Human Characteristics in Chatbots Cause an Impact on Customer Experience in The Banking Sector

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Abstract
This study investigates how the human characteristics of chatbots, such as warmth and competence, impact customer experience in the banking sector of Lima, Peru. Given the increasing adoption of artificial intelligence in the financial sector, this analysis is warranted by the need to understand its influence on user satisfaction and loyalty. Through a non-experimental quantitative methodology and virtual surveys, we evaluated whether the personalization and social presence of chatbots enhance user perception, particularly among younger generations. The findings reveal that, while users value these characteristics, neutral responses persist, indicating a lack of emotional connection in certain cases. This underscores the importance of optimizing chatbot implementation to maintain competitiveness in the digital age. This study highlights the relevance of tailoring AI solutions to customer expectations to foster a more positive and personalized experience. During the course of this study, we found no similar research conducted within the Peruvian market designed to measure the impact of relevant variables on consumer experience in the banking sector when interacting with a chatbot.

Keywords: Artificial Intelligence, ChatBots, Consumer Experience, Banking Sector, Personalization

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Introduction

Artificial intelligence (AI) has become a transformative force across various sectors, including banking, and its impact is projected to grow significantly in the coming years. According to McKinsey (2023), AI is estimated to increase productivity in the banking sector by 2.8% to 4.7%, resulting in additional annual revenues of $200 billion to $340 billion. Furthermore, the European Banking Authority (2022) reports that 83% of banks already employ AI in various operations, with full implementation of AI-based solutions expected by 2025. This advancement is crucial, as banks' competitive advantage will be closely tied to the effective adoption and implementation of AI. However, poor adoption and implementation could create challenges and risks for banking institutions, jeopardizing their competitiveness and their ability to meet the rising expectations of customers in the digital banking market.

One of the most notable manifestations of this transformation is the increasing use of chatbots in financial services. According to a Salesforce (2019) report, 62% of customers are willing to interact with chatbots if they enhance the user experience, and 73% believe that a positive chatbot experience raises their expectations for other companies. This study focuses on investigating the relevant factors for chatbot implementation from the perspective of user interaction and perception. It will examine in detail the anthropomorphic elements most valued by users and how these elements can impact the user experience.

Banking Sector in Lima, Peru

In Lima, Peru, the distribution of banks and branches is a crucial aspect of understanding the implementation and acceptance of technologies such as chatbots in the banking sector. The location of offices reflects the strategies and priorities of major financial institutions in positioning themselves in specific areas of the city. Lima is divided into four main sectors: Lima North, Lima East, Lima Center, and Lima South, each with particular characteristics that influence the presence of banking offices.

According to data from the Superintendence of Banking, Insurance, and AFP (2024), Lima Center has the highest number of branches, with a total of 388 offices, accounting for over 54.6% of the city's branches. This is due to the strong presence of districts such as San Isidro, Miraflores, and Santiago de Surco, which together host a large number of offices due to their high financial and commercial activity. For instance, San Isidro alone has 56 branches, and Miraflores has 51. Banks such as BCP and BBVA have more than 10 offices in each of these districts, demonstrating the high demand for financial services and the substantial purchasing power of their residents. Scotiabank, with 13 branches in San Isidro and Surco, also contributes to the intense competition in a highly consolidated market.

In contrast, Lima North, which includes districts such as Comas, Los Olivos, and San Martín de Porres, is the second region with the highest number of branches, totaling 187 offices or 26.3% of the city's total. This area is the most densely populated in Lima, with a predominance of middle-class families (Infobae, 2024). In this area, Mibanco and BCP are prominent players, with Mibanco focusing on attracting entrepreneurs and small local businesses (Aprenda, 2018). Districts such as Comas and Los Olivos have a significant concentration of offices, with 23 and 25 branches, respectively, reflecting financial institutions' efforts to cater to a growing segment.

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Lima East, which includes districts such as San Juan de Lurigancho, Ate, and Santa Anita, has 69 branches, representing 9.7% of the total in Lima. San Juan de Lurigancho, the largest and most populated district in the city, accounts for most of these branches, with a total of 37 offices. Here, BBVA and Mibanco have a strong presence, although more remote districts such as Chaclacayo have limited availability of banking services.

Lima South has the fewest bank branches, totaling only 67, which accounts for 9.4% of the total in Lima. Santiago de Surco is an exception in this zone, with 28 branches due to its high concentration of services in an established district. In contrast, districts such as Villa María del Triunfo and Villa El Salvador have only 11 and 15 branches, respectively.

Overall, the distribution of branches in Lima indicates that Lima Center remains the primary focus for banks, followed by Lima North, which has shown significant growth in terms of population and demand for financial services. Lima East and Lima South, although having fewer branches, present significant opportunities for expansion, particularly through digital solutions that can compensate for the lack of physical infrastructure and connect with customers with limited access to branch offices.

The significant number of branches in Lima highlights the need for effective virtual customer service channels in the banking sector. According to data from INEI (2023), 57.4% of adults over 18 have a financial system account, reflecting steady growth. This increase emphasizes the urgency of improving digital infrastructure to meet customer expectations and maintain competitiveness in the digital banking market.

Additionally, the Financial Inclusion Report by Credicorp (2022) indicates that the level of digitalization is significantly higher in socioeconomic levels (NSE) A and B, reaching 62%, compared to 53% in NSE C and only 31% in NSE D and E. Furthermore, the APEIM (2021) report reveals that most clients in NSE A and B are concentrated in Zone 7 of Lima, which represents 78.9% of these sectors' participation, followed by Zone 6 with 70.2% and Zone 8 with 24.8%, while the other zones have lower participation rates.

Regarding the different generations with financial system accounts and their specific characteristics and expectations regarding banking services, Generation Z (1997–2009) stands out as the most frequent user of digital channels among banked users, greatly valuing friendly treatment from brands. Millennials, also known as Generation Y (1981–1996), have the highest proportion of banked users with credits or loans. Meanwhile, Generation X (1965–1980) holds the most credit cards and is the demographic with the highest adoption of home internet services (Ipsos, 2022).

Chatbots in the customer experience

Recent research highlights that customers especially value chatbots' ability to exhibit human-like traits such as warmth and competence, which significantly impact customer experience (Pizzi et al., 2023; Li et al., 2023). This experience is defined as an empathetic and emotional interaction between a chatbot and a customer, perceived as pleasant and memorable (Song et al., 2022). Among the traits of warmth and competence relevant to customer experience, the quality of interaction and the efficiency in gathering information emerge as crucial factors for improving user experience (Ranieri et al., 2024). Other studies reveal that users appreciate friendly and personalized communication, transforming chatbots into social assistants that enhance user satisfaction (Roy & Naidoo, 2021; Guerreiro & Loureiro, 2023). Furthermore, features such as emoji use and humor can positively influence customer perceptions (Nguyen et al., 2023; Shin et al., 2023).

