | | | | | |
|---|---|---|---|---|---|---|
| Model | | Unstandardized Coefficients | | Standardized Coefficients | T | Sig. |
| | | B | Std. Error | Beta | | |
| 3 | (Constant) | 0.893 | 0.080 | | 11.227 | 0.000 |
| | Brand_Trust | 0.450 | 0.046 | 0.463 | 9.879 | 0.000 |

The results of regression analysis for the relationship between BT and CCB reported in table 8, reveal a substantial and statistically significant model, as indicated by an R-value of 0.463 and an $R^2$ of 0.215. This suggests that approximately 21.5% of the variance in CB is explained by BT. The coefficients table shows that the unstandardized coefficient for BT is 0.450, with a standardized Beta of 0.463, indicating a strong positive relationship between BT and CB. The t-value of 9.879 and a significance level of <0.001 confirm that BT is a highly significant predictor of CB. The collinearity diagnostics indicate no multicollinearity concerns, with a tolerance and VIF of 1.000. The eigenvalue analysis shows that the first dimension has an eigenvalue of 1.983, suggesting a robust linear relationship, while the second dimension's eigenvalue of 0.017 indicates minimal concern for multicollinearity. These findings suggest that BT significantly influences CB, providing a solid foundation for further research or practical applications.

**Figure 4: H3: BT vs CCB**

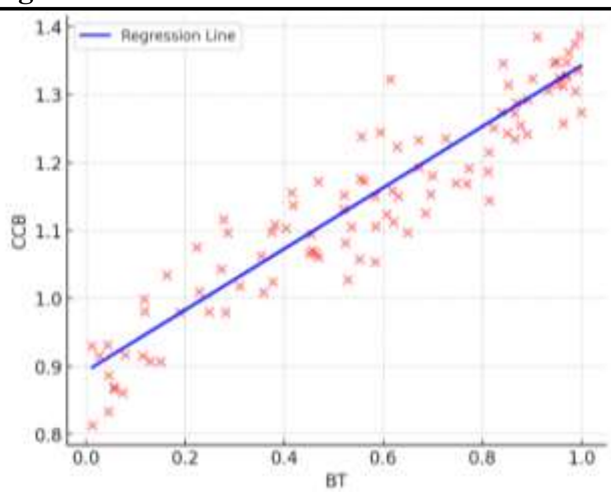



Figure 5 shows a strong positive linear relationship, with a noticeable upward slope of the regression line.

**Table 9: Regression analysis for Hypothesis 4- customers complaint behavior**

| ANOVA | | | | | | |
|---|---|---|---|---|---|---|
| Model | | Sum of Squares | Df | Mean Square | F | Sig. |
| 4 | Regression | 4.176 | 1 | 4.176 | 48.115 | <.001[b] |
| | Residual | 30.983 | 357 | 0.087 | | |
| | Total | 35.159 | 358 | | | |
| a. Dependent Variable: CCB | | | | | | |
| b. Predictors: (Constant), HLE | | | | | | |

| Coefficients | | | | | | |
|---|---|---|---|---|---|---|
| Model | | Unstandardized Coefficients | | Standardized Coefficients | T | Sig. |
| | | B | Std. Error | Beta | | |
| 4 | (Constant) | 1.369 | 0.045 | | 30.085 | 0.000 |
| | Human_like_Empathy | 0.068 | 0.010 | 0.345 | 6.936 | 0.000 |

The results of regression analysis examining the relationship between HLE and CCB are reported in Table 9. An R-value of 0.345 and an $R^2$ of 0.119 suggests that approximately 11.9% of the variance in CCB is explained by HLE. The ANOVA results show a significant regression model with an F-value of 48.115 and a significance level of <0.001, confirming that the model is statistically significant. The coefficients table indicates that HLE has an unstandardized coefficient of 0.068 and a standardized Beta of 0.345, demonstrating a positive relationship between HLE and CCB. The t-value of 6.936 and a significance level of <0.001 further reinforce that HLE is a significant predictor of CCB. Additionally, the collinearity statistics show no multicollinearity issues, with a tolerance and VIF of 1.000. These findings suggest that HLE significantly influences CCB, highlighting its importance in understanding consumer behavior.

