Social challenges and barriers in implementing AI chatbots as part of customer service digital transformation

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Abstract

The rapid advancement of artificial intelligence (AI) significantly reshapes customer service, posing notable social challenges and barriers within digital transformation. This study explores user perceptions and societal resistance toward AI-driven chatbots based on a large-scale survey of 11,628 respondents from Poland, Italy, and Sweden. Using a structured framework, chatbot attributes were categorized into essential (response accuracy, real-time assistance), and performance-enhancing (personalization, emotional intelligence, hybrid interactions). Results highlight significant social resistance, especially in emotionally sensitive interactions, where customers strongly prefer human agents over AI. Key barriers identified include privacy concerns, data security risks, and transparency issues. Crucially, trust, explainability, and user education emerged as vital for reducing societal hesitation and fostering acceptance. These findings offer critical insights into social dimensions of digital transformation, emphasizing the importance of developing hybrid customer service models that effectively balance automated technologies and human interaction to enhance consumer trust and overall service experience.

Keywords: social resistance, user trust, chatbot, service personalization, technological integration.

1. Introduction

The rapid advancement of artificial intelligence (AI) is reshaping customer service, with chatbots and virtual assistants increasingly replacing human agents. Companies adopt these technologies to boost efficiency, cut costs, and provide 24/7 support by leveraging natural language processing (NLP) and machine learning. Despite these benefits, the widespread use of AI in customer interactions faces notable barriers and societal resistance. A major concern is the lack of trust and emotional connection, as users often find AI impersonal and inadequate for handling complex or sensitive issues [12]. Data privacy, transparency, and ethical concerns further fuel scepticism toward AI-based support [21]. Resistance also comes from within organisations, especially among employees affected by automation. Businesses face additional hurdles such as high implementation costs, limited AI capabilities, and integration challenges with existing CRM systems [4, 9]. This study investigates the key factors driving resistance to AI in customer service, focusing on consumer trust, organisational barriers, and ethical implications [1,7]. It is structured around three core areas: the technological role of AI chatbots in operations, consumer perceptions and trust, and recommendations for balancing automation with human interaction [11]. Industry data confirms AI's growing presence. Gartner reports that 76% of CIOs in midsize firms are investing in generative AI to enhance chatbot performance [24]. Exploding Topics highlights that 41% of businesses use chatbots for sales and 37% for customer service due to improved efficiency [3]. Desk365 estimates that by 2025, AI will manage up to 95% of all customer interactions [1, 6]. Drawing on large-scale survey data from Sweden, Italy, and Poland, this study examines trust, transparency, emotional intelligence, algorithm aversion, and cultural variation as key factors in AI chatbot adoption. It provides a comprehensive view of customer attitudes supported by clear theoretical foundations and empirical validation [13].