For younger generations, such as Millennials (Generation Y) and Generation Z, an additional dimension exists in chatbot interactions. These demographic groups not only value warmth and competence but also prioritize personalization and the social presence chatbots can offer, even appreciating the inclusion of avatars (De Cicco et al., 2020; Ameen et al., 2022). Generation Z, in particular, expects chatbots not only to facilitate interactions but also to provide significant improvements over traditional banking services (Saklani et al., 2024).

Studies emphasize the importance of more human-like and personalized interactions to enhance user satisfaction and trust in the system (Nguyen et al., 2023). Additionally, perceived utility and problem-solving capacity are critical factors for a positive user experience (Rizomyliotis et al., 2022; Sari & Adinda, 2023). It is also essential to recognize that underlying experiences and attitudes toward chatbots may differ among generations, including Millennials (Generation Y), Generation X, and Generation Z (Dwivedi et al., 2023).

Based on these findings and given the importance of properly implementing chatbots in banking customer service channels, the main objective of this study is to analyze whether the inclusion of human-like or anthropomorphic characteristics—such as warmth, competence, and close or personalized attention—influences customer experience in the banking sector. Additionally, the study will evaluate whether these characteristics improve chatbot implementation and outcomes within financial companies' customer service strategies.

The general hypothesis of this research, derived directly from these findings, is as follows:

General Hypothesis (H1): Human-like characteristics in chatbots positively influence customer experience in the banking sector in Lima, Peru.

This hypothesis is supported by the idea that the Elaboration Likelihood Model (ELM), the Technology Acceptance Model (TAM), and the Theory of Perceived Humanity emphasize that human elements in technological interactions significantly influence users' attitudes and perceptions. The ELM suggests that appealing cues—such as empathy and politeness in interactions with technological assistants—can shape attitudes and behaviors by affecting both central and peripheral processing (Petty & Cacioppo, 1986; Chen et al., 2022). The extended

TAM, in turn, recognizes that beyond usefulness and ease of use, emotional dimensions such as warmth and perceived competence influence technology acceptance and, therefore, the user experience (Park et al., 2024; Liu, 2024). Moreover, the perception of humanity in chatbots—which integrates these dimensions—fosters a more personalized experience, generating greater trust and satisfaction (Belanche et al., 2021; Blut et al., 2021).

Studies also demonstrate that chatbots exhibiting human-like characteristics generate more satisfying user experiences, fostering loyalty and satisfaction in highly competitive sectors (Li et al., 2023).

To deepen the analysis and specifically evaluate the impact of each characteristic on customer experience, the different dimensions of the "human-like characteristics" variable were considered, leading to the development of the following specific hypotheses:

Specific Hypothesis (H2): The perception of warmth in chatbots positively impacts users' experience.

This hypothesis is grounded in the emotional presence and connection that can develop during interactions with a chatbot. The Social Presence Theory suggests that warmth, perceived through empathetic and friendly behaviors of chatbots, contributes to creating a more pleasant and memorable interaction (Song et al., 2022; Schmid et al., 2022). This is essential in environments like banking, where customers value efficiency but also expect close, human-like service.

Other research suggests that the perception of warmth improves user satisfaction and trust in the service (Roy & Naidoo, 2021; Ranieri et al., 2024). This reinforces the importance of chatbots not only providing precise responses but also doing so in a friendly and approachable manner.

Specific Hypothesis (H3): The perception of competence in chatbots positively impacts users' experience.

The perception of competence is linked to users' trust in technology and AI. Previous studies suggest that if chatbots are perceived as competent (i.e., fast, accurate, and effective), the user experience improves significantly, particularly in financial services where the accuracy of delivered information is crucial (Belanche et al., 2021; Liu & Sundar, 2018).

In the banking context specifically, perceived chatbot competence is essential for customer satisfaction. Users expect chatbots to not only provide quick solutions but also be accurate and reliable (Rizomyliotis et al., 2022). Studies indicate that a high perception of chatbot competence enhances overall satisfaction (Sari & Adinda, 2023).

This study acknowledges several limitations that must be considered. First, it focuses exclusively on the banking sector in metropolitan Lima, Peru, which may limit the generalization of the findings to other geographic contexts or industrial sectors. Additionally, the study is restricted to articles reviewed in Spanish and English and focuses solely on individuals aged 18 to 55, potentially excluding valuable perspectives from other age groups or speakers of different languages.

Literature Review

The theoretical framework of this research is based on four key theories: the Elaboration Likelihood Model (ELM), the Theory of Perceived Humanity, Psychological Experience Theories, and the Technology Acceptance Model (TAM).

The ELM, developed by Petty and Cacioppo (1986), describes how individuals process information through two distinct routes: the central route and the peripheral route. The central route involves deep, analytical processing based on solid arguments and evidence, whereas the peripheral route relies on appealing cues that require less cognitive effort. This model is used to evaluate how chatbots can influence users' attitudes and behaviors through cognitive cues—such as the information and intelligence they provide—and peripheral cues, such as design and visual elements (Chen et al., 2022; Lu et al., 2019). By optimizing chatbots to deliver persuasive messages, it is possible to align user responses with their level of motivation and interest (Nguyen et al., 2022).

The Theory of Perceived Humanity has been integrated into studies on technology and artificial intelligence to understand how human characteristics—such as competence and warmth—affect human-machine interactions. Competence refers to a chatbot's ability to adapt and provide effective service, while warmth implies empathy and courtesy, fostering a stronger emotional connection with the user (Belanche et al., 2021a; Maar et al., 2022). These qualities are essential for improving the perceived service quality of chatbots. The perception of humanity in chatbots, including characteristics such as anthropomorphism and empathy, can significantly enhance conversation quality and overall user satisfaction (Blut et al., 2021; Liu & Sundar, 2018).

Psychological Experience Theories, such as those proposed by Hassenzahl and Tractinsky (2006) and Hoffman and Novak (1996), provide a framework for understanding how users perceive and experience interactions with chatbots. These theories emphasize the importance of user experience in terms of emotional and cognitive factors, which can influence the perception of humanity in the chatbot and the user's intention to recommend the service. The integration of these theoretical approaches enables a deeper understanding of how cognitive and peripheral cues provided by chatbots—mediated by perceived humanity and psychological experience—affect the user experience throughout the pre-purchase and post-purchase stages (Mishra et al., 2021).

