sciendo
National University of Political Studies and Public Administration
Faculty of Management

Interactive AI is Smarter! The Role of AI Interactivity on Information Quality and Credibility in Times of Conflict

Miruna NICULESCU[1], Irina BOJESCU[2], Maria BARBUL[3], Corina PELAU[4]
Bucharest University of Economic Studies, 6 Piata Romana, 010374 Bucharest, Romania;
1 miruna_niculescu@yahoo.com
2 irina0927@yahoo.com
3 ; mariabarbul@gmail.com
4 ; corina.pelau@fabiz.ase.ro

Abstract: The increasing integration of artificial intelligence (AI) into everyday life has raised significant questions about the way they interfere and influence individuals in the present society. Especially in times of conflict, when a lot of information is disseminated with the help of AI, it is vital to study the perception of individuals on the information quality and credibility provided by AI. The objective of this paper is to examine the way interactivity and social attachment influence individuals' perception of AI as a credible and informative agent. While functional performance remains a key expectation, the ability of AI systems to build emotional connections and simulate human-like responsiveness is emerging as a critical factor in perceived usefulness. This analysis underscores the importance of designing AI not only for task efficiency but also for fostering trust, engagement, and relational value in user interactions. The results obtained indicate a strong positive relationship between social attachment and interactivity, suggesting that users who have a social attachment to AI devices are more likely to perceive them as highly interactive. Although social attachment alone does not directly enhance perceptions of information quality, it contributes indirectly by increasing interactivity. Eventually, increased interactivity significantly improves the perceived quality of information, as individuals associate responsive and personalized AI behavior with clarity, accuracy, and reliability. These findings highlight interactivity as a key mediating factor in the relationship between emotional connection and information quality, underscoring the importance of socially engaging AI design.

Keywords: social attachment; interactivity; artificial intelligence; information quality, perception; engagement.

Introduction

In recent years, social artificial intelligent (AI) devices and robots have enhanced their presence as a common feature of everyday life in both businesses, commercial and domestic environments (Gursoy et al., 2019). Social AI devices are used not only for resolving tasks in different jobs, but also for providing assistance and companionship for people (Liu & Hancock, 2024). Social robots can interact with individuals and respond to their needs by showing empathy through facial expressions, gestures and other social cues (Johnson et al., 2014). There is a growing tendency to deploy social AI devices in a variety of support roles and also integrate them in people's everyday life. A significant number of studies have demonstrated that people are influenced not only by the efficiency of AI devices but also by the social group and perception towards these new technologies (Gursoy et al., 2019).

Modern societies, founded on individual autonomy and freedom of choice, are increasingly shifting control to AI—challenging the very notion of personal sovereignty (Vidu et al., 2020). This shift is paralleled by the integration of social AI devices into daily life, as the rise of home virtual assistants and service robots continues to redefine user interactions and service delivery across domestic and commercial environments. As AI becomes embedded in customer touchpoints, there is growing interest in how the

How to cite
Niculescu, M., Bojescu, I., Barbul, M., & Pelau, C. (2025). Interactive AI is Smarter! The Role of AI Interactivity on Information Quality and Credibility in Times of Conflict. *Culture. Society. Economy. Politics. 5*(1), 10-22. https://doi.org/10.2478/csep-2025-0002
ISSN (online) 2810-2010
https://website.sciendo.com/publication/culture-society-economy-politics/
http://www.facultateademanagement.ro/culture-sep/

interactivity and human-like behavior of these systems shape individual perceptions. Especially in times of political conflict, the relationship between users and AI is very important, as AI is increasingly used in the creation and dissemination of information. Recent research focuses on the way generative AI has the ability to create biased messages based on previous political beliefs, increasing even more the polarization of society (Burton, 2023; Messer, 2025). Depending on the way individuals believe and trust the information generated by AI, will influence their future behavior. For this reason, understanding the relationship between social attachment, interactivity and information quality at AI is more important then ever.

Modern AI agents are progressively designed to replicate human conversational behaviors by utilizing natural language, adopting friendly and engaging tones, and incorporating emotional expressions, all with the aim of enhancing the sense of social presence during interactions (Gomes et al., 2025). This design strategy of AI anthropomorphism is not merely aesthetic; it has a profound impact on how users evaluate and respond to it (Gomes, Lopes, & Nogueira, 2025). Studies show that when an AI chatbot simulates human qualities, individuals tend to perceive it as more authentic and competent, and they report greater trust in his responses (Gomes et al., 2025). This kind of human-like interactivity can make the experience more engaging and enjoyable, conducting to higher user satisfaction and even influencing people's behavior.

Over time, beyond the occasional interactions, individuals may even develop a social attachment to AI devices. Social attachment refers to the emotional connection that can form between people and an AI agent or device (Pelau et al., 2023). Much like interpersonal attachments, this relationship is cultivated when the AI engages users in personalized, responsive ways and provides a sense of companionship or support. Critically, such attachment can influence user attitudes and behaviors. When individuals feel emotionally attached to AI, their willingness to interact with it frequently increases, and treat it favorably (Pelau et al., 2023). In essence, attachment creates a sense of trust and connection between the user and AI, leading to a more enjoyable and effective service experience and trust in the received recommendations.