2. Literature review

AI has rapidly transformed customer service by automating interactions, improving efficiency, and reducing costs. Integrated into CRM systems, AI chatbots and virtual assistants provide 24/7 support, predictive analytics, and personalised recommendations. However, despite these advantages, chatbot adoption faces significant challenges and societal resistance, creating strategic and managerial concerns. Many users remain dissatisfied with AI's inability to understand emotional cues, preferring human interaction in complex or sensitive situations [16]. While AI performs well with routine queries, its rigidity and lack of empathy often reduce customer satisfaction and loyalty. Concerns over automation, data security, and trust in non-human agents further complicate adoption [11]. Studies also show AI struggles with unexpected customer needs, leading to frustration and disengagement [12,15]. Addressing these issues requires more adaptable, emotionally responsive, and transparent chatbot designs [5, 8, 14]. Organisational barriers include high implementation costs, integration challenges, and employee resistance. Successful deployment demands infrastructure investment and staff training. Cultural and psychological factors also shape consumer acceptance, varying significantly across regions [15, 19]. Despite growing research on AI in customer service, key gaps remain. Much focus has been on technical performance, while psychological and behavioural factors behind consumer resistance are understudied [5, 18]. Future research should explore how trust-building, emotional intelligence, and transparency can foster acceptance [17]. This study aims to address these gaps by analysing the obstacles and social resistance surrounding AI chatbot adoption in customer service [22, 28]. The implementation of AI-driven chatbots in customer service presents significant societal and organisational problems. Customers frequently favour human engagement for jobs necessitating empathy or discernment and are wary of algorithmic determinations, data privacy, and security concerns [15]. Organisationally, significant obstacles encompass technological integration, staff adaption, and change management. Cultural influences additionally determine AI acceptability, underscoring the necessity for market-specific methods [26]. The subsequent research hypotheses are offered to address these issues: *H1: Customer trust in AI chatbots positively influences their willingness to use services based on this technology. H2: Transparency in communicating the use of AI in customer service reduces concerns related to privacy and data security.* Test these ideas to better understand AI chatbot acceptance and execute it across cultures [2, 9, 24]. One hypothesis examines whether AI with human help can improve empathy, problem-solving, and service quality. The findings can help enterprises and policymakers embrace AI technologies while reducing trust and satisfaction difficulties [25, 22]. The research also recommends ethical, adaptive, and user-focused AI service models. Two theoretical frameworks underpin the investigation. Positive attitudes towards AI depend on perceived competency and personalisation, according to the competence–personalisation model [27]. When capable, chatbots are liked, but algorithm aversion occurs when AI lacks performance or personality. The CASA paradigm and Media Equation theory reveal that users respond socially to chatbots, but the ELIZA effect shows that unmet emotional expectations can create disappointment [21, 23], explaining why trust may not always match perceived efficacy in complicated interactions.

3. Methodology

When chatbots are good and people value AI, personalisation becomes less important. When AI lacks skill or emotion, users dislike it. Users view chatbots as social agents, which can create trust but disappoint when human-like expectations aren't met—the ELIZA effect—according to the CASA paradigm and Media Equation theory. Trust and low perceived effectiveness in difficult situations can coexist [10, 20]. This work ties these principles to behavioural models, boosting academic and practical relevance. Swedish, Polish, and Italian SEM-PLS groups with different digital development levels reached culturally nuanced conclusions. The 11,628 AI chatbot users chosen for demographic balance by quota sampling provided correct statistics. Four weeks of data collection reduced bias, and a screening question ensured AI contact. The sample included respondents from varied demographics, industries, and digital skill levels to show AI acceptance and rejection across user profiles. The questionnaire assessed AI-driven customer service in several areas: Customer trust and perception of AI chatbots' reliability, efficiency, and ethics; How AI transparency and explainability affect client acceptance; AI-driven customer interactions are resisted due to human agent preferences, empathy issues, and data security concerns. How hybrid AI-human service models reduce consumer resistance. SEM-PLS was utilised to study complicated interactions between latent variables such AI trust, perceived benefit, technological acceptability, and automation resistance. It found key consumer attitudes regarding customer service chatbot adoption. The report discusses trust, transparency, and human-AI collaboration and offers AI tool usage tips. Cultural differences in AI adoption in Poland, Italy, and Sweden highlighted the need for specialist solutions. A 5-point Likert scale measured respondents' preferences for AI-only, human-only, and hybrid services, showing how hybrid models effect trust and resistance. Figure 1 shows how hybrid preferences support H1 and H2 relationships from participant selection, data collection, and hypothesis testing.

