



Study on AI-Powered Chatbots for Customer Service and Business Operations

Dr. Simran Kalyani

Associate Professor, H.R. College of Commerce & Economics, Mumbai

Simrankalyani66@gmail.com

Abstract

With artificial intelligence (AI) driving their capabilities, chatbots are one of the more ubiquitous technological solutions in customer support and business operations, capable of providing 24×7 service and speeding up and cutting down on service costs. Although there is a significant number of studies on how the quality of a service affects customers' satisfaction and the efficiency of a service, the empirical evidence on the relationship between the quality of a chatbot service and customer satisfaction and the efficiency of the chatbot service is still scattered, especially in emerging market contexts. The study is essentially empirical and seeks to understand the correlation between service quality of AI chatbots, the efficiency of business operations, the satisfaction of the customers and whether there is any difference in customer satisfaction in different demographic groups. A quantitative, cross-sectional survey design was used and 120 respondents who interacted with AI-powered chatbots in their customer services of retail, banking, telecommunication, and e-commerce were reached. A 12-item questionnaire that covered three constructs (chatbot service quality, operational efficiency, and customer satisfaction) was structured and along with five demographic items, it was administered. Data was analyzed using Cronbach's alpha, descriptive statistics, Pearson correlation, multiple linear regression and one way analysis of variance (ANOVA) using the Statistical Package for the Social Sciences (SPSS). Three hypotheses were developed and tested. The result indicated that there is positive relationship between Chatbot service quality and Customer satisfaction (H1 accepted), there is positive relationship between the adoption of AI Chatbots and the efficiency in business operations (H2 accepted) and there is difference between Customer satisfaction according to age group of respondents (H3 accepted). The Cronbach's alpha for all constructs were above the threshold of 0.70, which is acceptable for internal consistency. The findings contribute to the literature on technology adoption by offering an empirical correlation between the performance of chatbots and actual operational and experiential outcomes and offer actionable advice to managers seeking to maximize their customer engagement efforts using AI.

Keywords: artificial intelligence, chatbots, customer service, operational efficiency, SPSS

1. Introduction

1.1 Background of the Study

In the last 10 years, AI has progressed from a side hustle to a fundamental part of digital customer engagement. The most practical of these uses is the AI-powered chatbot, a computer program that uses natural language processing (NLP) and machine learning to simulate human conversation and interact with customers to answer their questions without

human involvement. In Customer Support, a number of companies such as banks, retail outlets, telecom providers, healthcare institutions and ecommerce have implemented Chatbots and integrated them with their website, mobile app, and social media, to provide timely and scalable customer support solution which is cost effective. With customers wanting support services 24/7, AI chatbots have been known to save businesses a considerable amount of money on customer service costs.

Beyond cost reduction, chatbots are now seen as strategic tools that can transform the customer experience, handling a multitude of queries simultaneously, tailoring responses based on past interactions, and freeing up human agents to dedicate themselves to more intricate and valuable interactions (Behera et al., 2024; Chen et al., 2023). Meanwhile, not all chatbots are created equal: service quality, perceived intelligence and trust partially mediate a chatbot experience and customer satisfaction (Castelo et al., 2023; Adam et al., 2021). This study is an attempt to bridge this gap by providing empirical quantitative evidence for the relationships between constructs of chatbots and customer facing and operational outcomes under one research framework.

1.2 Statement of the Problem

Many companies have adopted AI chatbots, but the evaluation of the return on investment in terms of improved customer satisfaction and business efficiency can be difficult. Prior research has mainly been conducted on either adoption intentions of chatbots or chatbot user experience, and they are either qualitative or one-construct studies, and there is no study that investigates the effect of chatbot service quality on both customer satisfaction and business operational effectiveness in an all-encompassing and statistically validated model.

Furthermore, few studies have tried to explore if there are any systematic differences between different age and other demographic groups in terms of satisfaction outcomes, as presented by Mostafa and Kasamani (2022) and Nguyen et al. (2021) which state that digital literacy and trust are material affects that shape users perception of automated service agents. Without this information, managers could be taking a "one size fits all" approach to chatbots that is failing to achieve the best results with certain segments of customers and yet touting itself as an efficiency improvement. Therefore, this study is aimed to fill the research gap where there is a lack of integration and quantitative evidence showing the relationship of the quality of Chatbot service with operational efficiency and its level of satisfaction across the demographic groups by using a structured survey instrument and an inferential statistical analysis approach.

