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Social Presence of Generative AI Conversational Agents and Users' Willingness to Communicate: The Mediating Role of Technology Trust

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Abstract. This study examines whether the social presence of generative AI conversational agents is associated with users' willingness to communicate and whether technology trust accounts for part of this relationship. The study treats interaction with a conversational agent as an informatics-enabled service encounter in which users evaluate both relational cues and the dependability of the underlying technology. Data were obtained through an online survey of 400 adult users in China who had interacted with a generative AI conversational agent during the previous three months. The measurement and structural models were estimated with covariance-based structural equation modeling in IBM SPSS Amos 26. The findings indicate that social presence has positive associations with technology trust and willingness to communicate. Technology trust is also positively associated with willingness to communicate. Bootstrap analysis shows a positive indirect association between social presence and communication willingness through technology trust, while the direct association remains significant. The pattern is consistent with partial statistical mediation. The study connects social presence research with trust in a specific technology and distinguishes communication willingness from broader adoption and continuance intentions. For digital service systems, the results suggest that socially responsive interaction can support communication, provided that conversational conduct is accompanied by reliable and helpful performance. Designers and service managers should therefore evaluate social cues together with response accuracy, consistency, and transparent handling of uncertainty.

Keywords: generative AI conversational agent; social presence; technology trust; willingness to communicate; digital service system; human-AI interaction

1. Introduction

Generative artificial intelligence has changed the role of conversational agents in digital services. Earlier chatbots usually followed decision trees or retrieved predetermined answers. Current agents can produce context-sensitive responses, remember earlier turns within a session, and adapt the wording of an answer to a user's request. Recent reviews describe a corresponding expansion of conversational agents across organizational and companionship settings (Chaturvedi et al., 2023; Liu et al., 2026). These capabilities make the exchange more flexible, but they also change what users evaluate. A user is assessing the information supplied by the system and the apparent quality of the interaction. This dual evaluation matters in customer support, health information, education, travel, and other service settings where communication is the primary interface between a person and an information system.

Within informatics and service science, a conversational agent can be understood as a service interface that translates computational capability into an interaction experienced by the user. Its technical functions remain important, yet users encounter those functions through language. The agent may acknowledge a concern, ask a relevant follow-up question, or refer coherently to an earlier message. Such behavior can create social presence, defined as the experienced salience of another social actor in mediated communication (Short et al., 1976). Research on chatbots has linked social presence with trust, acceptance, disclosure, and continued use across several digital service contexts (Gefen and Straub, 2004; Jiang et al., 2022; Li et al., 2023b). Generative AI extends this issue because its responses are less visibly scripted and often more contingent on the user's input.

Social presence can make an exchange easier to sustain. A responsive agent may appear attentive and capable of understanding what the user is trying to accomplish. That impression, however, does not settle whether the technology is dependable. Conversational presentation can increase credibility judgments even when some of the information is inaccurate (Anderl et al., 2024). Privacy concerns and perceived risk can further complicate trust in an AI chatbot (Li et al., 2023a; Shahzad et al., 2026). Conversational fluency may therefore increase a user's readiness to communicate while leaving questions about reliability and helpfulness unresolved. Treating social presence as a sufficient explanation would overlook the evaluative step through which users decide whether reliance on the agent is acceptable.

Technology trust offers a focused account of that step. Trust in a specific technology concerns beliefs that the system is functional, reliable, and helpful under conditions that involve uncertainty or dependence (McKnight et al., 2011). These beliefs are directly relevant when users decide whether to ask another question, provide more context, or return to the same agent. The distinction between social presence and technology trust is also practically useful. Social presence concerns how socially available the agent feels. Technology trust concerns whether the agent can be relied upon for the task. An agent may score highly on one evaluation and poorly on the other.

Much of the evidence on social presence and trust comes from electronic commerce, rule-based chatbots, voice assistants, or virtual humans (Gefen and Straub, 2004; Hsieh and Lee, 2024; Li et al., 2023b). Generative AI agents can produce more varied and personalized exchanges, so findings from earlier systems require direct examination in this setting. Prior studies also tend to use continuance intention, purchase intention, or disclosure as outcomes (Jiang et al., 2022; Jin and Youn, 2023; Pizzi et al., 2023). These measures capture related behavior, although none precisely represents a user's readiness to initiate, continue, and deepen a conversation. Communication willingness deserves separate attention because conversation is the operating channel through which the service is delivered. Trust is frequently modeled as a predictor of chatbot engagement or behavioral intention (Chandra et al., 2022; Prakash et al., 2023), leaving its role as an intervening evaluation less well understood for communication willingness.

This study addresses these issues by examining three constructs among experienced users of generative AI conversational agents: perceived social presence, trust in the specific technology, and

willingness to communicate. The hypothesized model examines whether social presence is associated with technology trust and communication willingness, whether technology trust is associated with communication willingness, and whether trust statistically mediates the relationship between social presence and willingness to communicate. A cross-sectional online survey and covariance-based structural equation modeling were employed to evaluate the measurement structure and the hypothesized relationships.

The study contributes to research on digital service systems in two ways. It separates communication willingness from general system adoption and positions it as a proximal response to the quality of a conversational encounter. It also explains why social presence may matter by introducing technology trust as a distinct evaluation of functionality, reliability, and helpfulness. This mechanism avoids assuming that social cues automatically create productive engagement. For practitioners, the model provides a basis for evaluating conversational design and technical dependability together. The remaining sections review the relevant literature, describe the research methods, report the analysis, and discuss the implications and limitations.

2. Literature Review

2.1 Generative AI Conversational Agents and Social Presence

Social presence was originally defined as the degree to which another person becomes salient in mediated communication (Short et al., 1976). Later work treated it as a multidimensional perception involving co-presence, psychological involvement, and behavioral engagement, while also warning that measures must fit the medium and interaction being studied (Biocca et al., 2003). This construct is especially relevant to conversational agents because natural-language exchanges invite users to apply interpersonal expectations to a technological system. Reviews of AI companionship and organizational conversational agents show that social responses, anthropomorphism, and relational experience now occupy a central place in research on agent use and governance (Chaturvedi et al., 2023; Liu et al., 2026).

For conventional chatbots, social presence depends on design cues rather than the mere availability of dialogue. Anthropomorphic appearance, personification, and conversational style can make an agent seem socially available, although their effects depend on how these cues are combined (Janson, 2023; Konya-Baumbach et al., 2023). Emotional expression increases perceived humanness and social interactivity through social presence, while interactivity paired with a warm conversational style can improve relationship evaluations in service encounters (Lin, 2025; Zhang et al., 2024). Generative AI extends these conditions by producing contingent and personalized responses. Tourism users perceive analytical and emotional AI capabilities as sources of warmth, competence, and automated social presence (Casaló et al., 2025). Anthropomorphic generative AI also produces stronger social presence in observed health consultations, which subsequently shapes source evaluations and intended responses (Li et al., 2025). Hoang and Tu (2026) found that chatbot self-promotion increased perceived competence but reduced perceived warmth, whereas self-deprecation produced the opposite pattern, with both evaluations positively predicting customer-service satisfaction. Megdadi et al. (2025) reported that chatbot responsiveness, ease of use, and personalization each improved customer experience in e-commerce, with responsiveness exerting the strongest effect.