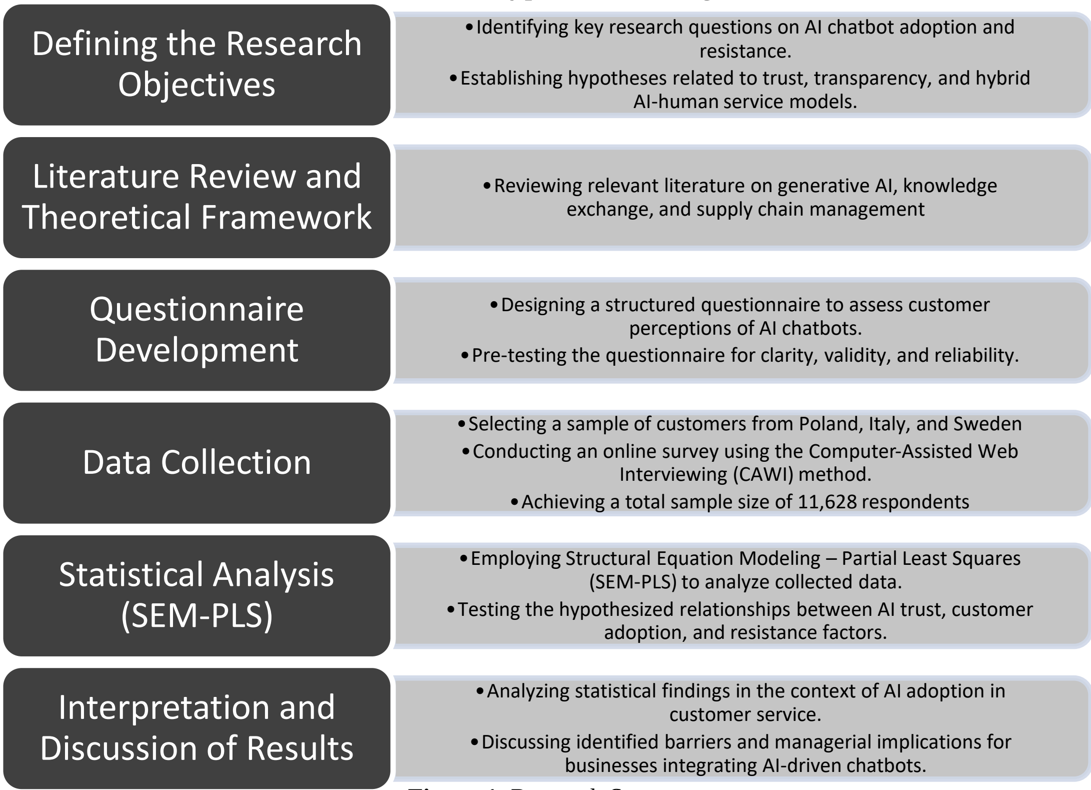

Figure 1. Research Steps

The study commenced by identifying research deficiencies, observing that despite the proliferation of AI chatbots in customer support, insufficient attention has been devoted to social resistance and cross-cultural disparities. Previous studies have predominantly concentrated on technical elements like as language processing and efficiency, neglecting considerations like trust, psychological resistance, and hybrid service models. A science mapping analysis utilising VOSviewer was conducted to identify major themes, trends, and spatial patterns throughout the literature. An examination of keywords and country-level data identified predominant study domains and regional contributions, indicating that AI acceptability differs among demographics and highlighting the necessity for customised methods to overcome social and psychological obstacles (Fig. 2)

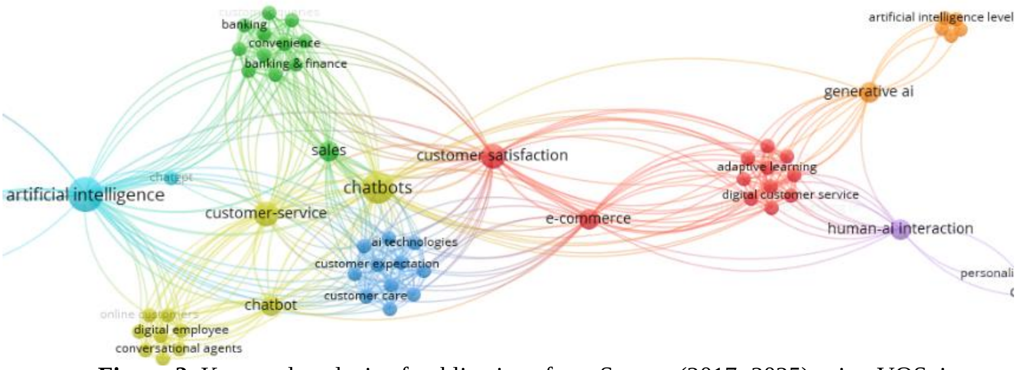

Figure 2. Keyword analysis of publications from Scopus (2017–2025) using VOSviewer