The Technology Acceptance Model (TAM), proposed by Davis (1989), establishes that perceived usefulness and ease of use are key factors in determining the acceptance of new technologies. However, in contexts where human-technology interaction requires a more empathetic and personalized connection—such as in the case of chatbots—this model may fall short. Recent studies have expanded TAM by incorporating emotional and perceptual dimensions such as warmth, competence, and anthropomorphic appearance, allowing for a more nuanced understanding of user attitudes toward intelligent technologies. It has been demonstrated that anthropomorphism and chatbot personalization significantly influence both usage intention and customer satisfaction (Park, Kim, Jiang & Kim, 2024). Furthermore, the appearance of the chatbot, along with its functional attributes, directly affects consumers' intentions to share information and make purchases, highlighting the moderating role of novelty-seeking behavior (Liu et al., 2024). The integration of these dimensions into TAM provides a more comprehensive framework for analyzing technology acceptance and its relationship with user experience, particularly in scenarios where emotional factors are critical for generating satisfaction, trust, and continued use intentions.

Methodology

This study focuses on investigating how the human-like characteristics of chatbots influence, either positively or not, user experience in the banking industry from a quantitative perspective. A non-experimental cross-sectional and correlational-causal research design has been chosen. It is considered non-experimental since the research will be conducted without manipulating variables, instead observing and analyzing them as they naturally occur in their environment. Furthermore, it is classified as cross-sectional and correlational-causal because the study aims to establish the relationship between two variables at a specific point in time, either in correlational or cause-effect terms (Hernández-Sampieri, 2018).

The research will focus on generations that use digital channels the most: Generation X, Millennials or Generation Y, and Generation Z. Based on the latest CPI study in 2023, 57.1% of Lima's population is aged between 18 and 55 years. This means that out of Lima's total population of 9,970,200 people, 5,692,984 belong to Generations Y, Z, and X and are adults.

Regarding the distribution of survey areas in Metropolitan Lima, the sample will include various zones of Lima, prioritizing districts with a higher number of digital users. As indicated in the Credicorp Financial Inclusion Report (2022), this includes, in particular, socioeconomic levels A and B, which are primarily concentrated in zones 7, 6, and 8 of Metropolitan Lima.

To define the sample, a 95% confidence level and a 5% margin of error were used, assuming the expected proportion of the population with the characteristic of interest (p) is 0.5. The resulting sample size is 385 individuals to be surveyed (see Figure 1), utilizing convenience sampling based on the availability and accessibility of participants.

Figure 1
Procedure for calculating the sample size for the survey

$$n = \frac{N * Z^2 * P * Q}{(Z^2*P*Q + (N-1)* E^2)} = \frac{5{,}692{,}984 * 1.96^2 * 0.5 * 0.5}{1.96^2 * 0.5 * 0.5 + (5{,}692{,}984-1) * 0.05^2}$$

$$n = \frac{5{,}467{,}542}{14233.42} = 384.13$$

For data collection, the virtual survey technique will be used. The questionnaire designed by Dwivedi et al. (2023) has been chosen as the basis for this study. This questionnaire, which will be shared via Google Forms, begins by informing participants about the study's objectives, how their data will be used, and any potential risks associated with participation. Participants will be asked to provide their consent before participating, ensuring that their involvement is voluntary.

The questionnaire by Dwivedi et al. (2023) uses a 7-point Likert scale ranging from strongly disagree (1) to strongly agree (7). However, for the purposes of this research, the scale will be adapted to a 5-point version, ranging from strongly agree (5) to strongly disagree (1). Additionally, sociodemographic data will be collected from participants to better contextualize the study results.

The validation of Dwivedi et al.'s (2023) questionnaire demonstrates that it is a consistent and reliable tool for measuring perceptions of human characteristics and their impact on interactions with chatbots, making it suitable for the objectives of this study.

The questionnaire has been used as published in the journal, maintaining the integrity of the original measurement tool and respecting established copyright. The only modification made is the exclusion of the variable "intention to recommend." This decision stems from the research's primary objective, which is to analyze how the human characteristics of chatbots influence customer experience, focusing on immediate perceptions and interaction quality rather than long-term impact. Customer experience theory highlights that immediate perceptions of warmth and competence can enhance user experience but do not necessarily influence the intention to recommend, as the latter may depend on additional and more complex factors (Hassenzahl & Tractinsky, 2006).

Since the questionnaire is being adopted from an already published and validated article (see Table 1 & 2), the reliability and validation format for the questionnaire is not included.

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Table 1

Validated Questions – Variable: Human Characteristics in Chatbots

AUTOR	QUESTION	DIMENSION
Dwivedi et al.	I perceive that this chatbot cares about me while interacting	Warmth
Dwivedi et al.	I perceived that this chatbot is kind to me.	Warmth
Dwivedi et al.	I perceive that this chatbot is friendly during the conversation.	Warmth
Dwivedi et al.	I perceive that the conversation with this chatbot is warm.	Warmth
Dwivedi et al.	I feel that this chatbot is sociable.	Warmth
Dwivedi et al.	I perceive that this chatbot is intelligent.	Competence
Dwivedi et al.	I perceive that this chatbot is skilled.	Competence
Dwivedi et al.	I perceived that, this chatbot is capable	Competence
Dwivedi et al.	I perceive that this chatbot is effective.	Competence
Dwivedi et al.	I perceive that this chatbot is efficient.	Competence
Dwivedi et al.	The interaction is more personalized.	Competence

Note: Adapted from "Do chatbots establish 'humanness' in the customer purchase journey? An investigation through explanatory sequential design" by Dwivedi et al., 2023. (https://doi.org/10.1002/mar.21888)

Table 2

Validated Questions – Variable: Customer Experience – Adapted

AUTOR	QUESTION	DIMENSION
Dwivedi et al.	The Interaction through chatbots is more appealing.	Experience
Dwivedi et al.	It is easy to navigate through chatbots during interactions.	Experience
Dwivedi et al.	The query results are returned promptly.	Experience
Dwivedi et al.	The query results are always up to date.	Experience
Dwivedi et al.	The query are always accurate	Experience

Note: Adapted from "Do chatbots establish 'humanness' in the customer purchase journey? An investigation through explanatory sequential design" by Dwivedi et al., 2023. (https://doi.org/10.1002/mar.21888)

The main dimensions to analyze within anthropomorphic characteristics include the perception of warmth and competence in chatbot interactions and their impact on customer experience. Additionally, demographic data such as age and gender will be collected to characterize the sample and perform comparative analyses.