Greater conversational capability does not guarantee an appropriate social response. ChatGPT's conversational presentation can raise credibility judgments even when information is partly inaccurate, indicating that users may rely on the interaction format when evaluating content (Anderl et al., 2024). Social presence in generative AI therefore concerns a user's experienced sense of social contact with the agent. It should be separated from anthropomorphic design, perceived intelligence, and factual accuracy, which are antecedents or related evaluations.

2.2 Social Presence and Technology Trust

Technology trust refers to beliefs that a specific technological system is functional, reliable, and helpful in a situation involving uncertainty or dependence (McKnight et al., 2011). The object of trust in this study is the generative AI conversational agent. This focus excludes general trust propensity, trust in the provider, and interpersonal trust in a human employee. The distinction matters because a socially appealing agent may still provide inaccurate information or handle personal data poorly.

Social presence can support technology trust by reducing psychological distance and providing cues that the agent understands and responds to the user. Evidence from electronic services established an association between perceived social presence and consumer trust before contemporary chatbots became common (Gefen and Straub, 2004). More recent experiments show that anthropomorphic appearance and verbal cues increase the social presence of health care agents; social presence then strengthens trust and reduces privacy concerns (Li et al., 2023b). In online health consultation, social presence also improves trust and communication quality, although the effects vary with disease severity (Liu et al., 2024). Studies of voice assistants similarly find that social presence contributes to perceived warmth, which combines with competence beliefs to build trust (Hsieh and Lee, 2024).

Recent evidence clarifies the limits of this relationship. Expertise, responsiveness, anthropomorphism, brand trust, and perceived risk contribute differently to trust in AI-chatbot communication (Li et al., 2023a). Interviews with customer-service chatbot users distinguish affective trust arising from empathy and social presence from cognitive trust grounded in reliability, accuracy, and transparency (Wang et al., 2026). A meta-analysis also supports separate affective and cognitive routes to chatbot trust and identifies cultural differences in their strength (Gupta and Chauhan, 2026). Generative AI users may simultaneously hold trust and distrust beliefs because efficiency and anthropomorphism coexist with privacy concerns and emotional detachment (Shahzad et al., 2026). Social presence should consequently increase trust when relational cues are supported by competent and dependable performance. In an experiment with young social-commerce users, Salhab et al. (2026) found that transparent AI disclosure and empathetic personalization increased trust and reduced perceived manipulation, with trust serving as the dominant mediator between these design cues and purchase intention.

H1: The social presence of generative AI conversational agents has a positive effect on users' technology trust.

2.3 Technology Trust and Willingness to Communicate

Willingness to communicate is defined here as a user's readiness to initiate, continue, and deepen communication with a generative AI conversational agent. The definition is narrower than general technology adoption. The unified theory of technology acceptance explains intention to use a system through performance expectancy, effort expectancy, social influence, and facilitating conditions, but it does not isolate the decision to engage in further dialogue (Venkatesh et al., 2003). Willingness to interact with chatbots is a closer construct. Meier et al. (2024) show that functional, emotional, epistemic, and social consumption values jointly shape this willingness and that disruptive situations change which configurations are sufficient. A bibliometric analysis of 287 studies identified trust as the most frequently examined antecedent of AI-chatbot intention and adoption and described anthropomorphism and service quality as prominent themes (Mei et al., 2025). Among 215 students, Paudel and Acharya (2024) found that system quality was the strongest predictor of ChatGPT use intention and that attitude fully or partially mediated the effects of the examined antecedents.

Several related outcomes help define the construct's boundaries. Users may disclose more to a virtual human when reduced fear of social judgment outweighs the loss of human contact (Lucas et al., 2014). Anthropomorphism and gaze direction can also influence disclosure through perceived warmth, competence, skepticism, and provider trust (Pizzi et al., 2023). Disclosure requires the release of

personal information and therefore carries a privacy vulnerability that ordinary conversation may not involve. Continuance intention concerns future system use and can occur without a willingness to sustain a substantive exchange. Even so, findings on continuance offer relevant evidence because communication is the principal mode through which conversational agents are used. Social presence predicts chatbot continuance intention in retail and tourism settings (Jiang et al., 2022; Jin and Youn, 2023), mediates the effect of hedonic motivation on intention to use (Dinh and Park, 2024), and contributes to continuous interaction with generative AI applications (Selem et al., 2025).

Trust provides a more immediate explanation for communication willingness. Communicating with a generative AI agent requires users to accept uncertainty about response quality, data handling, and whether further interaction will be useful. Research on customer-service chatbots shows that functional and social attributes build trust, which then predicts behavioral intentions (Prakash et al., 2023). Human-like cognitive, relational, and emotional competencies also encourage engagement through user trust (Chandra et al., 2022). Communication style and perceived anthropomorphism affect trust and subsequent usage intention in service encounters (Murtaza et al., 2024). These findings support the expectation that users who regard an agent as reliable and helpful will be more willing to ask follow-up questions, continue a current exchange, and initiate later conversations.

H2: Users' technology trust in generative AI conversational agents has a positive effect on their willingness to communicate.

Social presence may also influence communication willingness directly. Anthropomorphic cues increase compliance with a chatbot's conversational request through social presence (Adam et al., 2021). Research on chatbot design shows that emotional expression can affect perceived humanness and social interactivity, and that a warm, highly interactive conversational style can strengthen social presence and subsequent user responses (Lin, 2025; Zhang et al., 2024). Across these studies, a stronger sense of social contact makes the exchange feel more responsive and reduces the effort required to maintain dialogue. This evidence supports a direct relationship while leaving room for a separate trust mechanism.

H3: The social presence of generative AI conversational agents has a positive effect on users' willingness to communicate.

2.4 The Mediating Role of Technology Trust

The hypothesized mediating mechanism explains how a socially present interaction becomes a willingness to continue communicating. Social presence supplies relational information about attentiveness, responsiveness, and apparent understanding. Users interpret these cues together with evidence about competence and reliability. Trust forms when the combined evaluation suggests that dependence on the agent is acceptable. The resulting reduction in perceived relational and performance uncertainty makes further communication more likely.

Existing findings support separate parts of this sequence. Evidence in corporate responsibility communication indicates that social presence can support trust formation and, indirectly, chatbot acceptance (Jiang et al., 2026). In online health consultation, researchers have examined social presence and trust-related evaluations as pathways connecting AI-chatbot anthropomorphism to reuse intention (Liu et al., 2024). In voice assistants, social presence shapes perceived warmth, while warmth and competence build trust and continuous usage intention (Hsieh and Lee, 2024). Together with evidence that trust mediates the effects of human-like competencies on engagement (Chandra et al., 2022), these studies make technology trust a plausible mechanism linking social presence to communication willingness.