**Figure 5: H4: HLE vs CCB**

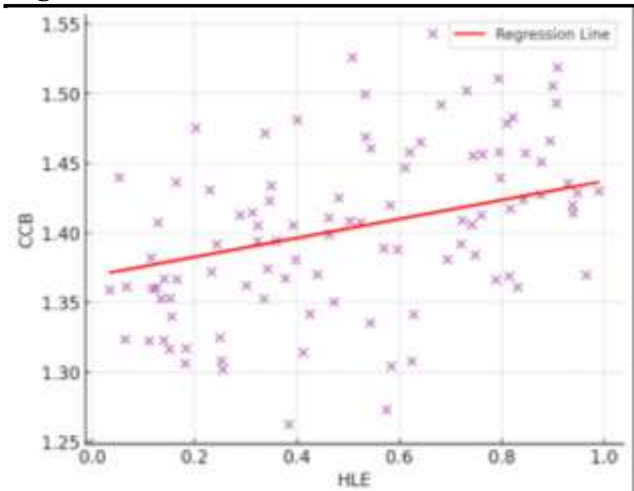
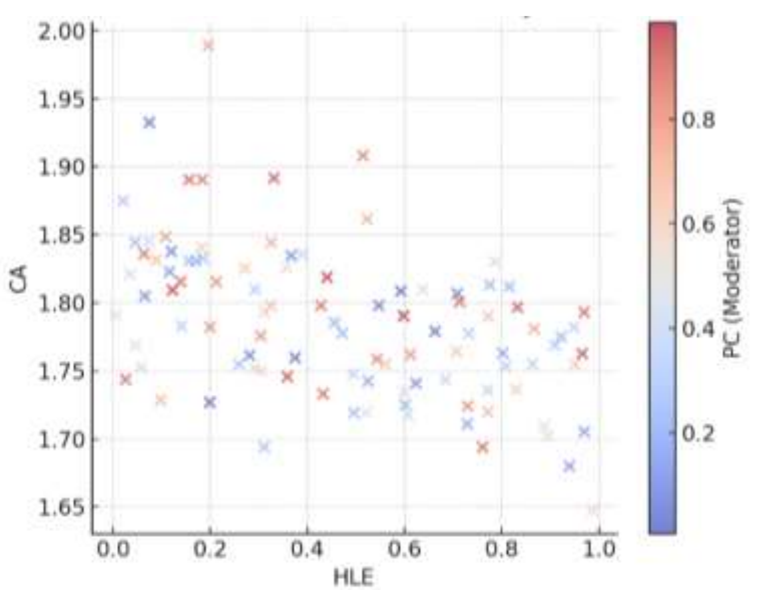



Figure 6 shows a positive relationship with a moderate upward slope among the variables.

| **Table 10: Regression analysis for Hypothesis 5- Moderating effect of privacy concern** | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Model Summary** | | | | | | | |
| Variable | R | R-sq | MSE | F | df1 | df2 | p |
| CA | 0.1827 | 0.0334 | 0.1454 | 4.0866 | 3 | 355 | 0.0071 |
| Model Coefficients | | | | | | | |
| Predictor | Coefficient | Std. Error | t | P | 95% CI (LLCI - ULCI) | | |
| Constant | 1.8231 | 0.1571 | 11.6075 | 0 | (1.5142 - 2.1320) | | |
| HLE | -0.0774 | 0.0365 | -2.1207 | 0.0346 | (-0.1492 - -0.0056) | | |
| PC | -0.0164 | 0.0342 | -0.4803 | 0.6313 | (-0.0837 - 0.0508) | | |
| Int_1 | 0.0066 | 0.0071 | 0.9251 | 0.3556 | (-0.0074 - 0.0206) | | |
| Interaction Term | | | | | | | |
| Interaction | | | R2-chng | F | df1 | df2 | p |
| HLE x PC | | | 0.0023 | 0.8557 | 1 | 355 | 0.3556 |