Statistical Analysis

The data analysis for this research was conducted using JASP software and Microsoft Excel. Initially, the data collected through Google Forms were visualized using bar charts to explore differences in perceptions across generational segments. These visualizations provided an initial overview of how users from Generation Z, Millennials, and Generation X rated chatbot warmth, competence, and their tendency to select neutral responses.

Following this, a data cleaning process was performed in Excel to identify and correct potential errors or outliers. Cronbach's Alpha was then applied to evaluate the internal consistency and reliability of the questionnaire scales.

Given the study's non-experimental, cross-sectional, and correlational-causal approach, descriptive statistics were used to summarize the characteristics of the sample and responses. Frequencies, percentages, means, and medians were calculated for the variables of warmth, competence, and customer experience, offering insight into the general perception of chatbot interactions.

To assess the normality of the data, the Kolmogorov-Smirnov test was conducted. As the results indicated that the data did not follow a normal distribution ($p < .001$ for all items), non-parametric tests were applied.

Spearman's correlation coefficient was used to examine the relationships between the emotional dimensions of chatbots (warmth and competence) and customer experience. All associations were found to be statistically significant, supporting the study's hypotheses.

Finally, multiple linear regression analyses were conducted in Excel to evaluate the predictive power of warmth and competence on user experience. Additional models were developed to include control variables such as gender and generation, revealing that both emotional dimensions significantly predict user experience even when demographic differences are considered.

Results

Through the survey designed for data collection, 385 valid responses were obtained and analyzed in depth for this research. This section presents the results, focusing exclusively on participants aged 18 to 55 who had recently interacted with banks via chatbots in different districts of Lima Metropolitana.

A key demographic highlight is that over 61% of the responses came from individuals aged 18 to 27, belonging to Generation Z. Additionally, 18% of participants were aged 28 to 43, representing Millennials (Generation Y), while 21% were aged 44 to 55, belonging to Generation X.

Regarding gender, a higher proportion of survey respondents were women, accounting for 59%, compared to 41% men. This significant disparity in gender distribution could influence the interpretation of results and the conclusions drawn from the study.

In terms of sample distribution across Lima Metropolitana, 48% of respondents came from Zone 7, while Zones 8 and 6 accounted for 14% and 11%, respectively. This indicates greater representation in the southern and western areas of the city. Conversely, Zones 1 through 5 had lower participation, ranging from 1% to 6%. This pattern aligns with the study's target distribution since, according to APEIM (2021), socio-economic levels (NSE) A and B, with the highest levels of digitalization in Lima Metropolitana, are predominantly located in Zones 6, 7, and 8.

In relation to the responses associated with the independent variable—which encompasses the human characteristics of warmth and competence—as well as the dependent variable, which refers to customer experience, the following findings are presented below.

Warmth Dimension

Regarding perceived warmth in chatbot interactions, the first five survey questions revealed the following:

Regarding the warmth perceived by participants during their interactions with chatbots, the first five survey questions were analyzed, revealing the following insights:

The results indicate that although perceptions of chatbot warmth are generally positive, there is a significant presence of neutral responses across all items. For the first question—whether the chatbot shows concern—32% of respondents were neutral, while 39% responded positively. In terms of kindness, 56% of participants responded positively, while 20% disagreed. Similarly, 56% rated the chatbot as friendly, but 24% responded neutrally and 20% disagreed.

The fourth question, which evaluated the warmth of the conversation, showed an increase in negative responses, with 33% of participants disagreeing—surpassing the 25% who were neutral—while only 42% responded positively. Finally, when assessing the chatbot's sociability, 44% responded positively, while 27% remained neutral.

These findings reflect a generally positive trend in the perception of chatbot warmth, although the high percentage of neutral responses suggests indecision or a lack of clear opinion among a considerable portion of participants. This is also supported by the statistical analysis, which showed a mean response of 3.28 and a median of 3, indicating that most responses clustered around the neutral midpoint of the scale.

Further analysis by age and gender revealed an interesting pattern: Generation Z reported the highest percentage of positive responses regarding warmth, with over 49%. In contrast, Generations Y and X reported 45% and 30% positive responses, respectively. This suggests that younger generations are more likely to identify and value attributes of warmth and emotional closeness in chatbot interactions. In terms of gender, no significant differences were found between male and female respondents.

To illustrate generational differences in the perception of the human characteristics of chatbots, the following graphical representations summarize the findings on perceived warmth and competence.

Table 1

Response to questions related to warmth

Response Level	Shows concern	Friendly	Amicable	Warm	Sociable
1	16%	9%	9%	16%	15%
2	14%	12%	11%	17%	14%
3	32%	24%	24%	25%	27%
4	24%	33%	33%	25%	24%
5	15%	22%	22%	17%	20%

Note: Data generated through Google Forms in the questionnaire "Do Human Characteristics in Chatbots Influence Customer Experience in the Banking Sector" (2024).

Competence Dimension

Regarding the competence perceived by respondents in chatbot interactions, survey questions 6 through 10 were considered, revealing the following results:

The findings indicate that although perceptions of chatbot competence are generally positive, a significant proportion of neutral responses—around 30% for each question—was observed, reflecting a degree of indecision among participants. For the first question, which addressed chatbot intelligence, 48% of respondents gave a positive rating, while 25% were neutral and 27% disagreed. In the second question, related to the chatbot's skill, a similar trend was found: 49% responded positively, 26% were neutral, and 25% responded negatively.

The third question showed a slight increase in neutral responses, reaching 28%, while positive responses declined to 46%, with negative responses remaining around 26%. In the fourth question, which assessed effectiveness in interaction, neutral responses again reached 28%, while 47% of respondents answered positively. Finally, for the fifth question on chatbot efficiency, 27% of respondents were neutral, and positive responses reached their lowest level, at 45%.

Notably, as the questions progressed, there was a slight downward trend in the proportion of respondents who perceived chatbot competence positively, while neutral and negative responses gradually increased.

These findings suggest that although chatbot capabilities are mostly perceived positively, there is a growing sense of concern or indecision among users—particularly regarding the bots' effectiveness and efficiency. The trend toward neutral responses may point to areas in which chatbots need improvement in order to build greater trust and satisfaction among users.

