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Does It Feel or Does It Understand? Communication Style and Task-Contingent Mind Attribution to Conversational AI

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Abstract

It is unclear what consumers infer from the social-oriented (SCS) and task-oriented (TCS) communication styles of conversational AI in e-commerce, or why these associations vary across tasks. Drawing on mind perception research, we examine affective (AH) and cognitive (CH) human-likeness, defined as attributions of human-like affective experience and cognitive understanding. Study 1 (N = 400 and 500) shows that AH and CH are distinguishable from warmth, competence, emotional and cognitive intelligence, experience, agency, and each other, and jointly explain additional variance in preference. Study 2, a three-wave survey of 415 users, measured SCS, TCS, and perceived task demands at Wave 1, AH and CH at Wave 2, and preference at Wave 3; interaction tests are therefore single-occasion. SCS is positively associated with AH and CH, and TCS with CH; both are positively associated with preference. The SCS–AH association is stronger under higher perceived social demands, and the TCS–CH association under higher perceived analytical demands. Analytical demands appeared to attenuate the SCS–AH association more than social demands attenuated the TCS–AH association, but this contrast rests on a single uncorrected test. These findings suggest that the associations of communication style with AH and CH vary across task demands.

Keywords: conversational AI agent; communication style; mind perception; affective human-likeness; cognitive human-likeness; perceived task demands; consumer preference; e-commerce

1. Introduction

Communication through conversational AI has become an important part of digital commerce, supporting personalized recommendation, comparison, and service recovery [1–3]. In these exchanges, communication style matters not only for how information is presented but also for how consumers evaluate the agent, trust its guidance, and respond to its recommendations [4,5]. More fundamentally, consumers cannot directly observe whether an AI agent genuinely feels, understands, or reasons; they must infer these mental qualities from observable interaction cues. Communication style is not only a way of delivering information; it is a potential basis for attributing mental qualities to the agent. Such attributions may be linked to whether the agent's responses are perceived as credible and appropriate, and in turn to disclosure, reliance on advice, and continued use in consequential commercial interactions [6,7].

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Communication-style research commonly distinguishes socially oriented communication style (SCS), which emphasizes relational attention and socio-emotional exchange, from task-oriented communication style (TCS), which emphasizes clarity, efficiency, and goal attainment [5,8]. Yet evidence regarding their relative effectiveness remains theoretically unsettled. One stream shows that SCS can enhance engagement, perceived warmth, and trust, especially when consumers expect social or empathic responses [2,9,10]. Another stream suggests that consumers may prefer direct and task-relevant communication in complex, functional, or performance-oriented tasks [11,12]. Existing work has primarily examined the evaluative and behavioral outcomes of communication styles, while devoting less attention to the interpretive processes through which consumers use these styles as attributional cues. Consumers may prefer an agent because its style signals specific human-like mental qualities, not merely because it appears socially appealing or operationally efficient. The central question, therefore, is not which style is generally superior, but whether SCS and TCS show distinct patterns of association with affective versus cognitive human-likeness (AH and CH) and how these attributions relate to consumer preferences.

Research on mind perception offers a foundation for addressing this question. People attribute different forms of mind to artificial agents on the basis of observable roles, behaviors, and interaction cues. For example, artificial agents assigned social rather than economic roles tend to be attributed more emotional experience [13]. Behavioral style is also related to perceived mental and emotional states [14], while warm or competent anthropomorphic interactions may influence experience- and agency-related mind perception across tasks [15]. Recent work further shows that conversational properties and affective speech can increase perceived humanness or experience attribution [4,16]. What remains less clear is whether established SCS and TCS communication styles show distinct patterns of association with AH and CH during consumers' ongoing use of conversational AI agents.

A second issue concerns the conceptual status of these attributions. Contemporary research treats anthropomorphism and human-likeness as multidimensional, but partitions them inconsistently. Prior work distinguishes attributed mental capacities from physical cues [17], foregrounds affective human-likeness yet operationalizes it alongside warmth and empathy [18], reports cognitive and affective components of perceived human-likeness in ChatGPT [19], and separates mental from physical human-likeness while treating thinking and feeling as a single dimension [20]. Departing from these accounts, we define affective human-likeness (AH) and cognitive human-likeness (CH) as consumers' attributions of human-like affective experience and cognitive understanding to AI agents. This definition sets AH and CH apart from social evaluation and capability appraisal—warmth, competence, perceived emotional intelligence (PEI), and perceived cognitive intelligence (PCI)—and thereby allows us to test their construct boundaries and to examine how they are associated with perceived communication style.