The perceived intelligence and usefulness of AI devices have become crucial success factors for user engagement and digital business strategy. Therefore, understanding these users' perception dynamics is critical (Davis, 1989; Venkatesh & Davis, 2000). Trust and perceived usefulness are crucial factors in technology adoption and continued willingness of use, a dynamic that holds true for AI systems in customer-facing roles (Gefen, Karahanna, & Straub, 2003). When users perceive AI assistants as intelligent, reliable, and useful, they are more likely to trust them, feel satisfied with the interaction, and maintain ongoing engagement with the brand (Pelau et al., 2023; Pentina et al., 2023). These perceptions can lead to tangible business outcomes, such as increased willingness to share personal data, greater satisfaction, customer loyalty, and stronger purchase intentions (Gomes et al., 2025). On the contrary, AI systems that fail to demonstrate interactivity or establish social rapport may be viewed as less competent or helpful, undermining user trust and discouraging usage (Ding & Najaf, 2024). Therefore, designing AI to foster trust, social connection, and perceived informativeness is increasingly recognized as a strategic priority for companies aiming to enhance user experience and build sustainable customer relationships in competitive digital environments (Arikan et al., 2023; Gu, Zhang, & Zeng, 2024).

Despite the widespread adoption of AI chatbots and virtual assistants in business practice, empirical research that examines how interactive and socially engaging features influence the perceptions of individuals remains underdeveloped (Gomes et al., 2025; Gu, Zhang, & Zeng, 2024). Key questions remain regarding the psychological mechanisms by which interactivity and social attachment affect users' evaluations of AI - particularly in terms of perceived informativeness, trust, and satisfaction (Pelau et al., 2023). Addressing this gap, the present study investigates whether increased interactivity and emotional attachment to AI improve users' perceptions of the system's intelligence and credibility. The results of this research will help inform strategies for leveraging AI's social and interactive capabilities to improve user experience and the perceived value of AI-provided information, aligning technological innovation with effective business and communication strategies.

Literature review

The significant development of AI has a major impact on the way people interact with robots and smart devices. Artificial intelligence has become an essential part of life, as people spend a considerable amount of time online and are surrounded by various intelligent devices. AI has increasingly become a key player in customer-focused services, driving innovation in the delivery of these services (Săniuță, Zbuchea, & Hrib, 2022). Interactions between clients and AI can take place in both online environments and in person. As AI-powered robots develop self-awareness similar to human consciousness, their interactions with humans are expected to become more natural, engaging, and human-like. This could lead to the formation of relationships between humans and robots, a trend that is already emerging in some parts of the world due to the openness of people towards new technological advancements (Nomura & Kanda, 2016). Especially in times of conflicts AI may play an important role in shaping decisions and individual behavior as it is an efficient tool in the creation and dissemination of information (Messer, 2025). For this reason, in times of political conflict and society polarization, it is even more important to understand the credibility of AI in the life of individuals (Burton, 2023).

During interactions with AI, individuals quickly form impressions based on its physical appearance, familiarity, and nonverbal behavior (Beer et al., 2011; Riegger et al., 2021). According to Lu, Zhang, and Zhang (2021), users are more likely to favor humanoid robots over those without human-like traits, perceiving them as more capable of performing tasks and facilitating emotional interactions. According to Kim, Kang, and Bae (2022), interactivity can be divided into two categories: human-to-human interaction and human-to-machine interaction. The first category, human-to-human interaction, refers to interpersonal and relational interactivity (Carey, 1989; Massey & Levy, 1999), while the second category, human-to-machine interaction, is defined as user-computer and user-system interaction (Liu & Shrum, 2002; McMillan, 2005).

De Ruyter et al. (2005) and Song and Kim (2020) describe social capability as the ability of an AI to engage in interpersonal interactions, which include skills like interactive communication, approachability, providing appropriate responses, and listening attentively without interrupting the customer. People who interact with AI-powered robots often perceive them as caring and trustworthy (Song & Kim, 2020). The use of devices with social AI is increasingly common in various customer service roles, including as concierges, waitstaff, and even in supporting the healthcare system. AI-powered social devices are employed not only to carry out tasks in different sectors but also to offer support and companionship to individuals (Liu & Hancock, 2024).

Social robots can interact with users and meet their needs by showing empathy through facial expressions, gestures, and other social indicators (Johnson et al., 2014). Moreover, experts suggest that robots will soon engage with humans in a collaborative way, creating mutual social value as both parties could learn from each other during their interactions (Lessiter et al., 2014). According to Jacucci et al. (2014), robots will improve their social learning capabilities by interacting with humans. Studies indicate that a robot's empathy and physical form are key factors affecting its social presence and the level of acceptance it receives from people (Kwak et al., 2013). According to Fong, Nourbakhsh, and Dautenhahn (2003), social interactive robots have the ability to recognize one another and engage in social interactions. They have memory, meaning they perceive and interpret the world through their own experiences, communicate, and learn from each other. Additionally, these robots are able to establish and maintain social relationships using natural reactions (such as eye contact and gestures), exhibit

Vol.5 (2025) no.1, pp.10-22; DOI 10.2478/csep-2025-0002

unique personalities and traits, and ultimately develop social skills (Hegel et al., 2009). According to Breazeal (2002), a sociable robot can communicate with humans, comprehend them, and connect with them on a personal level. It should be able to understand both humans and itself in social contexts. Additionally, Breazeal (2002) suggests that humans should be able to relate to the robot in the same social framework (engaging with it and feeling empathy toward it). However, studies suggest that interactions with robots that lack social abilities are frequently seen as clumsy, causing users to have less trust in them and perceive a diminished sense of social presence (Mende et al., 2019).