This poll included Polish, Italian, and Swedish participants to understand cultural and technological perspectives on AI chatbot acceptance and resistance. These countries were chosen for their different AI integration in customer service, public attitudes of automation, and legal systems. We used convenience sampling to ensure high involvement from AI experts. 11,628 people completed a CAWI questionnaire online. The insights were relevant and accurate since only people who used AI-driven products like chatbots or virtual assistants were included. Anonymous and voluntary participation reduced prejudice and improved statistics. An structured 24-item questionnaire was divided by theme. The first portion examined AI adoption by age, digital literacy, and automated service experience. The second investigated AI chatbot confidence, including reliability, transparency, and ethics. To identify cynicism, participants' preferences for human versus AI-driven service were assessed. Hybrid AI-human service models were tested for resistance reduction and satisfaction. The study also examined AI-driven relationship challenges like empathy, miscommunication, privacy, and algorithmic prejudice. Participants shared their predictions and suggestions for AI-driven customer service. This detailed study sheds light on customer attitudes, resistance reasons, and ways to improve AI chatbot acceptance and performance, emphasising the need to balance automation with human connection in varied market circumstances.

Table 1. Description of the research group

	description of the research group				
1	Sex	Man 37%		Woman 63%	
2	Age	18-29 years	26%	18-29 years	21%
		30-39 years	48%	30-39 years	47%
		40-49 years	22%	40-49 years	23%
		Over 50 years	4%	Over 50 years	9%
3	Frequency of technology use	rarely 12%		Sometimes 38%	Frequently 51%
4	Willingness to continue using AI chatbots	not at all 0%		Sometimes 39%	Willingly 61%
5	Primary purpose of chatbot use	customer support 41%		Shopping 33%	Banking 26%

The sample was 63% female, outnumbering males (37%), with the majority aged 30–39 (47–48%), followed by 18–29 (26% men, 21% women) and 40–49 (22% men, 23% women). Chatbot technology adoption is strongest among younger and mid-career users, as only 4% of participants over 50 (4% males, 9% women) expressed engagement. 51% claimed frequent technology use, 38% occasional use, and 12% rarely use, indicating a tech-savvy populace. AI-based customer help is becoming more accepted, with 61% eager to utilise it, 39% occasionally, and no outright rejection. Customer service (41%), commerce (33%), and banking (26%), show chatbots' expanding prominence in consumer-facing areas. Constructs were measured using validated multi-item Likert scales. Each scale was reliable (Cronbach's alpha: 0.82–0.94). Construct sources, item counts, formats, and reliability statistics are in Table 2. This study evaluated all critical qualities using confirmed multi-item Likert scales from previous literature. AI chatbot trust was measured using a human-automation interaction scale. Items measuring explainability and disclosure judged transparency. After AI failures, users' reluctance to use it was used to assess algorithm aversion. The emotional response of chatbots was measured using empathy and emotional intelligence measurements. Finally, hybrid AI–human interaction preference was measured using AI-augmented service delivery literature, showing respondents' support for mixed-mode service models. With Cronbach's alpha values between 0.82 and 0.94, each scale was reliable. Table 2 lists construct sources, item counts, response formats, and reliability coefficients.

Table 2. Constructs and their Theoretical Sources

Construct	Theoretical Basis & Key Reference
Trust	Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. Journal of Experimental Psychology: General, 144(1), 231–241.
Transparency	Kagan, E., Hathaway, B., & Dada, M. (2025). Deploying chatbots in customer service: Adoption hurdles and simple remedies. arXiv.
Emotional Intelligence	Shou, D., et al. (2024). Exploring mechanisms of sustained consumer trust in AI chatbots after service failures: A CASA and attribution perspective. Palgrave Communications, 10 (1).
Hybrid AI–Human Interaction	Based on frameworks integrating AI support in human-assisted service delivery (e.g., Chatbot + Agent synergy models).
Cultural Differences	Hofstede, G. (2001). Culture's Consequences: Comparing Values, Behaviors, Institutions and Organizations across Nations. Sage.