Task demands provide the boundary condition for these associations. Consumers do not evaluate the same AI cue identically across all activities. They are more receptive to algorithms in objective or analytical tasks than in subjective or affective tasks, and task assignment to artificial agents depends partly on the mental capacities attributed to them [21–23]. In conversational commerce, perceived social task demands (ST) arise when successful interaction requires emotional acknowledgment, relational engagement, or interpersonal sensitivity. Perceived analytical task demands (AT) arise when the interaction requires comparison, factual accuracy, or rule-based decision support. These demands can coexist within the same encounter, as a shopping assistant may move between personalized recommendation and policy or price comparison. Treating ST and AT

as continuous demands allows us to examine how task context conditions the association between communication style and each attribution.

Integrating these streams, we propose that perceived communication style is associated with AH and CH, because consumers may read it as a cue to each. SCS supplies evidence bearing on inner states (warmth in phrasing, acknowledgment of what the consumer is feeling, conversational give-and-take) and should therefore be associated with AH. TCS supplies evidence bearing on understanding and reasoning (ordered explanation, inference made explicit) and should therefore be associated with CH. Both AH and CH are expected to be positively associated with consumer preference because they imply different forms of fit between the agent and the interaction. We further propose that the SCS–AH association is stronger when ST is higher and that the TCS–CH association is stronger when AT is higher. Finally, we examine whether the two opposite forms of communication–task misalignment are associated with attenuation of equal size.

The framework is evaluated in two studies. Study 1 uses two independent samples of consumers (N = 400 and N = 500) to assess the discriminant validity of AH and CH relative to warmth, competence, PEI, PCI, experience, agency, and each other, as well as their incremental validity for consumer preference. Study 2 uses a three-wave survey of 415 current users of conversational AI agents to examine the proposed associations, indirect relationships, task contingencies, and misalignment asymmetry. The results show that SCS is positively associated with AH and TCS is positively associated with CH, while SCS also has a positive cross-path association with CH. Both attributions are positively associated with consumer preference. The SCS–AH association is stronger when ST is higher, and the TCS–CH association is stronger when AT is higher. For AH, the attenuation under higher analytical demands is larger for SCS than the attenuation under higher social demands is for TCS.

First, this study advances research on AI communication styles by shifting the focus from their downstream evaluative and behavioral outcomes to the AH and CH attributions with which they are associated. Prior studies have primarily examined outcomes such as trust, satisfaction, and usage intentions, yielding mixed findings [5,9,24]. We provide construct-boundary evidence for AH and CH, including their separability from experience and agency and their incremental value for consumer preference, and show that SCS is positively associated with both AH and CH, whereas TCS is positively associated with CH but not distinguishably with AH. This pattern fits the view that linguistic cues relate to separable forms of perceived human-likeness [14,15,17]. Second, it contributes to task-compatibility research by showing that the strength of communication-style–attribution links varies with perceived task demand [21,23,25]. Social demands are associated with a stronger link between relational cues and AH, whereas analytical demands are associated with a stronger link between structured cues and CH. Third, it adds to research on communication–task misalignment: for AH, the two opposite mismatches were not associated with equal attenuation, although this contrast rests on a single test and needs replication.

2. Theoretical Background and Hypotheses

2.1. Communication Style of Conversational AI Agents

Originating in research on interpersonal selling [8], work on conversational agents has largely adopted a dual framework of social-oriented communication style (SCS) and task-oriented communication style (TCS) [5,26]. SCS, akin to an interaction-oriented style, uses friendly greetings, affective wording, and responsive expressions to build rapport [26,27]. TCS uses direct, structured, and goal-focused language to organize information and move the consumer toward task completion [26,27]. We conceptualize SCS and TCS as two

dimensions that can vary within a single exchange. The distinction has gained traction because it separates the two functions an agent performs simultaneously in a commercial exchange: establishing a social connection and advancing task completion [5,11,26].

Traditional sales research suggests that TCS supports conversion, whereas SCS facilitates socio-emotional exchange [8], with effects that further depend on relational context and language sequencing [28,29]. Evidence from digital commerce is less settled (see Supplementary Table S1). One stream finds that SCS raises engagement, immersion, and purchase intentions by increasing social presence and perceived warmth [9,10,27]. Another finds that task-oriented language improves outcomes in functional or complex tasks [11,26]. A contingency view holds that a style's effectiveness depends on product characteristics, consumer competence, and task complexity [5,11,24,26]. Neither style is universally superior; each is more effective when matched to the consumer's situation.