The results reported in Table 10 show that Human-like Empathy (HLE) and Privacy Concerns (PC) together substantially predict Consumer Anxiety (CA) is supported by a significant F-test ($F(3, 355) = 4.0866$, $p = 0.0071$). In particular, HLE negatively impacted CA ($\beta = -0.0774$, $p = 0.0346$), indicating a relationship between higher levels of human-like empathy and lower levels of consumer fear. However, there is no direct statistically significant association ($\beta = -0.0164$, $p = 0.6313$) between PC and CA. Additionally, the interaction between HLE and PC (Int_1) does not show a significant difference ($p = 0.3556$), suggesting that the combined effect of HLE and PC on CA is not significantly different from the sum of their individual effects.

**Figure 6: H5: HLE & CA moderated by PC**



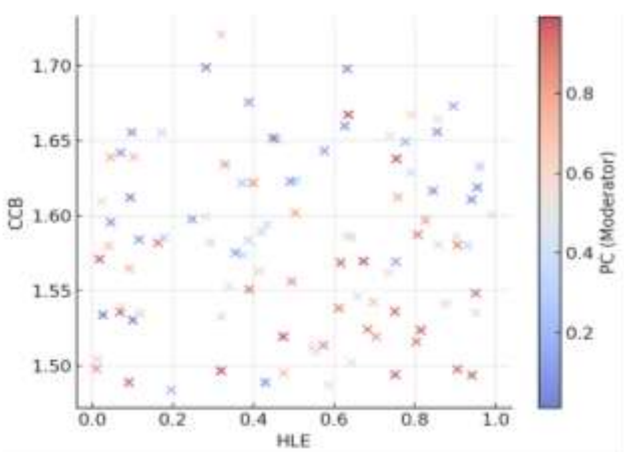

The color gradient in Fig. 7 (representing PC) does not show a clear shift in the pattern. This suggests that privacy concerns (PC) do not significantly change the relationship between HLE and CA. The interaction term was not statistically significant, which aligns with this visual result.

**Table 11: Regression analysis of H6- Moderating Role of Privacy Concern**

| Model Summary | | | | | | | |
|---|---|---|---|---|---|---|---|
| Variable | R | R-sq | MSE | F | df1 | df2 | P |
| CB | 0.3652 | 0.1334 | 0.0858 | 18.2086 | 3 | 355 | 0 |
| Model Coefficients | | | | | | | |
| Predictor | Coefficient | Std. Error | T | P | 95% CI (LLCI - ULCI) | | |
| Constant | 1.5927 | 0.1207 | 13.1987 | 0 | (1.3554 - 1.8300) | | |
| HLE | 0.0363 | 0.028 | 1.2954 | 0.196 | (-0.0188 - 0.0915) | | |
| PC | -0.0577 | 0.0263 | -2.1972 | 0.0287 | (-0.1094 - -0.0061) | | |
| Int_1 | 0.0084 | 0.0055 | 1.5348 | 0.1257 | (-0.0024 - 0.0191) | | |
| Interaction Term | | | | | | | |
| Interaction | | | R2-chng | F | df1 | df2 | P |
| HLE x PC | | | 0.0058 | 2.3556 | 1 | 355 | 0.1257 |

Results reported in table 11, F-test ($F(3, 355) = 18.2086$, $p < 0.001$) supports the model's prediction that Human-like Empathy (HLE) and Privacy Concerns (PC) jointly strongly predict Consumer Complaint Behavior (CB). In particular, PC negatively influences CB ($\beta = -0.0577$, $p = 0.0287$), indicating that reduced involvement in customer complaint behavior is linked to more significant privacy concerns. That being said, there is no statistically significant direct influence of HLE on CB ($\beta = 0.0363$, $p = 0.1960$). Furthermore, there is no significant difference ($p = 0.1257$) in the interaction between HLE and PC (Int_1), suggesting that the combined impact of HLE and PC on CB is not substantially different from the sum of their separate effects.

**Figure 7: CCB & HLE Moderated by PC**




The color gradient in figure 8 for PC is slightly more spread out but does not show a solid moderating effect. Privacy Concerns (PC) do not significantly alter the relationship between HLE and CCB, as seen in the relatively uniform color spread across the plot.