The data were carefully examined to determine customer behaviour and AI acceptability. The questionnaire used a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree) in various parts. Initial AI-driven customer service user experience evaluations highlighted efficiency, reliability, and usefulness. The next section examined AI decision-making trust variables such data privacy, accuracy, and equity. The study compared human and AI interactions on empathy, misunderstanding, and answer quality. The hybrid AI-human service strategy was also tested for its ability to reduce resistance and boost satisfaction.

A 0.01 significance threshold and 1% error margin (u = 3.1426) ensured statistical robustness. Poland, Italy, and Sweden—digital transformation and AI-driven service innovation nations—conducted research. Using Microsoft Excel, Statistica, and SmartPLS3, SEM-PLS was used to examine complex connections between adoption, trust, and AI-driven consumer interaction limitations. The approach provided reliable data to improve chatbot acceptability and performance.

4. Results

This study explores AI chatbot adoption, trust, and customer service performance, as well as social resistance and consumer readiness for AI-driven interactions. Table 3 reveals high chatbot recognition but modest consumer knowledge and familiarity (5.26), indicating limited engagement. Trust in AI customer service (4.80) and chatbot efficiency (5.28) suggest cautious automation optimism. Customers prefer human interaction (3.50), showing reluctance to accept AI. Ethical AI systems must be open and explainable to generate trust (4.24). The study found that digital literacy and AI experience affected chatbot efficacy across demographics. Despite their popularity, AI chatbots have moderate trust and contentment. Performance data showed AI-based service delivery strengths and weaknesses. Many consumers want tailored, human-assisted support, thus hybrid AI-human models may reduce pushback. Trust, customisation, and transparency in AI decision-making promote adoption, their data show. Table 3 shows the complexity of AI chatbot adoption and social acceptance.

Table 3. Mean values and Cronbach's α coefficient

	Variable	**Average value**	**Cronbach's α**
T1	Awareness and Familiarity with AI Chatbots	5,26	0,85
T2	Trust in AI-Driven Customer Service	4,8	0,9
T3	Perceived Efficiency of AI Chatbots	5,28	0,85
A1	Preference for Human vs. AI Interaction	3,5	0,84
A2	Transparency and Explainability of AI Decisions	4,24	0,89
A3	Privacy and Data Security Concerns	3,51	0,84

C1	User Experience and Satisfaction with AI Chatbots	4,32	0,82
C2	Impact of AI Chatbots on Brand Perception	4,16	0,81
C3	Social Resistance to AI in Customer Service	3,83	0,94
E1	Effectiveness of Hybrid AI-Human Service Models	3,97	0,92
E2	Willingness to Continue Using AI Chatbots	4,05	0,84

Table 3 shows mean values and reliability coefficients (Cronbach's alpha) for major customer service AI chatbot acceptance, trust, and social resistance factors. Customer awareness, trust in chatbots, perceived efficacy, preference for human versus AI engagement, and AI decision-making transparency were assessed. Data privacy, AI satisfaction, brand impression, and hybrid AI-human service models were also considered. Based on their AI-driven customer service experiences, participants scored these characteristics to examine acceptance and resistance. All structures had strong internal consistency. Research shows that while AI chatbots improve service efficiency, trust, a need for human engagement, and data security and transparency concerns continue. The findings emphasise the need to balance automation and human support. Hybrid versions reduce resistance and improve enjoyment. These insights help companies build trust, address social challenges, and improve AI-driven customer care.

Table 4. Relationships between factors.

	T1	T2	T3	A1	A2	A3	C1	C2	C3	E1	E2
T1	1.00	-	-	-	-	-	-	-	-	-	-
T2	0.97	1.00	-	-	-	-	-	-	-	-	-
T3	0.36	0.43	1.00	-	-	-	-	-	-	-	-
A1	0.95	0.96	0.82	1.00	-	-	-	-	-	-	-
A2	0.33	0.70	0.38	0.51	1.00	-	-	-	-	-	-
A3	0.92	0.18	0.28	0.19	0.12	1.00	-	-	-	-	-
C1	0.23	0.82	0.17	0.17	0.14	0.50	1.00	-	-	-	-
C2	0.17	0.42	0.20	0.60	0.22	0.09	0.35	1.00	-	-	-
C3	0.90	0.52	0.21	0.09	0.21	0.06	0.21	0.15	1.00	-	-
E1	0.20	0.13	0.67	0.38	0.56	0.92	0.35	0.46	0.78	1.00	-
E2	0.37	0.25	0.94	0.83	0.88	0.82	0.27	0.90	0.58	0.37	1.00