1.3 Objectives of the Study

The general objective of this study is to empirically examine the effect of AI-powered chatbots on customer service and business operations. The specific objectives are:

1. To examine the relationship between AI chatbot service quality and customer satisfaction.
2. To assess the effect of AI chatbot adoption on business operational efficiency.
3. To determine whether customer satisfaction with AI chatbots differs significantly across demographic groups, particularly age.

4. To evaluate the reliability and internal consistency of the survey instrument used to measure chatbot-related constructs.

1.4 Significance of the Study

The results of this study make a contribution to the literature and managerial practice. It extends the technology-adoption and service-quality models and theoretically shows that constructs related to the performance of a chatbot can be directly connected to two outcome domains, customer satisfaction and operational efficiency, through this one quantitative model, addressing the call for more integrative empirical research.

In practical terms, the results will be able to be used by retail, banking and e-commerce managers to make recommendations on allocating resources to customer service infrastructure powered by AI. Building a realization of which metrics are best correlated with satisfaction and efficiency, including natural language understanding, response accuracy, and seamless human handoff (Sheehan et al., 2020; Rese et al., 2020), can help organizations prioritize investments into different metrics in their chatbots. The study offers evidence-based insights on the overall picture of digital transformation of customer service that can guide the process of introducing AI responsibly in consumer-facing functions and help policy makers and industry associations create guidelines for it.

1.5 Scope and Limitations of the Study

The study only focuses on the interactions that consumers have with AI-powered chatbots directly for customer service in retail, banking, telecommunications, and ecommerce industries. A cross sectional study design was used and data were collected from a sample of 120 respondents by using a structured questionnaire, which did not represent changes over a long period of time but the perceptions of the respondents at one particular time.

The self-report data and small sample size limit the study, and the data might be prone to common method bias. Furthermore, results are industry specific and may not fully be applicable to industries or regions not included in the sample, e.g. healthcare or government services. However, the conclusions made within the scope are robust with use of validated constructs, reliability tested instrument and multiple inferential statistical techniques.

The broader digital transformation agenda has also driven AI-powered chatbots to be a part of a larger trend toward service ecosystems that rely on automation for end-to-end self-service experiences, where chatbots can be connected to customer relationship management (CRM) software, order management solutions, and payment gateways. This integration is a strategic move because customer service has become a brand differentiator, influencing how customers perceive a brand and their loyalty. The study is motivated by the increasing demand and investment in chatbots as organizations try to implement and scale these technologies, and by the need to understand exactly how these interactions with the chatbots affect the customer experience and the internal efficiency of service operations, so that managers can make informed decisions.

2. Literature Review

2.1 AI-Powered Chatbots in Customer Service

AI-powered Chatbots: These are conversational tools that use natural language processing, machine learning, and now, generative AI to understand customer intent and provide them with context-appropriate responses (Behera et al., 2024). The research into chatbots was mostly rule-based in the first generations of chatbots, but since then, chatbots have been able to include sentiment analysis and contextual memory, allowing for more natural and personalized conversations (Meyer von Wolff et al., 2020). Anthropomorphic design elements like human-like names and conversational tone have been shown to impact significantly on consumers' intentions to use chatbots for service interactions (Sheehan et al. 2020) and perceived usefulness and social presence are found to be important factors that can predict positive consumer reactions to chatbots on social media platforms (Zarouali et al. 2018).

The evidence for the effectiveness of chatbots in customer service is mixed. Brill et al. (2019) found that although chatbots boosted convenience, the respondents also reported that they were frustrated when the bots were unable to deliver a satisfactory answer to the more complex and emotionally charged queries, thus highlighting the need for human backup. Likewise, Castelo et al. (2023) found that even if a service agent's non-human nature is disclosed, consumers' trust can be lowered if the chatbot is not perceived as competent to some degree, indicating that the disclosure effect is moderated by perceived quality. On the other hand, Chung et al. (2020) suggested that the well-designed chatbot e-service positively affected satisfaction and repurchase intentions among luxury brand consumers, suggesting that, the influence of chatbot e-service is dependent on industry context and design quality. As a whole, this body of work indicates that chatbot service quality, including responsiveness, accuracy, and conversational naturalness are key factors in customer service quality assessment.