This is further reflected in the statistical analysis, which yielded a mean response of 3.31 and a median of 3, indicating that most answers were clustered around this neutral value, with a slight inclination toward positive perceptions.

When the data were analyzed by age and gender, a pattern similar to that observed in the warmth dimension emerged. Generation Z recorded the highest percentage of positive responses at 46%. However, in this case, Generation Y also showed a high level of positive ratings regarding chatbot competence, with 43% of responses being positive. In contrast, Generation X showed a significant difference, with only 22% responding positively, while neutral and negative responses were the most frequent in this group. As for gender, no significant differences were observed between male and female participants.

Table 2

Response to questions related to competence

Response Level	Intelligent	Skillful	Capable	Effective	Efficient
1	12%	11%	11%	11%	11%
2	15%	14%	15%	15%	17%
3	25%	26%	28%	28%	27%
4	24%	27%	27%	24%	23%
5	24%	22%	19%	23%	22%

Note: Data generated through Google Forms in the questionnaire "Do Human Characteristics in Chatbots Influence Customer Experience in the Banking Sector" (2024).

Experience

Regarding the responses collected on how participants perceived their experience interacting with chatbots in the banking sector, questions 11 to 16 were analyzed, yielding the following results:

The data revealed mixed perceptions about the experience of interacting with chatbots. Personalization and interaction appeal were poorly rated, with 39% and 36% of respondents, respectively, disagreeing or strongly disagreeing. Positive responses in these areas barely reached 37% and 35%, indicating that many users do not perceive the interaction as personalized or find chatbots to be an appealing channel.

In contrast, ease of navigation, quick responses, and updated information were aspects that respondents found more satisfactory, with 44%, 51%, and 45% agreeing or strongly agreeing, respectively. These findings underscore that efficiency and the up-to-date nature of chatbots are positively valued, representing strong points of the system. However, regarding response accuracy, 35% of respondents expressed disagreement or strong disagreement, with 26% giving neutral responses. Only 39% had a positive stance on this aspect, highlighting the need to address queries more effectively through this channel.

Overall, while there was a trend toward more positive responses in this area, the first two questions showed predominantly negative responses regarding aspects such as personalization and interaction appeal with chatbots.

The average response score for this section was 3.16, slightly lower than in the warmth and competence sections, aligning with the observations mentioned above. The median score for this category was consistent with previous sections, at 3.

Table 3

Response to questions related to customer experience

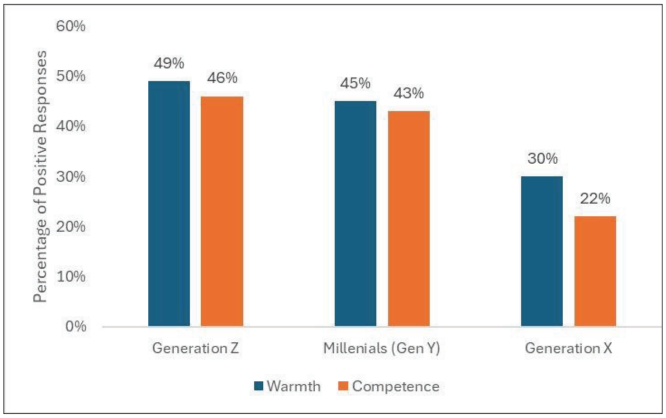
Response Level	Personalized Interaction	Appealing Interaction	Easy Navigation	Quick Responses	Updated Information	Accurate Responses
1	19%	18%	10%	10%	10%	12%
2	20%	18%	16%	15%	14%	23%
3	24%	29%	30%	24%	31%	26%
4	18%	19%	26%	28%	26%	24%
5	19%	16%	19%	23%	19%	15%

Note: Data generated through Google Forms in the questionnaire "Do Human Characteristics in Chatbots Influence Customer Experience in the Banking Sector" (2024).

Graphical Analysis of Generational Differences in Chatbot Perception

To complement the previously presented data and provide a visual representation that allows for a comparative understanding of generational differences in the perception of human characteristics in chatbots, the following charts summarize the findings related to perceived warmth and competence.

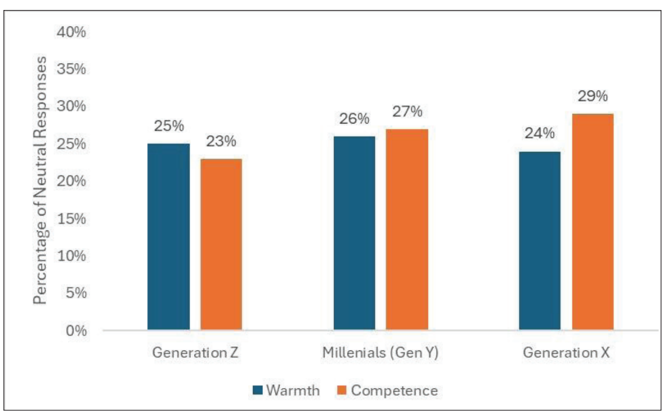
Figure 1
Percentage of Positive Responses in the Perception of Warmth and Competence by Generation



Note: Data generated by Google Forms from the survey "Human Characteristics in Chatbots and Their Influence on Customer Experience in the Banking Sector" (2024).

As shown in Figure 1, users from Generation Z and Millennials exhibit higher levels of positive perception in both warmth and competence compared to Generation X. This gap confirms that younger users value the human characteristics of chatbots more strongly.

Figure 2
Percentage of Neutral Responses in the Perception of Warmth and Competence by Generation



Note: Data generated by Google Forms from the survey "Human Characteristics in Chatbots and Their Influence on Customer Experience in the Banking Sector" (2024).

These results show that neutral responses played a significant role in the evaluation of both characteristics across all generations. Furthermore, it is observed that the proportion of neutral responses was slightly higher for the competence dimension than for warmth, particularly among older age groups (Generations Y and X). Notably, Generation X showed the highest percentage of neutral responses regarding competence (29%), which may suggest a greater tendency toward unfamiliarity compared to younger generations.

Factors Explaining the High Percentage of Neutral Responses

The high percentage of neutral responses observed in the surveys may reflect a greater tendency toward ambivalence or a lack of definitive judgment regarding the human characteristics of chatbots, particularly among older users. As evidenced in previous research, this phenomenon may be related to a "wait and see" phase toward new technologies, where users have not yet developed a clear frame of reference for evaluating emotional attributes such as warmth and competence. According to Shumanov et al. (2020), this uncertainty toward interactions that aim to appear human—but fall short of full authenticity—can lead to neutral responses, a phenomenon explained by the concept of the "uncanny valley."