Results analysis began with scale statistics. The scale's variance, mean, and standard deviation for all five items are in Table 5. Respondents' opinions can be measured from 1 to 75. The average score of 55.82 suggests people enjoy AI-driven customer care and chatbots. These findings imply AI technology integration may boost user trust, usefulness, and transparency.

Table 5. The scale statistics.

Mean	Variance	Standard Deviation
51,6181	93,52143	9,41736

The relationships between components can be analysed numerically (Table 3 and 4) and graphically. Structure equations can be created from estimated values to determine the strength of interactions between factor groupings. A higher degree of reliance indicates a stronger link between the variables. Figure 3 shows how the discovered dependencies affect AI chatbot adoption and customer views.

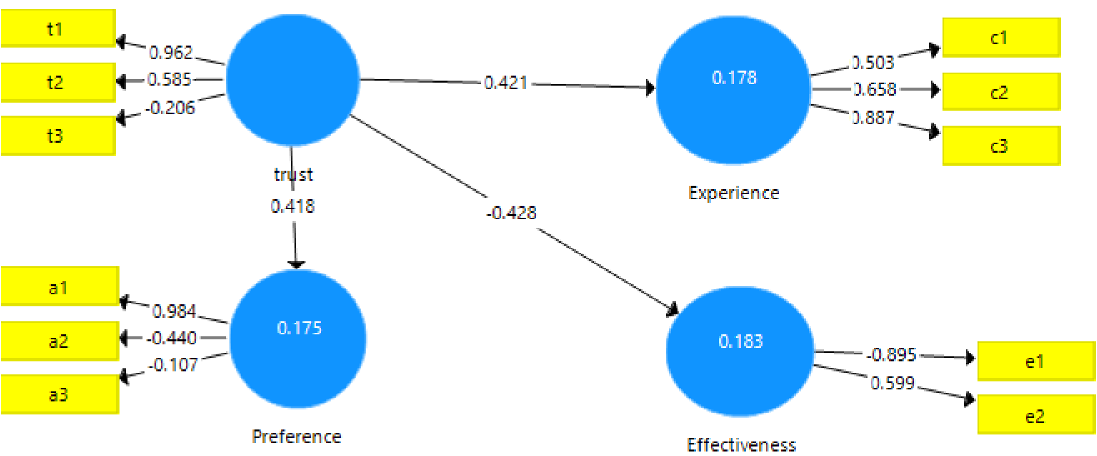

Figure 3. Structural equations for AI chatbox.

The structural model shows how trust, experience, preference, and perceived efficacy affect AI chatbot adoption. Trust positively impacts user experience (= 0.421) but negatively impacts perceived efficacy (= –0.428), indicating that trust can boost engagement but also raise expectations that AI cannot deliver. Trust strongly predicts adoption in the complete sample ($\beta = 0.45$, $p < 0.001$), accounting for 48% of variation ($R^2 = 0.48$). Transparency decreases social resistance ($\beta = -0.32$, $p < 0.001$; $R^2 = 0.35$), while emotional intelligence marginally impacts pleasure ($\beta = 0.28$, $p = 0.002$; $R^2 = 0.42$). Multi-group study shows cultural differences: Sweden has the largest Trust-to-Adoption impact ($\beta = 0.52$) and Poland has the least ($\beta = 0.41$, $\Delta = 0.11$, $p = 0.03$). Compared to Sweden (–0.31) and Poland (–0.29), Transparency Resistance has the highest impact in Italy ($\beta = –0.38$), showing cultural sensitivity to AI-related hazards. Both main approaches are moderated by hybrid AI–human interaction choice. High hybrid preference users exhibit higher trust-driven adoption ($\beta = 0.58$) and reduced transparency resistance ($\beta = –0.45$) compared to low-preference users ($\beta = 0.37$ and –0.21). These findings confirm that hybrid models improve AI acceptability across varied user profiles.