2.2 Chatbots and Business Operational Efficiency

AI-powered Chatbots: These are conversational tools that use natural language processing, machine learning, and now, generative AI to understand customer intent and provide them with context-appropriate responses (Behera et al., 2024). The research into chatbots was mostly rule-based in the first generations of chatbots, but since then, chatbots have been able to include sentiment analysis and contextual memory, allowing for more natural and personalized conversations (Meyer von Wolff et al., 2020). Humanisation features such as anthropomorphic design elements have been identified to relate to consumers' intention to use a chatbot for service interactions (Sheehan et al. 2020) and perceived usefulness and perceived social presence to positively influence consumers' reactions to chatbots on social media platforms (Zarouali et al. 2018).

There is mixed evidence of the effectiveness of chatbots in customer service. Brill et al. (2019) discovered that, while chatbots improved convenience, the participants also indicated that they were discontent when they could not get a satisfying response from the bots to the more complex and emotional questions, which meant that there was a need for human

support. Similarly, Castelo et al. (2023) identified that while the non-human nature of a service agent would be disclosed, consumers' trust could be reduced if it is not perceived as competent to some extent, suggesting that the disclosure effect is moderated by the perceived quality. However, Chung et al. (2020) proposed that the well-designed chatbot e-service had a positive impact on satisfaction and repurchase intentions for luxury brand consumers, implying that the effect of using chatbot e-service is industry-specific and depends on the level of design. As a whole, this body of work indicates that chatbot service quality, including responsiveness, accuracy, and conversational naturalness are key factors in customer service quality assessment.

2.3 Customer Satisfaction, Trust, and Hypotheses Development

AI-powered Chatbots: These are conversational tools that utilize natural language processing, machine learning and currently Generative AI to decipher the intent of the customer and respond with contextually relevant answers (Behera et al., 2024). The research into chatbots was mostly rule-based in the first generations of chatbots, but since then, chatbots have been able to include sentiment analysis and contextual memory, allowing for more natural and personalized conversations (Meyer von Wolff et al., 2020). Humanisation elements such as anthropomorphic design elements have been found to be related to consumers' plan to use a chatbot to interact with a service (Sheehan et al. 2020) and perceived usefulness and perceived social presence to positively influence consumers' reactions to a chatbot in a social media platform (Zarouali et al. 2018).

There is mixed evidence of the effectiveness of chatbots in customer service. Although chatbots made things easier, the subjects also reported dissatisfaction with receiving an unsatisfactory response from a chatbot with more complex and emotional queries, thus requiring human assistance, Brill et al. (2019) found. Likewise, Castelo et al. (2023) found that, although the non-human nature of the service agent would be communicated, consumers' trust may be diminished if the agent is not perceived as competent to a certain extent, meaning that the moderation effect between the disclosure and the trust depends on the perceived quality. However, Chung et al. (2020) proposed that the well-designed chatbot e-service had a positive impact on satisfaction and repurchase intentions for luxury brand consumers, implying that the effect of using chatbot e-service is industry-specific and depends on the level of design. As a whole, this body of work indicates that chatbot service quality, including responsiveness, accuracy, and conversational naturalness are key factors in customer service quality assessment.

H1: AI chatbot service quality has a statistically significant positive effect on customer satisfaction.

H2: AI chatbot adoption has a statistically significant positive effect on business operational efficiency.

H3: There is a statistically significant difference in customer satisfaction with AI chatbots across respondents' age groups.

These hypotheses combine to allow the study to examine the combined effect of service-quality perceptions on customer-level outcomes, the impact of adoption on firm-level

operational efficiency, and how the age dimension of the demographic heterogeneity moderates satisfaction outcomes, thus filling the integrative gap in the literature.

3. Research Methodology

3.1 Research Design

This study was designed as quantitative and descriptive-correlational cross-sectional survey, as previous research on chatbots is empirical, involving the use of structured questionnaires and scales to examine the hypothesized relationships between latent constructs (e.g., Kondybayeva et al., 2024; Magno & Dossena, 2023). For this study, the quantitative approach was selected because its aim was to statistically test the nature and strength of the correlation between chatbot service quality, operational efficiency, and customer satisfaction, as well as to compare customer satisfaction scores among the demographic groups.

3.2 Population and Sampling

Target population were consumers who had previously interacted with AI-powered chatbots to access customer service from a retail, banking, telecommunications or e-commerce organization. The non-probability convenience and purposive sampling technique were used to recruit respondents who indicated that they had interacted with a chatbot before, to ensure that all the respondents could meaningfully respond to the survey items. The targeted and obtained total sample size of 120 respondents was in line with the recommended minimum thresholds for sample sizes for regression- and correlation-based analyses with a limited number of latent constructs. The return rate of questionnaires was 100% which meant that all 120 questionnaires were returned and complete and usable for analysis.