Attachment to AI is defined as the emotional connection that develops between individuals and certain AI-powered devices and/or robots (Thomson, Macinnis, & Park, 2005), which necessitates feelings of connectivity and affection (Aron & Westbay, 1996; Fehr & Russell, 1991). Emotional attachment can significantly enhance interactions with AI devices, as consumers who feel connected to them are more likely to engage and recommend them to others (Martelaro et al., 2016). Furthermore, emotionally attached consumers are often more tolerant of mistakes and more likely to offer constructive feedback to help improve AI performance (Pelau et al., 2023).

Research in the service industry has long shown that users evaluate service quality by comparing their expectations with the actual experience (Parasuraman, Zeithaml, & Berry, 1985). Developers can more accurately forecast the success of technologies and companies can implement them effectively if they have a clear understanding of what consumers expect from AI. In this regard, many researches indicate that AI exhibiting human-like physical features and social capabilities often lead to higher levels of trust and acceptance of robotic technology among users (Song & Kim, 2020). In addition, some research shows that the readiness to share personal data and the level of social support are crucial elements in the AI-human relationship. The clearer these factors are established, the more inclined people will be to keep using their AI personal assistant and to trust it (Ki et al., 2020). One factor supporting this view is the expectations regarding the performance of AI devices, particularly the perceived benefits that customers believe they can gain from using these devices (Barbul, Bojescu, & Niculescu, 2024). In this context, when individuals perceive their interaction with an AI agent as resembling a conversation with a human, they tend to enjoy it more, are motivated to use the technology more often, and to rely on the data provided by the AI (Heerink et al., 2008).

Hypothesis development

Recent literature has emphasized the transformative effects of digitalization on peoples' behavior and attachment to virtual spaces and various forms of technology. For instance, Horakova et al. (2022) explored how digitalization disrupts consumers' attachment to retail places, highlighting the evolving nature of consumer interactions in digital contexts. Similarly, Hsieh and Lee (2021) examined the perceived socialness of AI assistant-enabled smart speakers, demonstrating the importance of social cues in fostering user engagement and trust. Ashfaq et al. (2020) modeled the determinants of user satisfaction and continuance intention for AI-powered chatbots, underscoring the significance of interactive and empathetic communication in improving user experiences. Furthermore, Kim and Baek (2018) investigated the antecedents and consequences of mobile app engagement, revealing how ease of use, convenience, and customization drive positive user experiences and engagement. Such studies provide a robust theoretical foundation for understanding the roles of social attachment and interactivity in improving information quality, thereby justifying the development and testing of the proposed econometric model.

The hypotheses proposed and tested in this study aim to empirically explore the relationships between social attachment, interactivity, and information quality in AI systems. The development of hypotheses is grounded in existing literature and theoretical frameworks that highlight the importance of these constructs in user-AI interactions. Therefore, we propose and test the following hypotheses and relations between constructs:

Social attachment and interactivity (H1)
Social attachment refers to the emotional bond and connection individuals form with AI systems. Personalization in AI systems fosters a sense of individuality and relevance, creating emotionally resonant experiences that enhance social attachment (Gong, 2025). This emotional connection is crucial, as it drives users to engage more deeply with AI systems, thus increasing interactivity. The tailored interactions make users feel understood and valued, which strengthens their attachment to the AI system and encourages more frequent and meaningful interactions (Chan et al., 2025) as well as increasing the enjoyment of interaction (Pelau et al., 2025). Therefore, we propose and test the following hypothesis: **H1:** Social attachment positively influences AI's ability to be interactive.

Interactivity and perceived information quality (H2)
The interactivity of AI systems is characterized by the dynamic and responsive nature of interactions between users and AI. High levels of interactivity ensure that AI systems can adapt to individuals' needs and preferences in real-time, providing relevant and accurate information (Gong, 2025). This responsiveness enhances the perceived information quality, as users receive timely and personalized information that meets their expectations. The ability of AI systems to engage users effectively and provide high-quality information is a key factor in their acceptance and ongoing use (Lee & Oh, 2025). Considering this, we propose and test the following hypothesis: **H2:** Interactivity positively influences the perceived information quality of AI.

Social attachment, interactivity, and perceived information quality (H3)
When users form strong emotional bonds with AI systems, they are more likely to engage interactively with these systems. This increased interactivity, driven by social attachment, ensures that AI systems can provide personalized and high-quality information (Gong, 2025). The social connection enhances the users' willingness to interact with the AI system, which in turn improves the perceived quality of the information provided (He, Yang, & Tang, 2025). In this regard, the following hypothesis is proposed and tested: **H3:** Social attachment positively influences the perceived information quality of AI systems.

Interactivity as a mediator (H4)
Interactivity plays a crucial mediating role between social attachment and perceived information quality. The emotional bond formed through social attachment leads to higher levels of interactivity, which is essential for delivering personalized and accurate information (Gong, 2025). This mediation highlights the importance of designing AI systems that can foster social attachment and facilitate interactive engagements to enhance the overall information quality perceived by users (Chan et al., 2025). Our study assesses interactivity as a mediator of the relation between social attachment and information quality and therefore assesses the following hypothesis: **H4:** Interactivity mediates the relationship between social attachment and perceived information quality in AI systems.

As already observed in previous studies, the integration of AI systems in service industries has significantly transformed user interactions, emphasizing the importance of personalization and interactivity. This study delves into the complex dynamics between social attachment, interactivity, and perceived information quality within AI systems, proposing an econometric model to understand these relationships.