Existing communication-style research shows that both SCS and TCS can support favorable consumer responses, but it offers limited explanation of the attributional process linking perceived communication style to preference. Research on AI mind perception shows that functional-role assignment [13], warmth- and competence-related anthropomorphic cues [15], behavioral style more broadly [14], and affective speech [16] are related to humanness and to experience- or agency-related attributions. None of these factors, however, corresponds to the classic two-dimensional SCS/TCS communication-style framework established in interpersonal sales and service research [5,8,11,26]. What remains unexamined is whether this established SCS/TCS dichotomy shows distinct patterns of association with affective versus cognitive human-likeness, and how these patterns vary with task demands treated as continuous rather than categorical. Building on this work, we examine how established SCS and TCS perceptions are associated with AH and CH during ongoing use of conversational AI agents, and whether those attributions are associated with consumer preference (see Supplementary Table S2).

2.2. Affective and Cognitive Human-likeness Within the Mind Perception Framework

Human-likeness was initially examined through appearance, embodiment, and motion [30–32]. More recent research treats anthropomorphism and human-likeness as multidimensional. A communication-theory account distinguishes attributed human mental capacities from physical cues and downstream personality or moral judgments [17]. Service research examines affective human-likeness as an attributed capacity for affective experience [18]; research on ChatGPT distinguishes cognitive and affective perceived human-likeness [19]; and virtual-influencer research separates mental from physical human-likeness [20,33]. This literature indicates that human-likeness cannot be represented adequately by a single continuum.

Drawing on the experience–agency framework of mind perception [34,35], we define AH and CH as distinguishable constructs capturing the extent to which consumers attribute human-like affective experience and cognitive understanding, respectively, to conversational AI agents. AH concerns attributed subjective feeling and affective experience. CH concerns attributed semantic understanding, contextual interpretation, and reasoned judgment. The terminology retains human-likeness because the measures use human mental attribution as the comparison standard. AH and CH are theoretically grounded in the broader experience–agency tradition; they are context-specific attributions nested within it and are not proposed as replacements for its general dimensions.

Table 1 distinguishes AH and CH from adjacent constructs. Warmth and competence evaluate benevolence and effectiveness, whereas PEI and PCI evaluate emotional and cognitive performance [36–38]. Anthropomorphism is broader and may include appearance, identity, personality, and behavior [17]. AH and CH instead concern attributed human-like

affective experience and cognitive understanding. An agent may appear friendly, effective, or intelligent without receiving either attribution. Study 1 tests these construct boundaries, including their relation to experience and agency.

Table 1. Conceptual positioning of AH and CH relative to adjacent constructs.

Construct Family	Primary Judgment	Core Question	Affective and Cognitive Scope	What It Does Not Require	Relationship to and Distinction from AH/CH
Experience/agency	General evaluation of mental capacities	Which experiential and agentic mental states are evaluated in relation to the entity?	Experience concerns the capacity to feel emotions, pleasure, pain, and other subjective states; agency concerns intention, planning, self-control, and action.	It does not necessarily require an explicit comparison with human beings.	Provides the broad theoretical foundation. Study 1b tests their empirical separability from AH and CH. AH focuses on attributed human-like affective experience, whereas CH focuses on attributed human-like semantic and contextual understanding.
Warmth/competence	Social evaluation	Does the agent appear well intentioned and effective?	Warmth concerns benevolence, friendliness, and caring; competence concerns ability, efficiency, and professionalism.	It does not require consumers to attribute human-like affective experience or cognitive understanding to the agent.	An AI agent may appear warm and perform effectively without being perceived as having human-like affective experience or cognitive understanding.
PEI/PCI	Capability appraisal	How effectively does the agent recognize emotional cues or process information?	PEI concerns effectiveness in recognizing and responding to emotional cues; PCI concerns effectiveness in understanding information and performing cognitive tasks.	It does not require consumers to attribute human-like affective experience or cognitive understanding to the agent.	An AI agent may recognize emotions or solve cognitive tasks accurately without being attributed human-like affective experience or cognitive understanding.
AH/CH	Specific attribution of human-like mental qualities	To what extent is human-like affective experience or cognitive understanding attributed to the agent?	AH concerns attributed human-like affective experience; CH concerns attributed human-like semantic understanding, contextual comprehension, and reasoned judgment.	It does not concern general favorability, social desirability, performance quality, or task effectiveness alone.	Attributing AH goes beyond judging an agent to be caring, and attributing CH goes beyond judging it to be accurate.