The evidence remains incomplete in three respects. Much of the established research concerns rule-based chatbots or voice assistants. Many studies use adoption, purchase, disclosure, or continued use as outcomes, while direct willingness to communicate receives less attention. Available generative AI studies are also concentrated in particular service, health, retail, or educational settings. Testing this

hypothesized mediation with experienced generative AI users therefore addresses a specific gap at the intersection of human-AI communication and digital service systems.

H4: Technology trust mediates the positive relationship between the social presence of generative AI conversational agents and users' willingness to communicate.

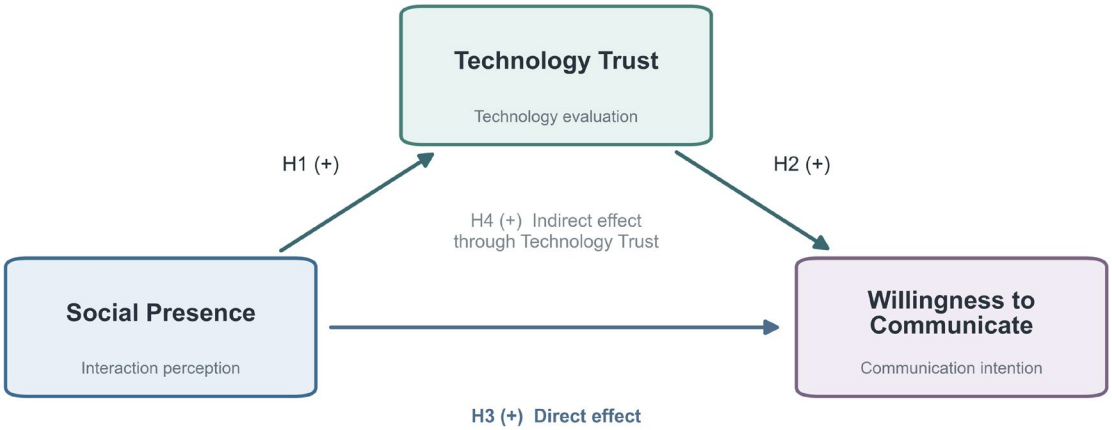


Fig.1: Research Model

3. Research Methods

3.1 Research Design

The study used a cross-sectional online survey to examine the hypothesized relationships among users with prior experience of generative AI conversational agents. The unit of analysis was an individual user's evaluation of one specific agent. Respondents were asked to identify the agent they had used most recently and to answer all construct items with that agent and a recent interaction in mind. This procedure gave the trust questions a defined technological object and reduced the risk that respondents would combine experiences across several systems. For descriptive reporting, stand-alone assistants accessed directly by users were classified as general-purpose agents, while agents integrated into a digital service were classified as service-embedded agents. The named-agent distribution and classification are reported in Table 2.

The study context included general-purpose generative AI assistants and generative agents embedded in digital services. Eligible interactions involved natural-language exchange in which the system generated a response to the user's prompt. Search engines without a conversational response, scripted menu bots, and voice interfaces limited to -- commands were outside the study definition. A survey design was appropriate for measuring experienced social presence and technology trust because both constructs concern user perceptions that cannot be inferred from interface features alone. For international systems not natively deployed in mainland China (such as ChatGPT and Gemini), respondents accessed them through overseas academic/institutional networks, virtual private networks (VPNs), or authorized API-based web interfaces.

3.2 Sample and Data Collection

The questionnaire opened with screening questions and a short definition of the study's conversational-agent category. Eligible respondents then recalled one recent information-search or digital-service interaction before completing the measures.

The panel provider invited 650 members who matched its initial profile. Of these, 487 reached the final questionnaire page. Data screening removed 87 records: 29 did not meet the recent-use criterion when screened in detail, 21 failed an instructed-response check, 18 completed the questionnaire in less than one third of the median completion time, 12 showed invariant responses across all 14 construct items, and 7 were identified as duplicate panel or device records. The final sample contained 400 complete cases. The questionnaire did not permit missing responses on the main scale pages, and respondents could withdraw before submission.

Participation was voluntary. The opening page explained the purpose of the study, the expected completion time, the use of anonymized responses for research, and the participant's right to stop without penalty. Consent was recorded before the screening questions. The survey did not request names, telephone numbers, account credentials, conversation transcripts, or other direct identifiers. Panel identifiers were replaced with study codes before analysis.

3.3 Measurement

All construct items used a seven-point Likert scale ranging from 1, strongly disagree, to 7, strongly agree. The questionnaire contained 14 indicators. Items were translated into Chinese and checked against the English wording through back-translation. Two researchers familiar with information-systems research reviewed the wording for meaning and contextual fit. A small cognitive pretest was used to identify ambiguous references to the agent, after which each item explicitly referred to the specific agent recalled by the respondent. The main construct blocks were presented on separate pages, and item order within each block was randomized.

Social presence was measured with five items adapted from established social-presence work (Biocca et al., 2003; Gefen and Straub, 2004). The items asked whether interacting with the recalled agent created a sense of interpersonal contact (SP1), felt personal (SP2), was social (SP3), conveyed interpersonal warmth (SP4), and indicated that the agent noticed human feelings (SP5). They measured experienced social contact rather than interface anthropomorphism or response accuracy.

Technology trust was measured with five items adapted from the trust-in-a-specific-technology framework (McKnight et al., 2011). The items assessed whether the recalled agent had the ability to complete communication tasks (TT1), could handle the respondent's question effectively (TT2), performed reliably (TT3), provided trustworthy information (TT4), and would offer useful help when needed (TT5). The wording consistently identified the conversational agent as the object of trust rather than artificial intelligence in general, the platform provider, or other users.

Willingness to communicate was measured with four items adapted to the conversational setting from work on willingness to interact with chatbots (Meier et al., 2024). The items asked whether the respondent was willing to continue the current exchange (WTC1), initiate a conversation with the agent for a similar problem (WTC2), ask further questions (WTC3), and choose the agent again for communication in a similar situation (WTC4). The construct focuses on readiness for dialogue and does not require disclosure of personal information or treat purchase intention as a communication outcome. The full English and Chinese wording, source mapping, and adaptation notes for all 14 items are provided in Appendix A.

3.4 Data Analysis

The analysis was conducted in IBM SPSS Amos 26 using covariance-based structural equation modeling. Maximum likelihood estimation was applied to the 14 observed indicators. Analysis proceeded in two stages. A confirmatory factor analysis first assessed whether social presence, technology trust, and willingness to communicate formed three empirically distinguishable constructs. The structural model then estimated the hypothesized structural paths and the indirect association through technology trust. Model fit was evaluated with the chi-square statistic, the chi-square-to-degrees-of-freedom ratio, CFI, TLI, IFI, GFI, AGFI, RMR, and RMSEA. The indices were considered

together because any single fit statistic can give an incomplete assessment (Kline, 2016). For the control-variable robustness models, gender was represented by two dummy variables with male as the reference category; age was entered in years; education was coded from 1 (high school or below) to 4 (master's degree or above); AI-use frequency was coded from 1 (once every few months) to 5 (daily); and AI-use duration was coded from 1 (less than 6 months) to 4 (more than 2 years). Composite-score equations included all five control domains. To examine duration heterogeneity, levels 1 and 2 were combined into a less-than-one-year group and levels 3 and 4 into a one-year-or-more group. The controlled equations were then estimated separately with HC3 robust standard errors, and the group coefficients were compared with a critical-ratio test.