Likewise, the local context of technological adoption in Lima, Peru—particularly within the banking sector—may contribute to this trend. Many users, especially those with less digital experience or from older generations, are still adapting to automated conversational channels, which limits their ability to evaluate these tools and increases the likelihood of neutral responses (Pizzi et al., 2023).

Finally, as noted by Dwivedi et al. (2023), users with limited prior exposure to AI-based technologies tend to have more difficulty assessing emotional dimensions such as warmth and competence, which increases the likelihood of providing neutral responses when interacting with innovations like chatbots.

Questionnaire reliability

To validate the reliability of the questionnaire, Cronbach's Alpha was calculated for competence, warmth, and experience, the dimensions of this research. Scores above 0.70 were deemed reliable, and the following results were found:

Table 4
Cronbach's Alpha

Dimension	Cronbach's Alpha	Reliability
Perceived Competence	0.905	Reliable
Perceived Warmth	0.868	Reliable
Chatbot Experience	0.856	Reliable

Note: Data generated by JASP (2024)

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Given the sample size and its general applicability, the Kolmogorov-Smirnov test was conducted to verify data normality, with the following hypotheses established:

- **H0:** The sample follows a normal distribution.
- **H1:** The sample does not follow a normal distribution.

The results revealed a p-value < .001 for all questions, leading to the rejection of the null hypothesis. Consequently, non-parametric tests were employed to evaluate both the general and specific hypotheses. The Spearman correlation coefficient was used for non-normal distributions, yielding the following results:

Tabla 5
Spearman Correlation Test for the General Hypothesis

		EXPERIENCE
HUMAN CHARACTERISTICS	Spearman's rho	0.454
	p-value	< .001

Note: Data generated by JASP (2024)

General Hypothesis (H1): Human characteristics in chatbots positively influence customer experience in the banking sector in Lima, Peru.

Based on the Spearman correlation analysis, a significant correlation of 0.454 was found between the variables "human characteristics" and "customer experience." Additionally, a p-value < .001, lower than the established significance level of 0.01, confirms the validity of the general hypothesis. Therefore, the hypothesis that human characteristics in chatbots positively influence customer experience in the banking sector in Lima, Peru, is accepted and supported.

Tabla 6
Spearman Correlation Test for Hypotheses 1 and 2

		EXPERIENCE
COMPETENCE	Spearman's rho	0.521
	p-value	< .001
WARMTH	Spearman's rho	0.454
	p-value	< .001

Nota: Data generated by JASP (2024)

For the specific hypotheses, the analysis showed the following:

Specific Hypothesis 1 (H2): Warmth in chatbots positively influences customer perception.
The Spearman correlation analysis revealed a moderate correlation of 0.454 between the warmth variable and customer experience. This result, accompanied by a p-value < .01, suggests that higher perceptions of warmth during chatbot interactions in the banking sector are associated with a better customer experience. Therefore, the hypothesis that warmth in chatbots positively influences customer perception is accepted.

Specific Hypothesis 2 (H3): Perceived competence in chatbots positively impacts customer experience.
To validate this hypothesis, the Spearman correlation analysis identified a significant relationship of 0.521 between perceived competence and customer experience. Additionally, the p-value < .01 indicates that higher perceptions of chatbot competence during interactions in the banking sector are associated with a more satisfying customer experience. Hence, the hypothesis that perceived competence in chatbots contributes positively to customer perception is validated.

Linear Regression Analysis
To complement the findings obtained through Spearman's correlation and provide greater robustness to the analysis of the general hypothesis (H1), a simple linear regression analysis was conducted using Excel. This analysis allowed us to further explore the extent to which the perceived human characteristics of chatbots predict customer experience in the banking sector.

Unlike correlation, which only indicates whether a relationship between two variables exists and whether it is positive or negative, regression analysis helps estimate the degree to which independent variables affect the dependent variable, allowing for more precise inferences about the relative impact of each dimension.

Regression Model Results
A linear regression model was used, where the dependent variable was customer experience, and the independent variable was a composite index of human characteristics, including perceived warmth and competence.

Table 7
Simple Linear Regression Model – Human Characteristics

RESULT	VALUE
R^2	0.700
F	F(1,383) = 99.302
p-value	p < .001
Warmth coefficient (β)	0.3181 (p < .001)
Competence coefficient (β)	0.5176 (p < .001)
Constant (β)	0.2557 (p = 0.294)

Note: Data generated by Excel (2024)

The model results indicate that the model is statistically significant (p < .001), meaning that human characteristics in chatbots, such as warmth and perceived competence, have a significant impact on customer experience. Additionally, the R^2 value of 0.700 suggests that approximately 70% of the variance in customer experience can be explained by these human characteristics.

The warmth coefficient (β = 0.3181) and the competence coefficient (β = 0.5176) are both positive and significant, implying that both warmth and perceived competence positively and significantly influence customers' evaluation of their experience. This suggests that for every one-unit increase in warmth, customer experience improves by 0.3181 units, and for each one-unit increase in perceived competence, experience improves by 0.5176 units, assuming other variables remain constant.

Finally, the constant (β = 0.2557, p = 0.294) represents the baseline customer experience in a hypothetical scenario where human characteristics (warmth and competence) are absent. However, the p-value of 0.294 indicates that this constant is not statistically significant, suggesting that customer experience is not significantly affected in the absence of these characteristics.

Multiple Linear Regression with Generational Control Variables

To explore whether perceptions of customer experience vary across age groups, a second regression model was built incorporating two control variables: Gen1 (Generation Z) and Gen2 (Generation X). Generation Y (Millennials) was used as the baseline comparison category and omitted from the model to avoid perfect multicollinearity.

Table 8

Multiple Regression Model with Generational Variables

RESULT	VALUE
R^2	0.695
Adjusted R^2	0.692
F	F(4,382) = 217.74, p < .001
Warmth (β)	0.3175 (p < .001)
Competence (β)	0.5031 (p < .001)
Generation Z (β)	-0.1108 (p = 0.132)
Generation X (β)	-0.1873 (p = 0.037)
Constant	0.5690 (p < .001)

Note: Data generated by Excel (2024)

The extended model remains highly significant (p < .001), with an R^2 of 0.695. This confirms that 69.5% of the variation in customer experience is still explained by the variables analyzed. Similar to the previous regression, both warmth and competence maintain positive and highly significant coefficients, confirming their influence on customer experience even when controlling for generational differences. The variable for Generation X shows a negative and statistically significant effect (β = -0.1873, p = 0.037), indicating that, all else being equal, users from this generation tend to rate their chatbot experience slightly lower than Millennials.