2.3. Communication Style as a Linguistic Cue for AH and CH Attributions

In consumer–agent interaction, perceived communication style provides observable cues from which consumers infer qualities they cannot inspect directly [13,14]. We use cue diagnosticity as a theoretical lens for describing the extent to which a communication-style cue is regarded as relevant and credible for a particular attribution [39,40]. The same cue need not be equally informative across tasks, because the usefulness of SCS and TCS depends on task requirements, user competence, and the function assigned to the agent [11,26]. SCS foregrounds relational responsiveness and emotional acknowledgment and should provide a basis for AH [13,14]. TCS foregrounds informational structure, goal focus, and reasoned explanation and should provide a basis for CH [5,11,26]. Each

style may relate to both attributions, but its most direct theoretical connection runs to the attribution reflected in its communication cues [13,14].

SCS emphasizes friendly, responsive, and relational communication centered on emotional exchange and relationship building [10,24]. Specific manifestations may include humor, self-disclosure, and emotional acknowledgment [5]. These cues address consumers' social motives and can make an agent appear more relationally responsive [9,41]. Beyond warmth or perceived emotional skill, such communication may also provide a basis for attributing human-like affective experience to the agent. We expect a positive association between SCS and AH, without assuming that SCS is unrelated to CH.

H1a. *SCS is positively associated with AH.*

AH may help explain why SCS is associated with consumer preference. When consumers attribute human-like affective experience to an agent, they may interpret the exchange as more socially responsive and personally relevant. Such attributions can reduce psychological distance and support affective trust, engagement, and hedonic value, which are associated with favorable evaluations of conversational agents [1,42,43]. This reasoning implies a positive indirect association between SCS and consumer preference through AH.

H1b. *There is a positive indirect association between SCS and consumer preference (CP) through AH.*

TCS emphasizes informational clarity, logical structure, and task focus [11,26]. Direct and structured language can signal relevance, coherence, and organized reasoning, and prior work links task-focused interaction to perceived usefulness and functional affordance [5,26]. These evaluations concern effective performance, but the same communication-style cues may also support a more specific attribution: that the agent understands the meaning and context of the problem and can form a reasoned judgment. We predict a positive association between TCS and CH, while allowing other communication cues to contribute to CH as well.

H2a. *TCS is positively associated with CH.*

CH may help explain why TCS is associated with consumer preference. When consumers attribute human-like cognitive understanding to an agent, they may be more confident that it recognizes their needs, interprets the task context, and offers reasoned support. Such attributions can reduce uncertainty and strengthen cognitive trust and perceived utilitarian value [1,6,44]. The corresponding indirect association between TCS and consumer preference through CH should also be positive. This proposed pathway is conceptually distinct from a simple performance evaluation because CH concerns attributed understanding, a judgment that task effectiveness alone does not establish.

H2b. *There is a positive indirect association between TCS and CP through CH.*

2.4. Perceived Task Demands as Boundary Conditions

Perceived task demands determine which qualities consumers regard as important in an interaction and, consequently, which communication-style cues appear relevant [6,23]. Perceived social task demands (ST) emphasize emotional acknowledgment, interpersonal responsiveness, and relationship maintenance. Perceived analytical task demands (AT) emphasize factual accuracy, comparison, structured reasoning, and objective goal attainment. AT reflects the requirements of the consumer's own task, such as comparing prices

or confirming a product's specifications, independent of how a given agent happens to communicate. This task-level origin distinguishes AT from TCS, which describes the structured, goal-focused language a specific agent is observed to produce, so that the two constructs can in principle diverge even though well-matched agents will tend to align style with task demands. The two demands are continuous and may coexist within one commercial encounter. For example, a consumer disputing a refund may expect both a clear policy explanation and acknowledgment of frustration. Treating ST and AT as separate continuous dimensions better reflects the mixed requirements of conversational commerce than assigning each encounter to a single task category.

Task compatibility should strengthen an association when a communication-style cue addresses what consumers regard as necessary for successful task completion [25]. In interactions with higher ST, relational responsiveness and emotional acknowledgment become more relevant to the consumer's goals. SCS should provide a stronger basis for AH because its communication cues align with the interpersonal requirements of the exchange.