Methodology of research

The main objective of the research is to empirically explore the relationships between social attachment, interactivity, and information quality in AI systems. Specifically, the study aims to understand how social attachment influences users' perceptions of interactivity and information quality, assess the mediating role of interactivity in this relationship, and evaluate the overall impact on information quality. By achieving these objectives, the research provides valuable insights into user-AI interactions and offers practical implications for designing AI systems that enhance user engagement and deliver reliable information.

Data collection took place using an online survey designed to measure the three constructs: social attachment, interactivity and information quality. The survey instrument used for this study consisted of two sections. The first section consisted of demographic information, with questions related to age, gender, and education. The second and main section of the survey consisted of the items used to measure the three latent constructs included in the proposed model. The items used were adopted from previous scales and were measured with 7-point Likert scales. Participants were asked to imagine having to interact with several AI types randomly shown in pictures and responded providing data on their perceptions and experiences with AI systems. Then they assessed their social attachment to the AI, their perception of interactivity with the AI and perception of perceived information quality provided by the AI. Social attachment to AI was measured using five items adapted after Horakova et al. (2022). Interactivity with the AI was measured with eight items adapted after Ashfaq et al. (2020), Kim & Baek (2018), and Roca, Chiu, and Martinez (2006). Information quality was measured based on seven items adapted after Ashfaq et al. (2020), Teo, Srivastava, and Jiang (2008), Kim and Baek (2018) and Lu, Cai, and Gursoy (2019). The items and their reliability are presented in Table 1.

Table 1: Reliability of constructs and outer loadings

Construct/ Item	Loading
Social attachment (adapted after Horakova et al., 2022) Cronbach Alpha=0.898; CR=0.924; AVE=0.710	
This AI keeps in contact with me.	0.878
This AI knows me.	0.868
This AI is interested in my needs.	0.856
It is important to me that I know AI well.	0.802
I feel like a part of a community by interacting with this AI	0.806
Interactivity (adapted after Ashfaq et al., 2020, Kim & Baek, 2018, Roca, Chiu, & Martinez, 2006) Cronbach Alpha=0.936; CR=0.947; AVE=0.693	
This AI facilitates two-way communication	0.830
This AI gives me the opportunity to talk back	0.860
This AI gives me the feeling that it wants to listen to its customers	0.756
This AI provides the right solution to my request	0.839
This AI is fast in responding to my feed-back	0.880
This AI processes my input very quickly	0.819
This AI gives me individual attention	0.805
This AI fits well my needs	0.863
Information quality (adapted after Ashfaq et al., 2020, Teo et al., 2008, Kim & Baek, 2018, Lu, Cai, & Gursoy, 2019) Cronbach Alpha=0.956; CR=0.963; AVE=0.790	
This AI provides sufficient information	0.856

This AI gives me the information I need in time	0.881
This AI gives me the information in a useful format	0.899
The information provided by this AI is clear	0.911
The information provided by this AI is accurate	0.910
The information provided by this AI is up-to-date	0.910
The information provided by this AI is reliable	0.851

After collection, the data were cleaned to remove any incomplete or inconsistent responses. This step ensures the quality and reliability of the dataset used for analysis. The processing of the data took place with structural equation modelling using the bootstrapping method with 5000 distinct samples in Smart-PLS 4.0 (Ringle et al., 2024). The reliability of the constructs is given by having higher values than the threshold for all constructs as follows: social attachment (Cronbach Alpha=0.898; CR=0.924; AVE=0.710), interactivity (Cronbach Alpha=0.936; CR=0.947; AVE=0.693) and information quality (Cronbach Alpha=0.956; CR=0.963; AVE=0.790). Convergent validity is ensured by having all outer loadings higher than the threshold of 0.700. Discriminant validity is confirmed because the square roots of the average variance extracted (AVE) for each construct are greater than the correlations between the constructs, indicating that each construct is distinct from the others. Factor Reliability is confirmed by showing all Composite Reliability (CR) values are greater than 0.70, indicating acceptable internal consistency and reliability of the constructs.

Using SmartPLS, the model was estimated to obtain the path coefficients, indirect effects, and r-square values. The estimation process involves fitting the model to the data and optimizing the parameters to best represent the observed relationships.

Results

The results of the econometric model reveal a significant positive relationship between social attachment and interactivity ($\beta = 0.605$, $T = 14.050$, $P < 0.001$). This indicates that individuals who feel a stronger social attachment to AI systems perceive these systems as more interactive. Social attachment, characterized by feelings of connection and community with the AI, enhances the user's perception of the AI's ability to facilitate two-way communication, respond quickly, and provide personalized attention. This finding underscores the importance of fostering social bonds between users and AI systems to improve user engagement and interaction quality.

Interactivity is found to have a substantial positive impact on information quality ($\beta = 0.834$, $T = 18.503$, $P < 0.001$). This suggests that AI systems perceived as highly interactive are also seen as providing higher quality information. The dimensions of interactivity, such as responsiveness, accuracy in processing input, and fitting user needs, contribute to the user's assessment of the information's sufficiency, clarity, accuracy, and reliability. This result highlights the critical role of interactive features in AI systems to ensure that users receive valuable and trustworthy information.