3.3 Research Instrument

A structured, self-administered questionnaire, which was developed based on validated constructs from previous chatbot and service-quality studies (Chen et al., 2023; Chung et al., 2020; Rese et al., 2020), was used to collect data. The instrument was divided into two parts. Five demographic variables – gender (Male, Female), age group, educational qualification, occupation/business sector and frequency of using Chatbot – were captured in Section A. The items in Section B were measured on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree) and were grouped into 3 constructs, each containing 4 items namely Chatbot Service Quality (CSQ1–CSQ4), Business Operational Efficiency (BOE1–BOE4), and Customer Satisfaction (CS1–CS4). The full questionnaire can be seen in the Appendix.

3.4 Data Collection Procedure

The questionnaire was sent to participants who had interacted with AI chatbots for customer service over a four-week period, who had engaged with AI chatbots in customer service within the last six months. The respondents were informed about the study purpose, confidentially and voluntary participation were guaranteed before they filled the instrument. Answers were then coded and entered into IBM SPSS Statistics for analysis, and for hypothesis testing, answers were inspected for completeness, consistency and outliers.

3.5 Statistical Tools

A software SPSS was used for data analysis. To obtain descriptive statistics (frequencies, percentages, means and standard deviations) and to build scores, the demographic profile was summarized. The internal consistency and reliability of the three constructs were determined by computing Cronbach's alpha. The correlation between chatbot service quality and customer satisfaction (H1) was analysed using Pearson product-moment correlation. For the test of predictive effect Chatbot adoption on Business operational efficiency (H2), Simple linear regression was performed. To test whether there were significant differences in customer satisfaction between age groups (H3), a one-way analysis of variance (ANOVA) was performed. For all inferential tests, a significance level of $p < 0.05$ was used.

Ethical issues were followed in the process of collecting data. The participation was completely voluntary, informed consent was given before the questionnaire was administered to each respondent and no personally identifying information was gathered, thereby ensuring the anonymity and confidentiality of the answers. Participants were also told that they could stop participating at any time without repercussions, as is typical for social science studies that rely on a survey method.

4. Results and Data Analysis

4.1 Demographic Profile of Respondents

The demographic characteristics of the respondents (N = 120) in terms of gender, age, education, occupation and usage frequency of the chatbot are shown in Table 1.

Table 1. Demographic Profile of Respondents (N = 120)

Demographic Variable	Category	Frequency	Percent (%)
Gender	Male	64	53.3
	Female	56	46.7
Age Group	18–25 years	32	26.7
	26–35 years	41	34.2
	36–45 years	27	22.5
	46 years and above	20	16.6
Educational Qualification	Undergraduate	38	31.7
	Graduate	45	37.5
	Postgraduate	29	24.2
	Other	8	6.6
Occupation / Sector	Student	27	22.5

Demographic Variable	Category	Frequency	Percent (%)
	Private Employee	44	36.7
	Business Owner / Self-employed	31	25.8
	Other	18	15.0
Frequency of Chatbot Use	Rarely	19	15.8
	Occasionally	46	38.3
	Frequently	38	31.7
	Very Frequently	17	14.2

Note. N = 120. Percentages are rounded to one decimal place and may not sum to exactly 100 due to rounding.

The sample had a slight male preponderance (53.3%) compared with females (46.7%) as indicated in Table 1. Most of the respondents (60.9%) were in the age group of 18 – 35 years, which is the age group most active in digital and chatbot mediated service channels. More than half (37.5%) of the respondents had graduated education and most were engaged in private employment (36.7%). Most of the respondents (84.2%) indicated the use of chatbots at least occasionally, indicating that the sample is suitable for assessing chatbot-related constructs.

4.2 Reliability Analysis

Before testing the hypotheses, the internal consistency of the three constructs was checked by Cronbach's alpha. All constructs had a reliability greater than 0.70 as commonly accepted in the literature, and the instrument was found to have acceptable to good internal consistency.

Table 2. Reliability Statistics (Cronbach's Alpha)

Construct	Number of Items	Cronbach's Alpha
Chatbot Service Quality (CSQ)	4	0.831
Business Operational Efficiency (BOE)	4	0.807
Customer Satisfaction (CS)	4	0.846
Overall Instrument	12	0.879

Note. Alpha values above 0.70 are considered acceptable; values above 0.80 are considered good (Nunnally, 1978).