Internal consistency was evaluated with Cronbach's alpha and composite reliability. Convergent validity was assessed through standardized loadings and average variance extracted. Values were interpreted in conjunction with construct content rather than as automatic deletion rules. Discriminant validity was examined with the Fornell-Larcker criterion and heterotrait-monotrait ratios (Fornell and Larcker, 1981; Henseler et al., 2015). Item skewness ranged from -.21 to .05, and excess kurtosis ranged from -.69 to .17. Mardia's multivariate kurtosis critical ratio was -2.01. Given the small multivariate departure, bias-corrected confidence intervals based on 5,000 bootstrap samples were retained for path and indirect-effect inference. All bootstrap samples converged and were usable.

3.5 Common Method Bias Procedures

Several survey procedures were used to limit common method bias. Respondents were told that there were no correct answers and that the study concerned their own experience. The main constructs appeared on separate pages, item order was randomized within blocks, and the wording used different focal descriptions for social experience, technological dependability, and intended communication. Anonymized participation reduced pressure to provide socially preferred answers. Statistical diagnostics consisted of Harman's first unrotated factor and a complementary single-factor CFA that constrained all 14 indicators to one common factor; its fit was compared with the hypothesized three-factor measurement model (Podsakoff et al., 2003). As an additional sensitivity analysis, a common latent factor was added to all 14 indicators while being specified as orthogonal to the three substantive factors. Changes in fit and standardized structural estimates were inspected together. These procedures provide sensitivity evidence about shared measurement variance, although they cannot exclude every possible source of method bias.

The indirect association was assessed with the product of the Social Presence to Technology Trust and Technology Trust to Willingness to Communicate paths. The main inference used the bias-corrected bootstrap confidence interval rather than a normal-theory test of the product term (Preacher and Hayes, 2008). Partial statistical mediation was inferred when the indirect confidence interval excluded zero and the direct path remained significant. This terminology describes the estimated pattern and does not add a causal interpretation to the cross-sectional design.

4. Results

4.1 Sample Profile, Descriptive Statistics, and Correlations

The final sample had a mean age of 32.24 years (SD = 10.48), with respondents ranging from 18 to 59 years. Participants varied in education and generative AI use experience. About three quarters used a generative AI conversational agent at least several times per week, while 56.50% had more than one year of experience. The sample included both stand-alone general-purpose assistants and agents embedded in digital services. Table 1 reports construct-level descriptive statistics and Pearson correlations; Table 2 reports the demographic profile, use experience, and named-agent distribution.

Social presence had a mean of 4.63 (SD = .92), technology trust had a mean of 4.57 (SD = .94), and willingness to communicate had a mean of 4.69 (SD = .97). The means were above the scale midpoint

without approaching the upper endpoint. Social presence was positively correlated with technology trust, $r = .51$, $p < .001$, and with willingness to communicate, $r = .51$, $p < .001$. Technology trust was positively correlated with willingness to communicate, $r = .56$, $p < .001$. The correlations were consistent with the expected directions, but the hypothesis decisions were based on the latent structural model.

Table 1 Descriptive Statistics and Correlation Matrix

Variable	Mean	SD	1	2	3
1. Social Presence	4.63	0.92	-		
2. Technology Trust	4.57	0.94	.51	-	
3. Willingness to Communicate	4.69	0.97	.51	.56	-

Note: N = 400. Construct scores range from 1 to 7. All Pearson correlations have $p < .001$.

Table 2 Sample Characteristics

Characteristic	Category	n	%
Gender	Male	207	51.75
	Female	184	46.00
	Other or Prefer Not to Disclose	9	2.25
Age Group	18-24 years	109	27.25
	25-34 years	149	37.25
	35-44 years	93	23.25
	45 years and above	49	12.25
Education	High School or Below	58	14.50
	Associate Degree	85	21.25
	Bachelor's Degree	206	51.50
	Master's Degree or Above	51	12.75
Generative AI Use Frequency	Once Every Few Months	24	6.00
	Several Times per Month	67	16.75
	Several Times per Week	142	35.50
	Four to Six Days per Week	105	26.25
	Daily	62	15.50
Generative AI Use Duration	Less Than 6 Months	75	18.75
	6-12 Months	99	24.75
	1-2 Years	135	33.75
	More Than 2 Years	91	22.75
Agent Evaluated	ChatGPT/General-purpose	90	22.50
	DeepSeek/General-purpose	82	20.50
	Doubao/General-purpose	65	16.25
	ERNIE Bot/General-purpose	42	10.50
	Qwen/General-purpose	36	9.00
	Kimi/General-purpose	30	7.50
	Yuanbao/General-purpose	15	3.75
	Hunyuan/General-purpose	10	2.50
	Gemini/General-purpose	6	1.50
	Service-embedded generative agent/Service-embedded	24	6.00

Agent Category Total	General-purpose subtotal/General-purpose	376	94.00
	Service-embedded subtotal/Service-embedded	24	6.00
Total	All evaluated agents/All categories	400	100.00

Note: N = 400. Mean age = 32.24 years, SD = 10.48, range = 18-59 years.

4.2 Measurement Model

The hypothesized three-factor model fit the data well, chi-square(74) = 118.53, p = .001, chi-square/df = 1.60, CFI = .99, TLI = .98, IFI = .99, GFI = .96, AGFI = .94, RMR = .04, and RMSEA = .04, 90% CI [.03, .05]. The one-factor model fit poorly, chi-square(77) = 974.14, p < .001, chi-square/df = 12.65, CFI = .71, TLI = .66, and RMSEA = .17. The chi-square difference was 855.62 with three degrees of freedom, p < .001. Table 3 shows the complete comparison. The difference between the models supports treating the three constructs as distinct in the analysis.

Table 3 Confirmatory Factor Analysis Model Comparison

Model	chi-square	df	p	chi-square/df	CFI	TLI	IFI	GFI	AGFI	RMR	RMSEA	RMSEA 90% CI
Three Correlated Factors	118.53	74	.001	1.60	.99	.98	.99	.96	.94	.04	.04	[.03, .05]
One Common Factor	974.14	77	< .001	12.65	.71	.66	.71	.66	.54	.14	.17	[.16, .18]

Note: N = 400. The model comparison yielded delta chi-square(3) = 855.62, p < .001.

All freely estimated factor loadings were significant at p < .001. Standardized loadings ranged from .69 to .85 for social presence, from .73 to .81 for technology trust, and from .73 to .85 for willingness to communicate. Cronbach's alpha values ranged from .87 to .88, and composite reliability values followed the same range. Average variance extracted was .59 for social presence, .60 for technology trust, and .63 for willingness to communicate. The item-level estimates and construct-level statistics appear in Table 4. The pattern indicates satisfactory internal consistency and convergent validity.