5. Discussion and conclusion

The study shows that AI-driven chatbots are essential for customer assistance due to their efficiency, cost reduction, and 24/7 availability. Trust, transparency, and interpersonal interaction remain major barriers to mainstream adoption. Transparent and ethical AI is needed due to data privacy and algorithmic bias concerns. Chatbots handle routine questions well, but many consumers prefer human agents for complex or emotional issues, emphasising the need for hybrid AI-human models to reduce resistance and improve satisfaction. Results show rising demand for personalisation, sentiment analysis, and hybrid offerings. Localising chatbots is necessary due to age, gender, technological skill, and cultural differences in attitudes. The differences in Poland, Italy, and Sweden show how digital maturity and culture affect AI readiness. Research has limitations. It focusses on three European countries, uses self-reported information, and lacks objective performance metrics like response time or resolution rates. Expand geographic areas, use mixed-method designs that combine surveys and behavioural data, and analyse long-term effects with longitudinal research. It should also determine which interactions require human presence to maximise consumer satisfaction. The conclusions require firms to build trust through openness, ethical data, and clear AI. Services must meet users' customisation and digital skills. Resistance must be reduced using hybrid automation-human help solutions. Responsible AI governance requires revealing chatbot use, data management, and escalation mechanisms and following EU AI Act and FTC guidelines to build trust and compliance.

References

1. Akram S., Buono P., Lanzilotti R.: Recruitment chatbot acceptance in a company: a mixed method study on human-centered technology acceptance model. Pers Ubiquit Comput 28:961–984. https://doi.org/10.1007/s00779-024-01826-4 (2024)
2. Allal-Chérif O., Yela Aránega A., Castaño Sánchez R.: Intelligent recruitment: How to identify, select, and retain talents from around the world using artificial intelligence. Technological Forecasting and Social Change 169:120822. https://doi.org/10.1016/j.techfore.2021.120822 (2021)
3. Andrade de IM., Tumelero C.: Increasing customer service efficiency through artificial intelligence chatbot. REGE 29:238–251. https://doi.org/10.1108/REGE-07-2021-0120 (2022)
4. Berşe S., Akça K., Dirgar E.: The Role and Potential Contributions of the Artificial Intelligence Language Model ChatGPT. Annals of Biomedical Engineering 52:130–133. https://doi.org/10.1007/s10439-023-03296-w (2024)
5. Casaló LV., Millastre-Valencia P., Belanche D.: Intelligence and humanness as key drivers of service value in Generative AI chatbots. International Journal of Hospitality Management 128:104130. https://doi.org/10.1016/j.ijhm.2025.104130 (2025)
6. Exploding Topics 40+ Chatbot Statistics (2025). https://explodingtopics.com/blog/chatbot-statistics?utm_source=chatgpt.com. Accessed 25 Jun 2025