In contrast, the Generation Z variable shows a negative coefficient (β = -0.1108), but this effect is not statistically significant (p = 0.132), indicating no significant difference in experience compared to Millennials.

Unlike the previous model, the constant in this model (β = 0.5690, p < .001) represents the average level of customer experience for Generation Y (Millennials) in the absence of perceived warmth and competence. This value is statistically significant, indicating that even without these human characteristics, Millennials report a positive baseline experience. This contrasts with the previous model, where the constant was not significant.

Regression Analysis by Geographic Zone

To further explore whether user satisfaction varies based on their area of residence within Metropolitan Lima, categorical variables were incorporated into the linear regression model. To avoid perfect multicollinearity, Zone 10 was used as the reference category. This means that estimated coefficients for Zones 1 to 9 should be interpreted relative to Zone 10.

Table 9

Multiple Regression Model with Lima Zones as Variables

ZONE	COEFFICIENT	p-value
ZONE 1	0.2607	0.322
ZONE 2	0.1113	0.670
ZONE 3	-0.4403	0.217
ZONE 4	-0.0435	0.867
ZONE 5	0.1892	0.465
ZONE 6	0.1437	0.549
ZONE 7	0.2121	0.352
ZONE 8	0.0919	0.697
ZONE 9	0.1224	0.626
ZONE 10	Reference Category	-

Note: Data generated by Excel (2024)

The overall model showed a good fit ($R^2 = 0.700$), indicating that the explanatory variables account for 70% of the variance in customer satisfaction. The F-test was significant (p < 0.001), confirming the model's overall validity.

The results show that there were no statistically significant differences in satisfaction levels across the different zones of Metropolitan Lima (p > 0.05 for all zones). This suggests that, once perceptions of warmth and competence are considered, the geographic location of users does not have a relevant impact on their satisfaction levels.

In practical terms, customer satisfaction with the use of banking chatbots appears to be determined more by the perceived quality of service (warmth and competence) than by the district or zone in which the client resides.

This finding reinforces the importance of focusing on improving the human characteristics of chatbots rather than designing geographically differentiated strategies.

Discussion

The results of this study confirm that human-like characteristics in chatbots, such as warmth and competence, significantly enhance customer experience in Lima's banking sector, supporting our general hypothesis. This is supported by the positive correlation between the two variables (ρ = 0.454), indicating that the greater the perception of human characteristics in chatbots, the better the customer experience. This finding aligns with prior research that emphasizes how the perception of "humanness" in chatbots enables users to establish more positive and trustworthy connections, leading to more satisfying interactions (Nguyen et al., 2023; Ranieri et al., 2024). The positive association between these human traits and customer experience suggests that warmth and competence not only provide a more gratifying immediate experience but also foster long-term trust and loyalty, particularly in competitive environments like the banking sector.

These results not only offer empirical validation for our hypotheses but also strengthen the theoretical proposal that the Technology Acceptance Model (TAM) can be expanded to include emotional dimensions such as warmth and competence. These dimensions, traditionally absent from the original model, have become essential for explaining the acceptance and use of conversational technologies in service contexts like banking. This integration offers a deeper understanding of how emotions influence not only usage intention but also the overall customer experience. However, the high proportion of neutral responses suggests that while users value these human traits, achieving a deeper emotional connection remains a challenge.

A particularly relevant aspect of the findings is the high percentage of neutral responses in several survey items, especially within the warmth dimension. Although this was initially linked to the "uncanny valley" phenomenon, a deeper reading suggests multiple possible explanations. First, the degree of familiarity with banking chatbots may be a factor—many users, especially older individuals or those with low prior exposure, may not have developed clear criteria for evaluating emotional traits like empathy or friendliness. This lack of reference may explain the tendency toward neutral responses as a form of "wait-and-see," especially with a technology still perceived as emerging.

Second, the local context also plays a role. In Lima's banking environment, where much of the digitalization of services has occurred post-pandemic, not all users have undergone a full adaptation process to virtual channels. As a result, user expectations—particularly emotional ones—are not always clearly defined, generating neutral evaluations more due to ambiguity than indifference.

Finally, this pattern may reveal a "gray zone" within TAM itself, where users neither fully reject nor fully accept the technology, but are still forming judgments about AI's humanity. This neutrality should not be interpreted as a lack of impact, but rather as a sign that emotional experience is still under development. Full adoption requires not only technical efficiency but also a more mature empathic design, which is still evolving in the Peruvian banking sector.

This phenomenon reflects the concept of the "uncanny valley"—when AI becomes "too human" (National Geographic, 2023)—which suggests users may feel disconnected if interactions don't feel authentic, a concern also noted by Pizzi et al. (2023). This underscores the importance of effective personalization, especially in banking, where clients value interactions that are both efficient and empathetic.

Regarding warmth, the moderate correlation ($\rho = 0.454$) with customer experience supports our second hypothesis, showing that friendly and attentive interactions improve user perceptions. This finding aligns with Social Presence Theory, also known as "positive social relationships," which proposes that the perception of warmth and friendliness in chatbots contributes to a more positive user experience, as observed by Schmid et al. (2022) and Adam et al. (2020). This suggests that chatbot design in banking should incorporate both warmth and competence to enhance compliance and reduce user skepticism. Nevertheless, 26% of responses regarding warmth were neutral on average, reflecting a persistent "authenticity gap." As noted by Shumanov et al. (2020), chatbot personality impacts engagement and outcomes; a lack of personalization can limit perceptions of genuine connection. In their study, adapting to the user's personality increased engagement by 2.14 for extroverted users and 2.28 for introverted users.

Regarding competence, our third hypothesis is supported by the strong positive correlation ($\rho = 0.521$) between perceived competence and customer experience, emphasizing the importance of reliable and accurate AI in fostering user trust. This finding is consistent with studies by Bo Li et al. (2021) and Bach et al. (2022), who found that users are more likely to trust AI when they perceive strong and effective technical capabilities. These studies also highlight system credibility, perceived risk, and ease of use as key drivers of user trust in AI systems. In our study, 47% of participants rated chatbot competence positively, indicating considerable confidence in its technical capabilities. However, the presence of neutral responses regarding efficiency points to unmet expectations in terms of speed and precision—elements also highlighted by Kaushal et al. (2022) as essential.