The direct effect of social attachment on information quality has been shown to be not significant ($\beta = 0.020$, $T = 0.410$, $P = 0.682$), indicating that social attachment alone does not directly enhance the perceived quality of information provided by AI systems. However, the total effect, which includes both direct and indirect effects, is significant ($\beta = 0.525$, $T = 11.074$, $P < 0.001$), primarily driven by the indirect effect mediated through interactivity ($\beta = 0.505$, $T = 10.306$, $P < 0.001$). This mediation suggests that social attachment improves information quality indirectly by enhancing interactivity. Users who feel socially attached to AI systems are more likely to perceive these systems as interactive, which in turn leads to higher evaluations of the information quality. This finding emphasizes the importance of interactivity as a mediator in the relationship between social attachment and information quality. The conceptual model can be

Vol.5 (2025) no.1, pp.10-22; DOI 10.2478/csep-2025-0002

observed in Figure 1, while the coefficients and their significance for all relationships can be observed in Table 2.

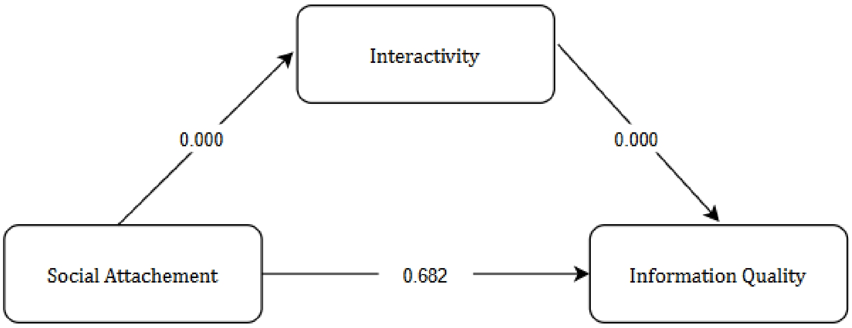

Figure 1. Structural Equation Model

Table 2. Path coefficients, direct, indirect and total effects in the structural equation model

Path	β	T statistics	P
Social attachment -> Interactivity	0.605	14.050	0.000
Interactivity -> Information Quality	0.834	18.503	0.000
Social attachment -> Information quality (direct effect)	0.020	0.410	0.682
Social attachment -> Information quality (total effect)	0.525	11.074	0.000
Social attachment -> Information quality (indirect effect)	0.505	10.306	0.000

The R-square values indicate the proportion of variance explained by the model for each dependent variable. The model explains 71.7% of the variance in information quality (R^2 = 0.717, T = 17.960, P < 0.001) and 36.6% of the variance in interactivity (R^2 = 0.366, T = 7.040, P < 0.001). The R-square values for all relationships can be observed in table 3. These values demonstrate that the constructs of social attachment and interactivity significantly contribute to explaining the perceived quality of information provided by AI systems. The high r-square value for information quality suggests that the model is particularly effective in capturing the factors that influence users' assessments of information quality.

Table 3. R-square values for specific relationships

	Coefficient	T statistics	P values
Information Quality	0.717	17.960	0.000
Interactivity	0.366	7.040	0.000

Discussion

The findings of this study provide significant insights into the interplay between social attachment, interactivity, and information quality in AI systems. The positive relationship between social attachment and interactivity suggests that users who feel a stronger connection to AI systems perceive these systems as more interactive. This perception of interactivity, characterized by responsiveness and personalized attention, is crucial for enhancing user engagement and satisfaction. In addition, the substantial impact of interactivity on information quality underscores the importance of interactive features in AI systems. Users tend to evaluate the quality of information based on the system's ability to respond accurately and meet their needs. Therefore, designing AI systems with high interactivity can lead to better user assessments of information quality.

Interestingly, although social attachment alone does not directly improve information quality, its indirect effect through interactivity is significant. This mediation highlights the role of interactivity as a crucial factor in translating social attachment into perceived information quality. AI systems that foster social bonds and interactive experiences are more likely to provide high-quality information, thereby improving user trust and reliability. These findings align with previous research by Horakova et al. (2022) and Ashfaq et al. (2020), which emphasize the importance of social connections and interactive features in the acceptance of technology and user satisfaction. The study contributes to the growing body of literature on user-AI interactions and offers practical implications for the development of AI systems that prioritize user engagement and information reliability.

In summary, the results of the econometric model provide valuable insights into the dynamics between social attachment, interactivity, and information quality in AI systems. Social attachment enhances interactivity, which in turn significantly improves the perceived quality of information. The indirect effect of social attachment on information quality through interactivity underscores the importance of designing AI systems that foster social connections and interactive features to deliver high-quality information. These findings contribute to the understanding of user-AI interactions and offer practical implications for the development of AI systems that prioritize user engagement and information reliability.

Conclusions

This study underscores the critical role of social attachment and interactivity in enhancing the perceived information quality of AI systems. The findings suggest that fostering a sense of social connection and designing interactive features are essential strategies for improving user engagement and satisfaction. AI systems that successfully integrate these elements are more likely to be perceived as reliable and trustworthy sources of information. The study also highlights the indirect effect of social attachment on information quality through interactivity, emphasizing the importance of creating AI systems that not only connect with users on a social level, but also provide responsive and personalized interactions. This dual approach can significantly enhance the overall user experience and the perceived value of the information provided by AI systems.