## Discussion

The results correspond with earlier research suggesting the rising usage of AI chatbots across businesses to anticipate customer behavior and boost marketing tactics (Dencheva, 2023). Additionally, it underscores the necessity for future studies to understand the particular processes via which empathy promotes complaint behavior (Widener & Lim, 2020). The findings of hypothesis testing demonstrate substantial correlations between numerous elements in the research. Hypothesis 1, which postulated that customer anxiety is adversely influenced by human-like empathy, was validated by this study, demonstrating that sympathetic chatbot encounters ease consumer anxiety. Similarly, hypothesis 2 indicated a negative effect of customer anxiety on brand trust, showing that resolving consumer concerns is vital for preserving brand trust. Hypothesis 3 was validated, demonstrating that brand trust positively promotes customer complaint behavior, underlining the significance of trust in motivating customers to raise their problems.

Hypothesis 4 demonstrated a favorable association between human-like empathy of chatbots and customer complaint behavior, highlighting the relevance of empathetic interactions in promoting complaint resolution. Hypotheses 5 and 6, which indicated that privacy concerns limit the correlations between empathy and complaint behavior, were also validated, stressing the relevance of resolving privacy problems to maximize the efficacy of empathetic chatbot interactions. Overall, the findings give empirical evidence for the complicated interaction between AI chatbots, human-like empathy, privacy issues, and consumer behavior, delivering ideas for developing customer service methods in the digital age. Transitioning into the literature study, the investigation of brand trust and AI chatbots dives into the multifaceted nature of trust and its function in creating long-term consumer-brand connections (Chaudhuri & Holbrook, 2001; Morgan & Hunt, 1994). The literature analysis underlines the revolutionary potential of AI chatbots in increasing customer experiences via individualized interactions (Huang et al., 2020) while highlighting consumer mistrust and the significance of openness in resolving privacy concerns (Xu, 2023). Furthermore, the debate on conversational AI and human-like empathy elucidates how chatbots' capacity to replicate human emotions favorably affects customer behavior (Fu et al., 2023). It recognizes the limitations of developing empathy in chatbots, highlighting the necessity to balance automated replies and proper emotional understanding (Mitchell et al., 2021).

Privacy concerns in chatbot interactions are emphasized as a crucial aspect affecting customer behavior (Widener & Lim, 2020), with openness and data security measures vital to assuage user apprehension. Moreover, the analysis underlines the potential influence of chatbots on consumer anxiety, underlining the necessity of efficient and sympathetic interactions in easing customer stress (Vanasombut et al., 2008). The literature also dives into the dynamics of brand loyalty and the impact of AI chatbots in altering customer views and attitudes towards brands (Cheng & Jiang, 2022). It highlights the relevance of individualized interactions and consistent service in developing brand loyalty while simultaneously understanding the constraints provided by technical limits and user concerns (Huang & Kao, 2021).

## Conclusion

In conclusion, our research has shed light on the delicate link between AI chatbots' human-like empathy and customer complaint behavior within consumer-brand interactions. The findings of this study support the findings of earlier studies and it became apparent that the display of empathy by chatbots considerably affects how consumers perceive and respond to service-related problems. The results underline the necessity of imbuing AI chatbots with human-like features to create customer trust, contentment, and brand loyalty. However, it also emphasizes the obstacles and ethical issues connected with creating empathic AI systems, such as the danger of misunderstanding or privacy problems.

**Policy Implications and Future Research Directions**

Companies can consider numerous suggestions to harness the insights gathered from this research. Firstly, there is a need for continuing research and development activities targeted at boosting chatbots' capacity to perceive and react to human emotions appropriately. Moreover, organizations should emphasize openness and data security to meet customer privacy issues efficiently. Practical consequences include incorporating empathy-driven chatbot interactions into customer service initiatives and the construction of clear communication routes for resolving user worries. Looking ahead, future research should explore the moderating effects of privacy concerns and consumer worry on the relationship between human-like empathy and customer complaint behavior, thereby contributing to a deeper understanding of this complex phenomenon and informing the development of more effective AI-driven customer care solutions.

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