Table 4 Measurement Model Reliability and Convergent Validity

Construct	Item	B	SE	C.R.	p	Standardized Loading	Cronbach's Alpha	CR	AVE	Square Root of AVE
Social Presence	SP1	1.00	--	--	--	.85	.88	.88	.59	.77
	SP2	.94	.05	19.23	< .001	.82				
	SP3	.87	.05	16.82	< .001	.75				
	SP4	.82	.05	16.25	< .001	.73				
	SP5	.77	.05	14.95	< .001	.69				
Technology Trust	TT1	1.00	--	--	--	.81	.88	.88	.60	.78
	TT2	.96	.06	17.29	< .001	.79				
	TT3	.87	.06	15.58	< .001	.73				
	TT4	.93	.05	17.59	< .001	.80				
	TT5	.89	.06	16.07	< .001	.75				
Willingness to Communicate	WTC1	1.00	--	--	--	.84	.87	.87	.63	.79
	WTC2	.99	.05	19.64	< .001	.85				
	WTC3	.79	.05	15.91	< .001	.73				
	WTC4	.84	.05	16.58	< .001	.75				

Note: B is the unstandardized loading. CR = composite reliability; AVE = average variance extracted.

The square root of AVE for each construct exceeded its latent correlations with the other constructs. HTMT ratios ranged from .58 to .64 and remained below .85. Table 5 reports both assessments. The measures therefore showed adequate discriminant validity under the Fornell-Larcker and HTMT criteria. The distinction is substantively important because a respondent can experience an agent as socially present without regarding it as reliable, and willingness to continue a conversation is an intended response rather than an evaluation of the agent.

Table 5 Discriminant Validity

Construct or Construct Pair	Square Root of AVE	Latent-Factor Correlation	HTMT Ratio
Social Presence	.77	-	-
Technology Trust	.78	-	-
Willingness to Communicate	.79	-	-
Social Presence and Technology Trust	-	.57	.58
Social Presence and Willingness to Communicate	-	.56	.58
Technology Trust and Willingness to Communicate	-	.63	.64

Note: The square root of AVE is reported for each construct. Latent-factor correlations and HTMT ratios are reported for each construct pair. All HTMT ratios are below .85.

4.3 Common Method Bias Results

Harman's first unrotated factor accounted for 47.34% of the total item variance. This proportion was below 50%, although its proximity to that reference point calls for caution. A complementary single-factor CFA that constrained all 14 indicators to one common factor showed poor fit, chi-square(77) = 974.14, $p < .001$, chi-square/df = 12.65, CFI = .71, TLI = .66, RMR = .14, and RMSEA = .17. Its fit was substantially worse than the hypothesized three-factor model, delta chi-square(3) = 855.62, $p < .001$. In the common-latent-factor sensitivity model, the fit was chi-square(60) = 67.00, CFI = .998, TLI = .997, and RMSEA = .017. The standardized coefficients for Social Presence to Technology Trust, Technology Trust to Willingness to Communicate, and Social Presence to Willingness to Communicate were .38, .35, and .29, respectively, and each remained significant at $p < .001$. Relative to the three-factor estimates of .57, .46, and .30, the first two coefficients were attenuated while the direct coefficient changed little. The direction and significance of all focal paths remained stable. These results suggest that shared measurement variance may affect effect-size magnitude, so the primary estimates should be interpreted with the procedural safeguards and sensitivity results in Table 9.

4.4 Structural Model and Hypothesis Testing

The structural model showed good fit, chi-square(74) = 118.53, p = .001, chi-square/df = 1.60, CFI = .99, TLI = .98, IFI = .99, GFI = .96, AGFI = .94, RMR = .04, and RMSEA = .04, 90% CI [.03, .05]. These values are identical to those of the three-factor CFA because all three latent relations were specified, leaving a saturated structural component among the constructs.

Social presence was positively associated with technology trust. The unstandardized coefficient was .55 (SE = .05, C.R. = 10.33, $p < .001$), and the standardized coefficient was .57 with a bias-corrected 95% CI [.48, .65]. H1 was supported. Social presence explained 33% of the variance in technology trust. Technology trust was positively associated with willingness to communicate, B = .48, SE = .07, C.R. =

7.45, p < .001. The standardized coefficient was .46, with a bias-corrected 95% CI [.35, .56], supporting H2.

The direct association between social presence and willingness to communicate remained significant after technology trust was included. The unstandardized coefficient was .31 (SE = .06, C.R. = 5.13, p < .001), and the standardized coefficient was .30 with a bias-corrected 95% CI [.19, .41]. H3 was supported. Together, social presence and technology trust explained 46% of the variance in willingness to communicate. Table 6 gives the complete path estimates.

Table 6 Structural Paths and Hypothesis Tests

Hypothesis	Path	B	SE	C.R.	beta	BC 95% CI for beta	p	R-squared	Decision
H1	Social Presence to Technology Trust	.55	.05	10.33	.57	[.48, .65]	< .001	.33	Supported
H2	Technology Trust to Willingness to Communicate	.48	.07	7.45	.46	[.35, .56]	< .001	.46	Supported
H3	Social Presence to Willingness to Communicate	.31	.06	5.13	.30	[.19, .41]	< .001	.46	Supported

Note: B is the unstandardized estimate. SE and C.R. refer to B. Beta denotes the standardized estimate. Bias-corrected confidence intervals are based on 5,000 bootstrap samples. R-squared is reported for the endogenous construct associated with each path.