The results of our research have important implications for both theory and practice. From a theoretical point of view, they extend existing theories about the trust and acceptance of AI and robots. Our empirical model points out the importance of social attachment and interactivity in enhancing the credibility of AI by providing information quality. Having an increased interactivity makes the AI seem smarter in the eyes of the users. This has important implications for the practical application of AI. On one hand it emphasizes the role of interaction abilities and social characteristics that should be designed in AI to make them look smarter. This is important for both companies and public institutions which aim to implement AI in their communication strategies. On the other hand, it points out the vulnerabilities of users in believing information provided by AI. Our empirical model highlights the subjective perception in which interaction abilities and social attachment may influence users more than the information itself. Considering that AI is increasingly used in public communication, especially in times of political conflict it is important to understand the mechanism by which user perceive information provided by AI. There is a dual understating of this mechanism, by knowing both how to influence users and public opinion and also by increasing awareness of how to perceive public information.

Future research should explore additional factors that may influence the relationship between social attachment, interactivity, and information quality, such as cultural differences and individual user preferences. Additionally, longitudinal studies could provide deeper insights into how these relationships evolve over time and impact long-term user engagement with AI systems.

Overall, the findings of this study contribute to the growing body of literature on user-AI interactions and offer practical implications for the development of AI systems that prioritize user engagement and information reliability. By understanding and leveraging the dynamics of social attachment and interactivity, developers can create more effective and user-friendly AI systems that meet the needs and expectations of their users.

References

Arikan, E., Altinigne, N., Kuzgun, E., & Okan, M. (2023). May robots be held responsible for service failure and recovery? The role of robot service provider agents' human-likeness. *Journal of Retailing and Consumer Services, 70*, 103175. https://doi.org/10.1016/j.jretconser.2022.103175

Aron, A., & Westbay, L. (1996). Dimensions of the prototype of love. *Journal of Personality and Social Psychology, 70,* 535–551. https://doi.org/10.1037/0022-3514.70.3.535

Ashfaq, M., Yun, J., Yu, S. B., & Loureiro, S. M. C. I. (2020). Chatbot: Modeling the determinants of users' satisfaction and continuance intention of AI-powered service agents. *Telematics and Informatics*, 54, 101473. https://doi.org/10.1016/j.tele.2020.101473

Barbul, M., Bojescu I., & Niculescu, M. (2024). Exploring generational differences in attitudes toward human-like robots. *Analele Universității din Oradea. Seria Științe Economice TOM XXXIII*, 2, 295-306.

Beer, J. M., Prakash, A., Mitzner, T. L., & Rogers, W. A. (2011). Understanding robot acceptance. *Human Factors and Aging Laboratory, School of Psychology, Georgia Institute of Technology*, Technical Report HFA-TR-1103.

Breazeal, C. (2002). *Designing Sociable Robots.* MIT Press.

Burton, J. (2023). Algorithmic extremism? The securitization of artificial intelligence (AI) and its impact on radicalism, polarization and political violence. *Technology in Society*, 75, 102262. https://doi.org/10.1016/j.techsoc.2023.102262

Carey, J. (1989). Interactive media. In E. Barnouw (Ed.), *International Encyclopedia of Communications* (pp. 328–330). Oxford University Press.

Chan, T., Chan, I. C. C., Lam, L. W., & Law, R. (2025). Riding on uncertainty: Leveraging human agents and service robots during service delivery. *Journal of Service Research, 23*(4), 456-472. https://doi.org/10.1016/j.ijhm.2024.104000

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340.

De Ruyter, B., Saini, P., Markopoulos, P., & Van Breemen, A. (2005). Assessing the effects of building social intelligence in a robotic interface for the home. *Interacting with Computers, 17*(5), 522–541.

Ding, Y., & Najaf, M. (2024). Interactivity, Humanness, and Trust: A Psychological Approach to AI Chatbot Adoption in E-Commerce. *BMC Psychology*, *12*, 595. https://doi.org/10.1186/s40359-024-02083-z

Fehr, B., & Russell, J. A. (1991). The concept of love viewed from a prototype perspective. *Journal of Personality and Social Psychology*, 60, 425–438. https://doi.org/10.1037/0022-3514.60.3.425

Fong, T. W., Nourbakhsh, I., & Dautenhahn, I. K. (2003). A Survey of Socially Interactive Robots: Concepts, Design, and Applications. *Robotics and Autonomous Systems, 42*(3–4), 142–166.

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly*, *27*(1), 51–90.

Gomes, S., Lopes, J. M. & Nogueira, E. (2025). Anthropomorphism in artificial intelligence: a game-changer for brand marketing. *Future Business Journal, 11*(1), 1-15. https://doi.org/10.1186/s43093-025-00423-y

Gong, T. (2025). Bridging the gap: Exploring the nexus of service robot personalization, customer identification, and citizenship behaviours. *Journal of Retailing and Consumer Services*, 82, 104105. https://doi.org/10.1016/j.jretconser.2024.104105

Gu, C., Zhang, Y., & Zeng, L. (2024). Exploring the mechanism of sustained consumer trust in AI chatbots after service failures: A perspective based on attribution and CASA theories. *Humanities and Social Sciences Communications*, 11. https://doi.org/10.1057/s41599-024-03879-5

Gursoy, D., Chi, O. H., Lu, L., & Nunkoo, R. (2019). Consumer's acceptance of artificially intelligent (AI) device use in service delivery. *International Journal of Information Management*, 49, 157-169. https://doi.org/10.1016/j.ijinfomgt.2019.03.008

He, Y., Yang, L., & Tang, Y. (2025). Preference for assistance from service robots or human staff: The impact of social exclusion experience. *International Journal of Hospitality Management*, 125, 102-113. https://doi.org/10.1016/j.ijhm.2024.104018

Heerink, N., Kröse, B. J. A., Wielinga, B. J., & Evers, V. (2008). Enjoyment, continuous usage and actual use of a conversational robot by elderly people. In *Proceedings of the Third ACM/IEEE International Conference on Human-Robot Interaction* (pp. 113–120).