7. Goot van der MJ., Koubayová N., Reijmersdal van EA.: Understanding users' responses to disclosed vs. undisclosed customer service chatbots: a mixed methods study. AI & Soc 39:2947–2960. https://doi.org/10.1007/s00146-023-01818-7 (2024)
8. Graham G., Nisar TM., Prabhakar G.: Chatbots in customer service within banking and finance: Do chatbots herald the start of an AI revolution in the corporate world? Computers in Human Behavior 165:108570. https://doi.org/10.1016/j.chb.2025.108570 (2025)
9. Gu C., Zhang Y., Zeng L.: Exploring the mechanism of sustained consumer trust in AI chatbots after service failures: a perspective based on attribution and CASA theories. Humanit Soc Sci Commun 11. https://doi.org/10.1057/s41599-024-03879-5 (2024)
10. Hoyer WD., Kroschke M., Schmitt B. et al.: Transforming the Customer Experience through New Technologies. Journal of Interactive Marketing 51:57–71. https://doi.org/10.1016/j.intmar.2020.04.001 (2020)
11. Huang M-H., Rust RT.: Artificial Intelligence in Service. Journal of Service Research 21:155–172. https://doi.org/10.1177/1094670517752459 (2018)
12. Kasneci E., Seßler K., Küchemann S. et al.: ChatGPT for Good? On Opportunities and Challenges of Large Language Models for Education (2023)
13. Lemon KN., Verhoef PC.: Understanding Customer Experience Throughout the Customer Journey. Journal of Marketing 80:69–96. https://doi.org/10.1509/jm.15.0420 (2016)
14. Lifewire (2025) The Future's Powered by AI. Just Don't Expect Everyone to Love It. https://www.lifewire.com/ai-adoption-vs-consumer-confidence-11759640?utm_source=chatgpt.com. Accessed 25 Jun 2025
15. Lu Y., Zhang J.: Balancing identity diversity and product contexts: Understanding consumer trust in AI-enhanced chatbot services. Journal of Retailing and Consumer Services 84:104205. https://doi.org/10.1016/j.jretconser.2024.104205 (2025)
16. Mariani MM., Fosso Wamba S.: Exploring how consumer goods companies innovate in the digital age: The role of big data analytics companies. Journal of Business Research 121:338–352. https://doi.org/10.1016/j.jbusres.2020.09.012 (2020)
17. Mende M., Scott ML., Doorn van J et al.: Service Robots Rising: How Humanoid Robots Influence Service Experiences and Elicit Compensatory Consumer Responses. Journal of Marketing Research 56:535–556. https://doi.org/10.1177/0022243718822827 (2019)
18. Nash JF.: Equilibrium Points in N-Person Games. Proc Natl Acad Sci U S A 36:48–49. https://doi.org/10.1073/pnas.36.1.48 (1950)
19. Nass C., Moon Y.: Machines and Mindlessness: Social Responses to Computers. Journal of Social Issues 56:81–103. https://doi.org/10.1111/0022-4537.00153 (2000)
20. Park JE., Fan A., Wu L.: Chatbots in complaint handling: the moderating role of humor. IJCHM 37:805–824. https://doi.org/10.1108/IJCHM-05-2024-0762 (2025)
21. Qin X., Zhou X., Chen C. et al.: AI aversion or appreciation? A capability-personalization framework and a meta-analytic review. Psychol Bull 151:580–599. https://doi.org/10.1037/bul0000477 (2025)
22. Samudrapu M., Ramineni V., Rao GRM.: (2025) A survey on artificial intelligence (AI) chatbots and language models. In: International Conference On Emerging Technologies In Engineering And Science: ICETES2023. AIP Publishing, p 20106
23. Shaping Europe's digital future (2025) AI Act. https://digital-strategy.ec.europa.eu/en/policies/regulatory-framework-ai. Accessed 25 Jun 2025
24. Sheng ML., Natalia N., Rusfian EZ.: AI Chatbot, Human, and In-Between: Examining the Broader Spectrum of Technology-Human Interactions in Driving Customer-Brand Relationships Across Experience and Credence Services. Psychology and Marketing 42:1051–1071. https://doi.org/10.1002/mar.22165 (2025)
25. Trivedi J.: Examining the Customer Experience of Using Banking Chatbots and Its Impact on Brand Love: The Moderating Role of Perceived Risk. Journal of Internet Commerce 18:91–111. https://doi.org/10.1080/15332861.2019.1567188 (2019)
26. Upadhyay AK., Khandelwal K.: Applying artificial intelligence: implications for recruitment. SHR 17:255–258. https://doi.org/10.1108/SHR-07-2018-0051 (2018)
27. Żywiołek J.: Knowledge-Driven Sustainability: Leveraging Technology for Resource Management in Household Operations. ECKM 25:974–982. https://doi.org/10.34190/eckm.25.1.2375 (2024)
28. Żywiołek J.: Trust-Building in AI-Human Partnerships Within Industry 5.0. System Safety: Human - Technical Facility - Environment 6:89–98. https://doi.org/10.2478/czoto-2024-0011 (2024)