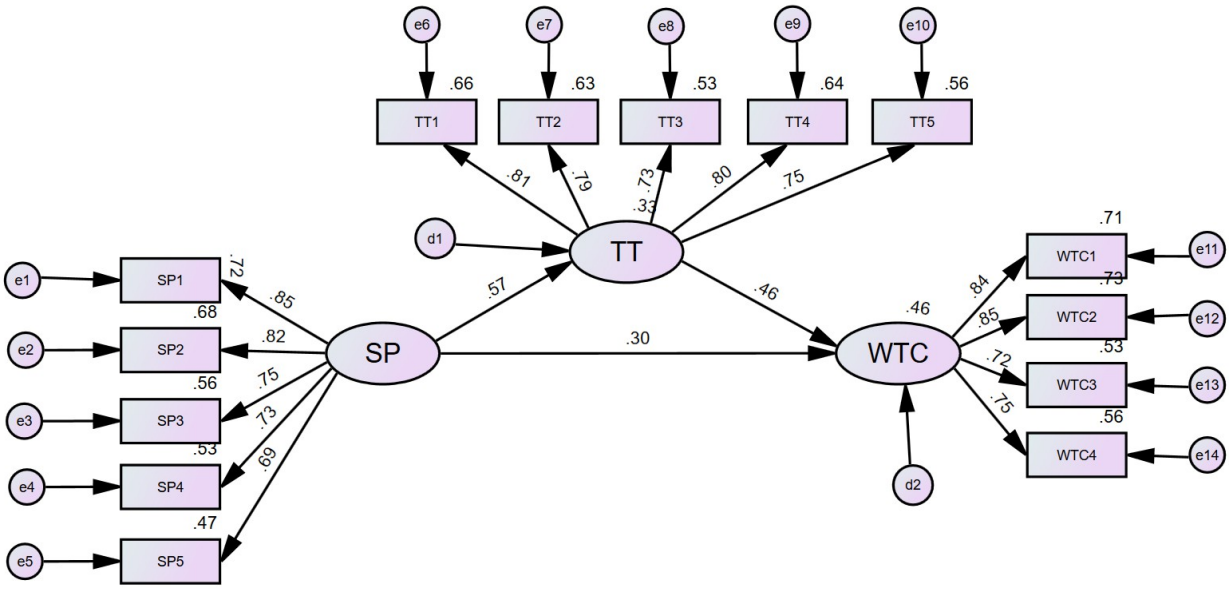


Fig.2: Standardized Structural Model Results

4.5 Mediation Analysis

The indirect association of social presence with willingness to communicate through technology trust was positive. The unstandardized indirect effect was .27 (bootstrap SE = .04, bias-corrected 95% CI [.20, .36], p < .001). The standardized indirect effect was .26, with a bias-corrected 95% CI [.20, .34]. Because neither interval included zero, H4 was supported.

The direct effect remained significant, B = .31, bootstrap SE = .06, standardized effect = .30, bias-corrected 95% CI for the standardized effect [.19, .41], p < .001. The total standardized effect was .56, with a bias-corrected 95% CI [.48, .64]. This combination of a significant indirect effect and a remaining direct effect is consistent with partial statistical mediation. The descriptive proportion mediated was .46. This ratio helps describe the allocation of the total association, while the hypothesis decision rests on the bootstrap confidence interval. Table 7 reports the direct, indirect, and total effects.

Table 7 Bootstrap Mediation Analysis

Effect	B	Bootstrap SE	BC 95% CI for B	Standardized Effect	BC 95% CI for Standardized Effect	p	Interpretation
Indirect Effect via Technology Trust	.27	.04	[.20, .36]	.26	[.20, .34]	< .001	H4 Supported
Direct Effect	.31	.06	[.20, .43]	.30	[.19, .41]	< .001	Significant
Total Effect	.58	.05	[.48, .69]	.56	[.48, .64]	< .001	Significant

Note: N = 400. Bias-corrected confidence intervals are based on 5,000 bootstrap samples. The indirect and direct effects are positive, and both confidence intervals exclude zero. This pattern is consistent with partial statistical mediation. The descriptive proportion mediated is .46; the mediation inference relies on the bootstrap confidence interval.

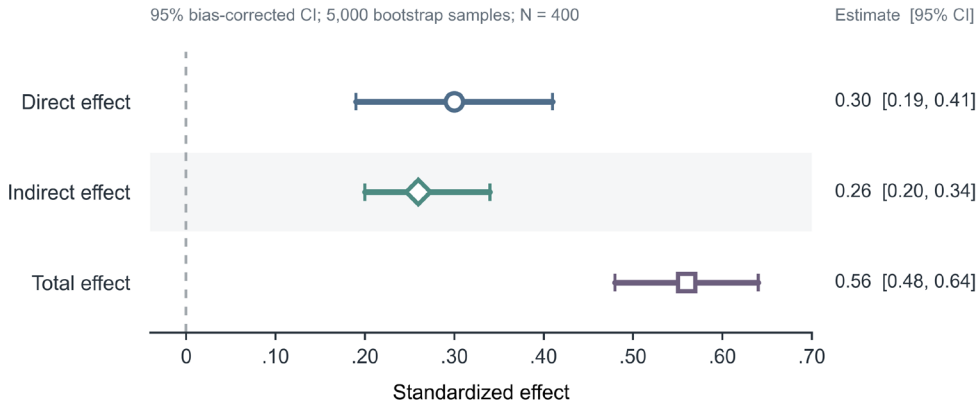


Fig.3: Direct, Indirect, and Total Effects of Social Presence on Willingness to Communicate

4.6 Robustness Analysis with Control Variables

As a robustness check, two composite-score regressions included gender, age, education, AI-use frequency, and AI-use duration as controls. All variables were standardized, and HC3 robust standard errors were used. Social presence remained positively associated with technology trust (beta = .513, 95% CI [.426, .600], p < .001; R-squared = .282). In the willingness-to-communicate model, social presence (beta = .297, 95% CI [.213, .381], p < .001) and technology trust (beta = .398, 95% CI [.310, .486], p < .001) remained positively associated with willingness to communicate (R-squared = .396). These results serve as sensitivity checks and do not replace the latent-variable structural model. Table 8 reports the focal coefficients.

The duration-based comparison split the sample into respondents with less than one year of generative AI experience (n = 174) and those with one year or more (n = 226). Construct means were similar across groups: social presence was 4.62 versus 4.63, technology trust was 4.51 versus 4.61, and

willingness to communicate was 4.67 versus 4.70; Welch tests gave p = .934, .307, and .800, respectively. In the controlled group equations, the Social Presence to Technology Trust coefficient was .47 for the shorter-experience group and .55 for the longer-experience group; the Social Presence to Willingness to Communicate coefficients were .29 and .32; and the Technology Trust to Willingness to Communicate coefficients were .40 and .39. None of the between-group differences was statistically significant. Table 10 summarizes the comparison.

Table 8 Robustness Checks with Control Variables

Outcome	Focal predictor	β	HC3 SE	t	p	95% CI
Technology trust	Social presence	.513	.044	11.57	< .001	[.426, .600]
Willingness to communicate	Social presence	.297	.043	6.90	< .001	[.213, .381]
Willingness to communicate	Technology trust	.398	.045	8.88	< .001	[.310, .486]

Table 9 Common Latent Factor Sensitivity Analysis

Model	chi-square	df	CFI	TLI	RMSEA	SP to TT beta	TT to WTC beta	SP to WTC beta	Assessment
Three-factor baseline	118.53	74	.990	.980	.040	.57	.46	.30	Reference model
Three-factor model + CLF	67.00	60	.998	.997	.017	.38	.35	.29	Paths retained; magnitudes attenuated

Note: CLF = common latent factor. The CLF was specified as orthogonal to the three substantive factors and loaded on all 14 indicators. All three focal paths remained positive and significant at p < .001. The CLF model is a sensitivity check and does not replace the primary three-factor model.