Hegel, F., Muhl, C., Wrede, B., Hielscher-Fastabend, M., & Sagerer, G. (2009). Understanding social robots. In *2009 Second International Conference on Advances in Computer-Human Interactions* (pp. 169–174).

Horakova, J., Uusitalo, U., Munnukka, J., & Jokinen, O. (2022). Does the digitalization of retailing disrupt consumers' attachment to retail places?. *Journal of Retailing and Consumer Services,* 67, 102958. https://doi.org/10.1016/j.jretconser.2022.102958

Hsieh, S. H., & Lee, C. T. (2021). Hey Alexa: Examining the effect of perceived socialness in usage intentions of AI assistant-enabled smart speaker. *Journal of Research in Interactive Marketing, 15*(2), 267–294. https://doi.org/10.1108/JRIM-11-2019-0179

Jacucci, G., Spagnolli, A., Freeman, J., & Gamberini, L. (2014). Symbiotic interaction: A critical definition and comparison to other human-computer paradigms. In G. Jacucci, L. Gamberini, J. Freeman, & A. Spagnolli (Eds.), *Symbiotic Interaction: Third International Workshop, Symbiotic 2014, Helsinki, Finland, October 30–31, 2014, Proceedings* (pp. 3–20). Springer International Publishing, https://doi.org/10.1007/978-3-319-13500-7_1

Johnson, D. O., Cuijpers, R. H., Juola, J. F., Torta, E., Simonov, M., Frisiello, A., Bazzani, M., Yan, W., Weber, C., Wermter, S., Meins, N., Oberzaucher, J., Panek, P., Edelmayer, G., Mayer, P., & Beck, C. (2014). Socially assistive robots: a comprehensive approach to extending independent living. *International Journal of Social Robotics, 6*, 195–211. https://doi.org/10.1007/s12369-013-0217-8

Ki (Chloe), C. W., Cho, E. & Lee, J. E. (2020). Can an intelligent personal assistant (IPA) be your friend? Para-friendship development mechanism between IPAs and their users. *Computers in Human Behaviour*, 111, 1-10. https://doi.org/10.1016/j.chb.2020.106412

Kim, J., Kang, S. & Bae, J., (2022). Human likeness and attachment effect on the perceived interactivity of AI speakers*. Journal of Business Research*, 144, 797–804. https://doi.org/10.1016/j.jbusres.2022.02.047

Kim, S., & Baek, T. H. (2018). Examining the antecedents and consequences of mobile app Engagement*. Telematics and Informatics, 35*, 148-158. https://doi.org/10.1016/j.tele.2017.10.008

Kwak, S. S., Kim, Y., Kim, E., Shin, C., & Cho, K. (2013). What makes people empathize with an emotional robot? The impact of agency and physical embodiment on human empathy for a robot. In *2013 IEEE RO-MAN: The 22nd IEEE International Symposium on Robot and Human Interactive Communication* (pp. 180–185). IEEE.

Lee, S., & Oh, H. (2025). Service task compatibility for human staff vs. service robots: Roles of product type and brand level. *Journal of Business Research*, 124, 342-

354. https://doi.org/10.1016/j.ijhm.2024.103952

Lessiter, J., Freeman, J., Miotto, A., & Ferrari, E. (2014). Ghosts in the machines: Towards a taxonomy of human-computer interaction. In G. Jacucci, L. Gamberini, J. Freeman, & A. Spagnolli (Eds.), *Symbiotic interaction: Third international workshop, Symbiotic 2014, Helsinki, Finland, October 30–31, 2014, Proceedings* (pp. 21–31). Springer International Publishing. https://doi.org/10.1007/978-3-319-13500-7_2

Liu, X. S., & Hancock, J. (2024). Social robots are good for me, but better for other people: The presumed allo-enhancement effect of social robot perceptions. *Computers in Human Behavior: Artificial Humans, 2*(2), 100079. https://doi.org/10.1016/j.chbah.2024.100079

Liu, Y., & Shrum, L. J. (2002). What is interactivity and is it always such a good thing? Implications of definition, person, and situation for the influence of interactivity on advertising effectiveness. *Journal of Advertising, 31*(4), 53–64. https://doi.org/10.1080/00913367.2002.10673685

Lu, L., Cai, R., & Gursoy, D. (2019). Developing and validating a service robot integration willingness scale. *International Journal of Hospitality Management*, 80, 36–51. https://doi.org/10.1016/j.ijhm.2019.01.005

Lu, L., Zhang, P., & Zhang, T. (2021). Leveraging "human-likeness" of robotic service at restaurants. *International Journal of Hospitality Management*, 94, Article 102823. https://doi.org/10.1016/j.ijhm.2020.102823

Martelaro, N., Nneji, V. C., Ju, W., & Hinds, P. (2016). Tell me more: Designing HRI to encourage more trust, disclosure, and companionship. In *Proceedings of the 11th ACM/IEEE International Conference on Human-Robot Interaction* (pp. 181–188). IEEE. https://doi.org/10.1109/HRI.2016.7451750