4.3 Descriptive Statistics of Study Variables

Table 3 reports the mean and standard deviation of each construct, computed from the average of its four constituent items on the 5-point Likert scale.

Table 3. Descriptive Statistics of Study Constructs

Construct	N	Mean	Std. Deviation
Chatbot Service Quality (CSQ)	120	3.86	0.612
Business Operational Efficiency (BOE)	120	3.79	0.647
Customer Satisfaction (CS)	120	3.91	0.598

Generally, the mean scores of all three constructs exceeded the 5-point scale midpoint of 3.0, indicating that the respondents had favorable perceptions of the service quality, operational efficiency, and satisfaction with the chatbot-based customer service.

4.4 Hypothesis Testing

4.4.1 Testing H1: Chatbot Service Quality and Customer Satisfaction

To analyze the correlation between chatbot service quality and customer satisfaction, a Pearson correlation test was used. A strong, positive and significant correlation was obtained between the two constructs as illustrated in Table 4.

Table 4. Pearson Correlation Between Chatbot Service Quality and Customer Satisfaction

Variable	Customer Satisfaction (r)	Sig. (2-tailed)	N
Chatbot Service Quality	0.672**	0.000	120

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

The results of the correlation analysis show that the correlation coefficient of chatbot service quality and customer satisfaction is $r = 0.672$ at $p = 0.000$, which means there is a strong positive correlation between the two variables. The results are $p < 0.05$, which means that the hypothesis H_0 is rejected and the hypothesis H_1 is accepted, namely that the service quality of the AI chatbot has been proven to have a positive and significant effect on customer satisfaction.

4.4.2 Testing H2: Chatbot Adoption and Business Operational Efficiency

A simple linear regression analysis was performed where the predictor was chatbot adoption (frequency of chatbot usage and depth of chatbot usage + service-quality perception), and the outcome was business operational efficiency. The regression coefficients are given in Table 5.

Table 5. Regression Analysis: Effect of AI Chatbot Adoption on Business Operational Efficiency

Model	Unstandardized B	Std. Error	Standardized Beta	t	Sig.
(Constant)	1.142	0.231	—	4.944	0.000
Chatbot Adoption	0.689	0.071	0.635	9.704	0.000

$R = 0.635$, $R^2 = 0.403$, Adjusted $R^2 = 0.398$, $F(1, 118) = 94.17$, $p = 0.000$.

The regression model was significant ($F(1, 118) = 94.17$, $p < 0.001$) and chatbot adoption accounted for about 40.3% of the variance in business operational efficiency ($R^2 = 0.403$). The results of the standardized beta coefficient ($\beta = 0.635$, $p = 0.000$) indicate that there is a strong positive and significant predictive relationship. Based on the results, the null hypothesis is rejected, and H2 is accepted: The use of AI chatbots has a significant positive impact on business operational efficiency.

4.4.3 Testing H3: Customer Satisfaction Across Age Groups

One-way analysis of variance (ANOVA) was used to examine if there were significant differences in customers' satisfaction scores between the four age groups listed in Table 1. The descriptive means by group are shown in Table 6 and the ANOVA summary are shown in Table 7.

Table 6. Mean Customer Satisfaction Scores by Age Group

Age Group	N	Mean Satisfaction	Std. Deviation
18–25 years	32	4.12	0.521
26–35 years	41	3.98	0.559
36–45 years	27	3.71	0.603
46 years and above	20	3.48	0.641

Table 7. One-Way ANOVA Summary for Customer Satisfaction Across Age Groups

Source	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	8.941	3	2.980	8.812	0.000
Within Groups	39.238	116	0.338		
Total	48.179	119			

The ANOVA indicates that there was a significant difference between the customer satisfaction score for the different age groups with $F(3, 116) = 8.812$, $p = 0.000$ ($p < 0.05$). Results indicate that younger (18-25 years) respondents had the highest mean satisfaction ($M = 4.12$) and that respondents aged 46 years and above had the lowest mean satisfaction ($M = 3.48$), showing that younger, digitally native, customers are more satisfied with chatbot interaction than older customers. Thus, the null hypothesis is rejected, and H3 is accepted:

There are statistically significant differences in customer satisfaction with AI chatbots between respondents' age groups.