Table 10 Duration-Based Multi-Group Robustness Analysis

Path	Less than 1 year beta (HC3 SE)	1 year or more beta (HC3 SE)	Delta beta	C.R.	p	R-squared (short / long)	Interpretation
Social Presence to Technology Trust	.473 (.070)	.553 (.059)	.080	.88	.381	.266 / .332	No significant difference
Social Presence to Willingness to Communicate	.287 (.069)	.317 (.062)	.030	.32	.748	.387 / .409	No significant difference
Technology Trust to Willingness to Communicate	.396 (.070)	.385 (.064)	-.011	-.11	.910	.387 / .409	No significant difference

Note: n = 174 for less than 1 year and n = 226 for 1 year or more. Estimates are standardized coefficients from controlled composite-score regressions with HC3 robust standard errors. Gender used two dummy variables with male as the reference category; age, education, and frequency were retained as covariates. C.R. compares the two group coefficients.

5. Discussion

This study examined whether users who experience stronger social presence in a generative AI conversational agent are more willing to communicate with it and whether technology trust accounts for part of that relationship. All four hypotheses were supported. Social presence was positively associated with technology trust and willingness to communicate. Technology trust also had a positive association with communication willingness. The indirect path through trust was significant, while the

direct path remained, a pattern consistent with partial statistical mediation. The model accounted for 33% of the variance in technology trust and 46% of the variance in willingness to communicate.

5.1 Interpretation of the Findings

The association between social presence and technology trust supports H1. Users who experienced the agent as attentive, socially available, and sensitive to their situation also tended to regard it as more dependable and helpful. This finding agrees with evidence from electronic services, health care agents, and voice assistants (Gefen and Straub, 2004; Hsieh and Lee, 2024; Li et al., 2023b). A generative agent's apparent responsiveness gives users information that can enter a trust judgment. Coherent reference to earlier turns may suggest that the system is following the task, and an appropriately framed acknowledgement may indicate that the response was tailored to the user's concern.

The coefficient should not be interpreted as evidence that anthropomorphic language itself creates warranted trust. Social presence is an experienced perception, and technology trust includes beliefs about actual functionality and reliability. A fluent agent can appear attentive while returning incorrect information. Anderl et al. (2024) found that conversational presentation can raise credibility judgments even when content is partly inaccurate. The present association may therefore contain both appropriate updating based on useful responsiveness and overreliance on interactional fluency. This tension is especially relevant for generative AI because the form of an answer can be convincing even when its factual basis is weak.

H2 was also supported. Users who trusted the agent were more willing to continue the current exchange, ask follow-up questions, and initiate communication in a similar situation. This result is consistent with studies in which trust predicts behavioral intentions toward customer-service chatbots (Prakash et al., 2023) and transmits the association of human-like competence with engagement (Chandra et al., 2022). Communication requires a small act of dependence. The user spends time, supplies context, and accepts some uncertainty about the response. Trust makes that dependence more acceptable because the expected benefit of another conversational turn appears to exceed its effort and risk.

This result also helps separate willingness to communicate from general adoption. A person may have access to an agent and use it occasionally without wanting to sustain a substantive exchange. Conversely, a user may be willing to ask several follow-up questions during one interaction even when long-term adoption has not been decided. Meier et al. (2024) frame willingness to interact as a response shaped by several forms of consumption value. The present findings add a focused technological evaluation: when users see the specific agent as capable and helpful, their readiness for further dialogue is higher.

The direct association posited in H3 remained significant after technology trust was included. Social presence therefore relates to communication willingness through a route not fully represented by dependability judgments. One plausible explanation is that a socially responsive exchange lowers the interpersonal effort of maintaining dialogue. An agent that acknowledges the user's point and responds contingently can make the next conversational move easier to formulate. Prior studies link social presence to continuance intention and compliance with conversational requests (Adam et al., 2021; Jin and Youn, 2023). The present result extends this reasoning to a communication-specific outcome among users of generative systems.

The remaining direct path may also reflect affective or experiential responses that the technology-trust measure does not cover. McKnight et al.'s (2011) framework centers on functionality, reliability, and helpfulness. Users can enjoy a sense of responsiveness or feel less socially exposed when speaking with an agent, even if those reactions do not change their judgment of technical dependability. Lucas et al. (2014), for example, found that virtual humans can increase disclosure when concern about social

judgment is reduced. Communication willingness is broader and less sensitive than disclosure, but both outcomes can respond to how socially demanding an interaction feels.

H4 received support through the positive indirect association. Technology trust accounted for a substantial part of the relationship between social presence and communication willingness, but the descriptive mediated proportion should be read cautiously. The important result is the bootstrap interval for the indirect effect, which excluded zero. The mediation pattern aligns with research that links social or relational cues with trust and subsequent chatbot acceptance or reuse (Jiang et al., 2026; Liu et al., 2024). It also sharpens the theoretical mechanism. A socially present interaction is associated with stronger willingness partly because users evaluate the agent as a technology on which they can rely.

Temporal and causal qualifications matter here. Social presence, trust, and willingness were measured in the same questionnaire. Users who already prefer an agent may retrospectively rate both its social presence and its reliability more favorably. A stable positive response tendency could also raise all three scores. The CFA and common-method tests reduce concern that the constructs are indistinguishable or that one factor fully dominates the covariance matrix. They cannot establish the direction of influence. The results support statistical mediation within the conceptual model, with causal mediation left for experimental or longitudinal work.

5.2 Theoretical Implications

Social presence is often treated as a desirable endpoint of anthropomorphic or conversational design. The present model positions it as an input to two user evaluations with different content. One concerns whether the agent is dependable; the other concerns whether the user is ready to continue the exchange. This separation helps explain why the same relational cues can have mixed consequences. They may ease communication and inform trust, yet they can also encourage confidence that exceeds the quality of the response. Social presence should therefore be studied alongside performance evidence rather than used as a proxy for service quality.

Willingness to communicate also warrants treatment as a distinct outcome in digital service systems. Adoption and continuance measures answer whether users intend to use a system. Communication willingness asks whether they are ready to engage through the system's conversational channel. The distinction matters when service completion depends on clarification, iterative questioning, or the communication of situational details. Its measurement focuses on the interaction that produces the service outcome.

Technology trust provides the intervening evaluation in this account. Research on chatbot trust distinguishes affective responses to human-like cues from cognitive judgments of accuracy and reliability (Gupta and Chauhan, 2026; Wang et al., 2026). The partial mediation result is compatible with this distinction. Social presence can affect communication through the experienced quality of contact, while technology trust carries the part associated with accepted dependence on the system. The model links an interaction-level perception to an informatics evaluation and then to a service behavior intention.

5.3 Practical Implications

Designers should test social behavior and technical performance in the same evaluation program. A conversational response should acknowledge relevant user information, preserve context across turns, and ask follow-up questions only when they help complete the task. These features can support social presence. They should be assessed together with factual accuracy, response consistency, and successful task completion. A design team that optimizes warmth or personification without checking these outcomes may increase subjective trust without improving the grounds for that trust.

Service managers should provide visible evidence that helps users calibrate trust. The agent can identify the source or date of time-sensitive information, state when a response is uncertain, and offer

transfer to a human employee when the request exceeds its authority. Users also need clear notice about how conversation data are stored and used. These features may make an exchange feel less seamless, but they give users information needed for a more accurate dependability judgment. Trust calibration is preferable to maximizing trust scores.