The analysis also revealed significant generational differences in chatbot perception. Generation Y (Millennials) and Generation Z valued warmth and personalization more during chatbot interactions, whereas Generation X placed less emphasis on these attributes. This finding supports the studies by Ameen et al. (2022), which highlight a preference for warmer digital interactions among digital natives. Adapting chatbot interactions to generational expectations could help optimize satisfaction across customer segments.

Furthermore, this study expands the Technology Acceptance Model (TAM) by incorporating emotional dimensions that complement utility and ease of use, which have traditionally been core predictors of technology acceptance (Davis, 1989; Ameen et al., 2022). In this context, warmth and perceived competence function as emotional variables that not only influence usage intention but also directly shape user experience—especially in service-driven contexts like banking. This empirical evidence helps enrich TAM by adapting it to scenarios where social relationships, empathy, and trust weigh as much as functionality (King et al., 2006). In line with findings from Park et al. (2024), who identified the impact of anthropomorphism and personalization on use intention and satisfaction, and Liu (2024), who demonstrated the influence of chatbot appearance and emotional attributes on attitudes and purchase decisions, this study provides further evidence of the need to incorporate emotional variables into TAM to better explain the acceptance of conversational technologies.

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Additionally, this research contributes to Social Response Theory (SRCT), which posits that users respond to technologies such as chatbots in ways similar to how they respond to humans—applying social norms and expectations (Jelahut et al., 2021). In this regard, the perception of warmth and competence in banking chatbots increases user satisfaction by fulfilling these social norms, as also observed in the findings of Dwivedi et al. (2023).

The study's findings offer relevant practical implications for the banking sector. First, it is recommended that chatbot design be tailored to the preferences of each generational group. Generation Z and Millennials showed a preference for warmer, more personalized interactions; therefore, banks could incorporate more informal language, carefully used emojis, and empathetic responses for these segments. In contrast, Generation X users prioritize technical competence, suggesting that interactions should focus on clarity, precision, and response speed. Additionally, implementing progressive personalization mechanisms—such as recognizing interaction patterns or preferred language—could enhance perceptions of warmth and reduce neutral responses. This segmentation in chatbot design not only improves individual customer experience but can also strengthen strategic indicators such as retention, frequency of digital channel usage, and Net Promoter Score (NPS). This user-centered approach reinforces the strategic value of chatbots as tools for customer loyalty and differentiation in the competitive digital banking landscape. Based on these findings, key conclusions can be drawn for strategy development in the Peruvian banking sector.

Conclusion

The results of this study confirm that human-like characteristics in banking chatbots, such as warmth and competence, significantly influence user experience. Although technical aspects such as speed and accuracy are valued, they are not sufficient on their own to ensure a satisfactory experience. Therefore, financial institutions must evolve toward a digital interaction model that combines efficiency with a more human approach, integrating empathy and personalization alongside advanced technical capabilities.

Today, the mere implementation of chatbots no longer constitutes a significant competitive advantage in the banking industry. This study underscores the importance of understanding the expectations of younger generations, who show a marked preference for warm and personalized digital interactions. In emerging markets such as Peru, financial institutions that adapt their conversational interfaces to meet these evolving demands will be better positioned to improve customer satisfaction and strengthen loyalty. This study offers an original contribution by empirically analyzing, from Lima, Peru, how emotional perception influences chatbot experiences—an area rarely explored in Latin American contexts.

Moreover, the findings reveal the need to expand traditional success metrics by incorporating indicators that assess not only operational efficiency, but also the quality of emotional connection and perceived personalization in each interaction. A comprehensive evaluation framework should include aspects such as long-term customer retention, the quality of the customer-bank relationship, and the chatbot's ability to proactively anticipate and respond to user needs. A deeper analysis of customer satisfaction surveys would help capture not only transactional effectiveness but also the level of emotional closeness generated—an essential factor in building loyalty.

This analysis also extends the Technology Acceptance Model (TAM) by incorporating emotional dimensions, demonstrating that the perception of humanness in AI has an impact that goes beyond technical functionality. The findings also support Social Response Theory by showing that users apply social norms in their interactions with chatbots, highlighting how warmth and competence foster trust, closeness, and authenticity.

In addition, this research makes a meaningful contribution to the banking sector in Lima, Peru, by offering a generationally segmented analysis that helps to understand how different customer profiles experience interactions with banking chatbots. Results show that Generation Z—young adults familiar with technology from an early age—highly value warmth in digital interactions, especially when conveyed through casual language, empathetic responses, and conversational design. This segment represents a major opportunity for banks, given their high level of technological adoption combined with greater emotional personalization expectations. Millennials, who blend digital habits with high service expectations, also place importance on warmth, while highlighting the need for progressive personalization—meaning the chatbot should adapt to their habits and preferences. In contrast, Generation X customers—a key group due to their level of bank engagement and purchasing power—prioritize perceived competence, expecting clear, efficient, and technically accurate interactions, where the chatbot functions as an effective extension of traditional service. This generational breakdown not only allows for optimization of conversational design strategies, but also provides banks in Lima with a clear roadmap to personalize their digital channels according to user profiles—maximizing perceived value, satisfaction, and customer loyalty. In a competitive and urbanized banking environment like Lima's, where digital differentiation is increasingly critical, these findings offer a solid empirical foundation for designing conversational experiences tailored to the socio-digital reality of the Peruvian market.

This study constitutes one of the first empirical efforts in the Peruvian banking sector to integrate emotional dimensions into the Technology Acceptance Model (TAM). This contribution is especially relevant within the Latin American context, where research on emotional interaction with chatbots remains limited despite the rapid growth of digital financial solutions. Thus, the integration of emotional dimensions into TAM not only enriches the model but also provides banks with concrete tools to redesign more human, effective, and personalized experiences.

The study also suggests exploring the potential of chatbots as tools for promoting financial inclusion, particularly among traditionally underserved segments. These conversational interfaces, by combining

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human-like interaction with technical efficiency, can help expand access to banking services and lower entry barriers—supporting the democratization of finance in environments where mobile devices outnumber access to traditional banking.

For future research, it is recommended to expand the demographic and geographic scope of this analysis, exploring whether perceptions of warmth and competence vary across cultural contexts. Longitudinal studies would also be valuable to examine how user perceptions evolve as technology advances, allowing for the development of continuous improvement strategies more closely aligned with users' real expectations and experiences in the banking sector.

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