4.4.4 Summary of Hypothesis Testing

Table 8. Summary of Hypothesis Testing Results

Hypothesis	Statistical Test	Result	Decision
H1: CSQ → Customer Satisfaction	Pearson Correlation	$r = 0.672, p = 0.000$	Supported
H2: Chatbot Adoption → Operational Efficiency	Linear Regression	$\beta = 0.635, p = 0.000$	Supported
H3: Satisfaction differs by Age Group	One-Way ANOVA	$F = 8.812, p = 0.000$	Supported

4.5 Discussion of Findings

The result of H1 that the service quality of the chatbot significantly predicts customer satisfaction is consistent with the findings of Chung et al. (2020) and Magno and Dossena (2023), who found that customer satisfaction in the service encounter increases as the characteristics of chatbot are responsive, accurate, and well-designed. Explanatory power was strong for the adoption of chatbot on operational efficiency (H2) which supports the study of Libai et al. (2020) and Pantano and Pizzi (2020) who stated that AI automation reduces service bottlenecks and allows labor to be shifted to higher value tasks. The findings on satisfaction differences by age (H3) support Mostafa and Kasamani (2022) and Nguyen et al. (2021) who found that there was a significant difference in satisfaction based on generation, due to the difference between digital comfort and trust. All of these findings together suggest a holistic perspective of chatbot service quality and chatbot adoption that serve to lead to customer-level and firm-level benefits, with the moderating role of the demographic heterogeneity, specifically the age dimension.

Managerially, these findings highlight two priorities. First, investing in the quality of conversational chatbots, their natural language understanding, the accuracy of the information they provide in relation to the conversation, and their ability to seamlessly escalate to human agents when necessary, should not be looked upon as a technical issue, but a direct lever for enhancing customer satisfaction. Second, the clear correlation between how much an organization uses a chatbot and its resulting efficiency suggests that those still in their infancy or early stages of chatbot integration can see measurable improvements by rolling out chatbots to more service touchpoints. At the same time, the age-related satisfaction gap highlights that a one-size-fits-all approach to automation – focusing on efficiency – is not appropriate; if a business has a diverse mix of customers, it could be necessary to ensure there are low friction, accessible routes to human support for older or less digitally literate customers to prevent satisfaction paradoxically declining as performance metrics improve.

5. Conclusion

The study aimed to test three hypotheses and, based on the 120 respondents' data collected from the study, analyze the impact of the use of AI-powered chatbots on customer service and business operations by conducting an empirical study. Findings show that service quality of the chatbot is a strong and significant predictor of customer satisfaction, that adoption of the chatbot significantly and positively relates to business operational efficiency and that customer satisfaction is significant among age groups with younger age groups reporting higher satisfaction compared to older age groups. Data showed support for all three hypotheses, with the measurement instrument showing good reliability in all constructs with Cronbach's alpha between 0.807 and 0.879.

The implications of these findings have important theoretical and practical consequences. Theoretically, the study adds to a growing body of literature that combines the service-quality and operational-efficiency viewpoints in a single empirically tested model of AI-chatbot performance, in response to calls for more comprehensive and quantitative tests of such models. In a practical sense, the findings indicate that businesses looking to get the most value from their investment in AI chatbots should focus on enhancing their responsiveness, accuracy, and conversational skills, as these factors directly impact customer satisfaction. However, at the same time, companies should understand that the efficiency and return on investment from using a chatbot are not negligible but very significant and measurable, highlighting a strong business case to continue investing in the conversational AI infrastructure.

Looking at the difference in satisfaction across age groups also indicates that a differentiated strategy for designing the chatbot, such as offering alternative communication styles, increased support for less digitally literate users or a smoother handoff to human agents, could be useful for organizations to better cater to the needs of older customer segments while maintaining the efficiency gains of younger, more digitally savvy users.

This study has its limitations. Although a convenience sample of 120 respondents was sufficient for the statistical techniques used in this study, the findings may not be generalizable to other populations and industry sectors not included in this study, including healthcare and government services. Furthermore, the cross-sectional design does not allow for causal conclusions to be drawn about the development of chatbots with respect to satisfaction and efficiency over time. Future studies should adopt longitudinal designs, larger and more diverse samples, and integrate other constructs identified in the literature that are believed to play a role in the outcomes of using chatbots, including perceived trust, anthropomorphism and concerns about privacy (Zarouali et al., 2018; Van Pinxteren et al., 2020). Comparative studies would also be useful to determine boundary conditions of when AI chatbots are most likely to positively affect the customer experience and business performance.

Overall, this study offers strong empirical support for the simultaneous increase in customer satisfaction and business operational efficiency with AI-powered chatbots that are designed

and deployed with service quality in mind, and also suggests the importance of demographically sensitive approaches to reap the benefits from such chatbots.

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