Communication willingness can be monitored at the level of conversational behavior rather than inferred from a satisfaction rating. Useful operational measures include voluntary follow-up turns, completion after clarification, abandonment at specific dialogue states, and transfer requests. These indicators can show whether users are willing to keep communicating when the agent needs more information. Managers should review them with error and complaint data because a long conversation can signal engagement or unresolved failure.

The findings also support segment-specific review. The duration-based comparison found no statistically significant differences in the three focal paths: Social Presence to Technology Trust, delta beta = .08, C.R. = .88, p = .381; Social Presence to Willingness to Communicate, delta beta = .03, C.R. = .32, p = .748; and Technology Trust to Willingness to Communicate, delta beta = -.01, C.R. = -.11, p = .910. These results provide no statistical support for treating experience length as a boundary condition in this sample. Segment-specific design review remains useful because future studies may observe differences under higher-risk tasks, longer panels, or behavioral outcomes. High-risk services such as health, finance, or identity support require stricter limits on anthropomorphic cues and clearer escalation rules.

5.4 Limitations and Future Research

The cross-sectional design is the main limitation. Statistical mediation does not establish that social presence preceded trust or that trust preceded willingness. A randomized experiment could vary social-presence cues while holding information quality, response length, latency, and task outcome constant. Technology trust and communication willingness could then be measured at separate points, with actual voluntary dialogue turns recorded as a behavioral outcome. A longitudinal design could also examine whether early social presence predicts later trust after users accumulate direct evidence about system performance.

All focal measures came from the same respondent. Procedural controls, model comparisons, and the common-latent-factor sensitivity analysis were used, but shared measurement conditions may still inflate associations. The common-latent-factor model reduced the standardized Social Presence to Technology Trust coefficient from .57 to .38 and the Technology Trust to Willingness to Communicate coefficient from .46 to .35, while the Social Presence to Willingness to Communicate coefficient remained close to the primary estimate (.29 versus .30). Future studies should separate measurement occasions, add marker variables before data collection, or combine self-reports with observed conversational behavior.

The sample consisted of adult users in China with recent generative AI experience. Cultural expectations about relational communication and trust may affect the size of the paths (Gupta and Chauhan, 2026). Replication is needed in other countries and among users with lower digital familiarity. Logistics tracking, platform dispute resolution, travel support, and public-information services offer useful settings because they differ in urgency, data sensitivity, and the consequences of an inaccurate answer.

The model includes one mediator and no boundary condition. Privacy concern, task risk, agent error history, and the availability of a human alternative may alter how social presence enters trust judgments. Future work should test these moderators prospectively. Researchers should also distinguish appropriate trust from overtrust by comparing perceived reliability with observed response quality. That comparison would clarify whether social presence helps users recognize dependable systems or encourages reliance on fluency.

6. Conclusions

This study examined the relationships among perceived social presence, technology trust, and willingness to communicate with generative AI conversational agents. Survey results from 400 experienced users indicated positive associations among all three constructs. Technology trust carried part of the association between social presence and communication willingness, while social presence retained a direct association with willingness. The findings are consistent with partial statistical mediation and support a view of conversational-agent use in which relational experience and technological evaluation jointly shape intended dialogue.

For informatics and service-science research, the study distinguishes willingness to communicate from general adoption and continuance intention. It also shows the analytical value of separating social presence from trust in the agent's functionality, reliability, and helpfulness. The practical implication is specific: designers should pair socially responsive language with evidence of competent performance. Context retention, relevant acknowledgement, and useful clarification can support an exchange, but uncertainty statements, source information, and human escalation remain necessary for calibrated trust.

The conclusions are limited by the cross-sectional self-report design, the single-country sample, and the use of intended communication rather than observed behavior. The model estimates associations and statistical mediation, not causal effects. Future research should manipulate social-presence cues under controlled information quality, collect trust and behavior at different times, and compare perceived reliability with independently rated response quality. Tests in logistics, platform, and other digital service systems would establish how task risk and service consequences change these focal relationships.

Declarations

The study was reviewed and approved by the Research Ethics Committee of Management and Science University and the Academic Committee of the Graduate School of Management prior to data collection. All participants received study information and provided informed consent before completing the questionnaire. Participants were recruited through Credamo and received RMB 8 after completing the eligibility and quality checks.

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Conflict of Interest. The authors declare no conflict of interest.

Data Availability. The anonymized data supporting the findings of this study are available from the corresponding author upon reasonable request, subject to applicable ethical and data-protection requirements.

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Appendix A. Bilingual Measurement Items and Source Mapping

All items were assessed on a seven-point Likert scale ranging from 1 = strongly disagree to 7 = strongly agree. The Chinese wording below corresponds to the questionnaire version used with respondents.

Table A1. Social Presence Items

Source mapping and adaptation. SP1-SP5 were adapted from social-presence measures in Biocca et al. (2003) and Gefen and Straub (2004) for the specific generative AI conversational agent recalled by the respondent.

Code	English wording	Chinese wording
SP1	Interacting with this agent gave me a sense of interpersonal contact.	与该对话代理互动时，我感到有人际接触。
SP2	Interacting with this agent felt personal.	与该对话代理互动时，我感到交流具有个人化特征。
SP3	Interacting with this agent felt social.	与该对话代理互动时，我感到交流具有社交性。
SP4	Interacting with this agent conveyed interpersonal warmth.	与该对话代理互动时，我感到有人际温度。
SP5	Interacting with this agent indicated that it noticed human feelings.	与该对话代理互动时，我感到它能注意到人的感受。

Table A2. Technology Trust Items

Source mapping and adaptation. TT1-TT5 were adapted from McKnight et al. (2011) and worded to identify the recalled conversational agent as the object of trust.

Code	English wording	Chinese wording
TT1	I believe that this agent has the ability needed to complete communication tasks.	我认为该代理具备完成沟通任务所需的能力。
TT2	I believe that this agent can handle my question effectively.	我认为该代理能够有效处理我的问题。
TT3	I believe that this agent performs reliably.	我认为该代理的表现是可靠的。
TT4	I believe that the information provided by this agent is trustworthy.	我认为该代理提供的信息值得信赖。
TT5	I believe that this agent will provide useful help when needed.	我认为该代理会在需要时提供有用帮助。

Table A3. Willingness to Communicate Items

Source mapping and adaptation. WTC1-WTC4 were adapted to the conversational-agent setting from Meier et al. (2024).

Code	English wording	Chinese wording
WTC1	I am willing to continue communicating with this agent in the current exchange.	我愿意继续与该代理完成当前沟通。
WTC2	When I encounter a similar problem, I am willing to initiate a conversation with this agent.	遇到相似问题时，我愿意主动与该代理开始对话。
WTC3	I am willing to ask this agent further questions.	我愿意向该代理提出进一步的问题。
WTC4	When I encounter a similar problem, I am willing to choose this agent again for communication.	遇到相似问题时，我愿意再次选择该代理进行沟通。