Massey, B. L., & Levy, M. R. (1999). Interactivity, online journalism, and English language web newspapers in Asia. *Journal of Mass Communication Quarterly, 76*(1), 138–151. https://doi.org/10.1177/107769909907600110

McMillan, S. J. (2005). The researchers and the concept: Moving beyond a blind examination of interactivity. *Journal of Interactive Advertising, 5*(2), 1–4. https://doi.org/10.1080/15252019.2005.10722096

Mende, M., Scott, M. L., van Doorn, J., Grewal, D., & Shanks, I. (2019). Service robots rising: How humanoid robots influence service experiences and elicit compensatory consumer responses. *Journal of Marketing Research, 56*(4), 535–556. https://doi.org/10.1177/0022243718822827

Messer, U. (2025). How do people react to political bias in generative artificial intelligence (AI)?. *Computers in Human Behavior: Artificial Humans, 3*, 100108. https://doi.org/10.1016/j.chbah.2024.100108

Nomura, T., & Kanda, T. (2016). Rapport-expectation with a robot scale. *International Journal of Social Robotics, 8*(1), 21–30.

Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1985). A conceptual model of service quality and its implications for future research. *Journal of Marketing, 49*(4), 41-50. https://doi.org/10.2307/1251430

Pelau, C., Volkmann, C., Barbul, M., & Bojescu, I. (2023). The role of attachment in improving consumer-ai interactions. *Proceedings of the International Conference on Business Excellence, 17*(1), 1075-1084. https://doi.org/10.2478/picbe-2023-0097

Pelau, C., Barbul, M., Bojescu, I., & Niculescu, M. (2025). AI, How Much Shall I Tell You? Exchange and Communal Consumer–AI Relationships and the Willingness to Disclose Personal Information. *Behavioral Sciences*, 15(3), 386. https://doi.org/10.3390/bs15030386

Pentina, I., Xie, T., Hancock, T., & Bailey, A. A. (2023). Consumer–machine relationships in the age of artificial intelligence: Systematic literature review and research directions. *Psychology & Marketing*, *40*(8), 1593–1614. https://doi.org/10.1002/mar.21853

Riegger, A.-S., Klein, J. F., Merfeld, K., & Henkel, S. (2021). Technology-enabled personalization in retail stores: Understanding drivers and barriers. *Journal of Business Research,* 123, 140–155.

https://doi.org/10.1016/j.jbusres.2020.09.039

Roca, J. C., Chiu, C. M., & Martinez, F. J. (2006). Understanding e-learning continuance intention: An extension of the Technology Acceptance Model. *International Journal of Human-Computer Studies*, *64*(8), 683-696. https://doi.org/10.1016/j.ijhcs.2006.01.003

Săniuță, A., Zbuchea, A., & Hrib, B. (2022). Innovation in the Book Market Retail. Preferences among Romanian Readers. *Management Dynamics in the Knowledge Economy*, *10*(2), 179-209. https://doi.org/ 10.2478/mdke-2022-0013

Song, S. Y., & Kim, Y.-K. (2020). Factors influencing consumers' intention to adopt fashion robot advisors: Psychological network analysis. *Clothing and Textiles Research Journal, 40*(1), 3–18. https://doi.org/10.1177/0887302X20941261

Teo, T. S. H., Srivastava, S. C., & Jiang, L. (2008). Trust and Electronic Government Success: An Empirical Study. *Journal of Management Information Systems*, *25*(3), 99–132. https://doi.org/10.2753/MIS0742-1222250303

Thomson, M., Macinnis, D.J. & Park, C.W. (2005). The ties that bind: Measuring the strength of consumers' emotional attachments to brands. *Journal of Consumer Psychology, 15*(1), 77–91. https://doi.org/10.1207/s15327663jcp1501_10

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model. *Management Science*, 46(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926

Vidu, C., Zbuchea, A., Mocanu, R., & Pinzaru E. (2020). Artificial intelligence and the ethical use of knowledge. In *Strategica. Preparing for Tomorrow, Today* (pp. 773-784). Tritonic.

Received: April 18, 2025
Accepted: May 20, 2025

Author biographies

Miruna NICULESCU is PhD student at the Bucharest University of Economic Studies. Her research focuses on consumers' perception and behavior towards artificial intelligence and robots, emphasizing the different categories of relationships between consumer and AI. She explores the way in which robots and AI are accepted and trusted as well as their contribution to our daily life.

Irina BOJESCU is PhD student at the Bucharest University of Economic Studies. Her research focuses on measuring consumer attitudes toward intelligent virtual assistants and how these technologies are integrated into current business models. She investigates how consumers interact with virtual assistants depending on their perceived level of intelligence and autonomy, aiming to identify the ideal features of virtual assistants that support widespread adoption in everyday life.

Maria BARBUL is PhD student at the Bucharest University of Economic Studies. Her research focuses on consumers' perception and acceptance of artificial intelligence. She explores how these systems shape consumer experience, satisfaction, and privacy in an era increasingly influenced by advanced AI. Her work also investigates the dynamics of interaction between consumers and cognitive computing technologies and their role in business development.

Corina PELAU is Professor Ph.D. and Ph.D. coordinator at the Bucharest University of Economic Studies, UNESCO Department for Business Administration. Her main research field is consumer research, with focus on the relation between consumers and artificial intelligence. Starting with 2021 she is part of the Executive Committee of the European Marketing Academy as National Representative for Romania and co-coordinator of the Climber Community Interest Group at EMAC.