H3a. *The positive association between SCS and AH is stronger when ST is higher.*

In interactions with higher AT, consumers place greater emphasis on clarity, logical structure, and dependable decision support [26,45]. The organized and goal-focused cues associated with TCS should provide a stronger basis for CH because they align with the cognitive requirements of the exchange. We accordingly expect the positive association between TCS and CH to become stronger as perceived analytical task demands increase.

H3b. *The positive association between TCS and CH is stronger when AT is higher.*

Misalignment should weaken the association between a communication style and the attribution it ordinarily supports. Under higher AT, consumers approach the agent primarily as a source of structured reasoning and decision support [22]. Extensive relational content or small talk may then appear poorly matched to the task and provide less credible evidence for either affective experience or cognitive understanding. We expect AT to attenuate the associations of SCS with AH and CH.

H4a. *The associations of SCS with AH and CH are weaker when AT is higher.*

The reverse misalignment—TCS under higher ST—may be less consequential for AH. Task-focused communication supplies limited evidence of emotional responsiveness, but it remains consistent with the instrumental role commonly assigned to AI [5,22]. Consumers may read TCS as withholding social evidence. By contrast, SCS under higher AT introduces relational content into an exchange organized around analysis and decision support. We expect the attenuation associated with the latter mismatch to be greater for AH.

H4b. *In the equation predicting AH, the interaction between SCS and AT will be significantly more negative than the interaction between TCS and ST.*

No parallel asymmetry is predicted for CH. CH concerns attributed understanding of meaning, context, and task requirements. SCS may become less relevant under higher AT because it diverts attention from structured reasoning, whereas TCS may become less relevant under higher ST because narrowly instrumental communication can overlook the interpersonal meaning of the exchange. Both mismatches may weaken the basis for CH to a similar degree, as summarized in Figure 1.

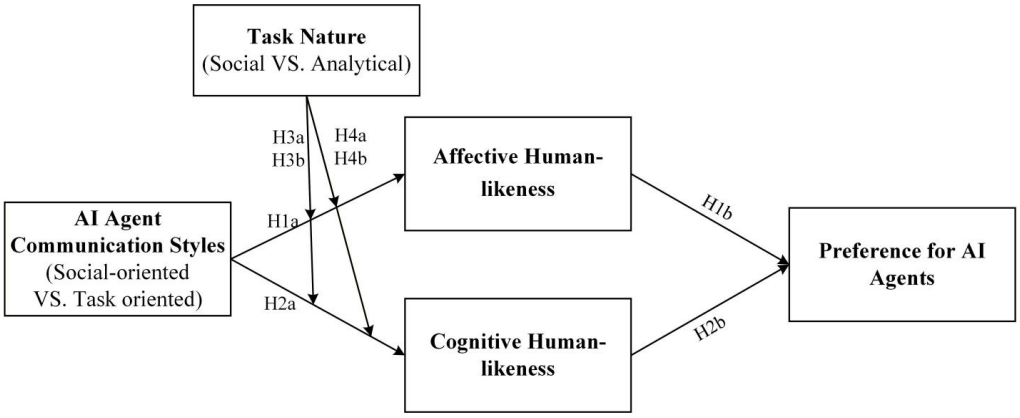


Figure 1. Research framework.

3. Study 1: Assessing the Distinctiveness of AH and CH from Adjacent Constructs

3.1. Purpose of Study 1

A plausible objection to the framework developed in Section 2 is that AH and CH merely relabel constructs already established in the literature, namely social evaluation, capability appraisal, or the experience and agency dimensions of mind perception on which they are grounded. If AH is indistinguishable from warmth or PEI, and CH from competence or PCI, then the two indirect pathways carry no theoretical content beyond existing accounts of social evaluation, capability appraisal, or the experience–agency framework itself. Study 1 therefore comprises two independent samples. Study 1a (N = 400; Sections 3.2–3.4) examines the empirical distinctiveness of AH and CH from warmth, competence, PEI, and PCI before Study 2 treats them as intermediate attributions. It also tests whether AH and CH are separable from each other, as the argument for two distinct attributions requires. Study 1b (N = 500; Section 3.5) adds established experience and agency measures. It tests whether AH and CH remain separable from them and whether they explain consumer preference beyond all six adjacent constructs. Because AH and CH are theoretically nested within the experience–agency tradition, we do not expect them to be independent of it. The question is whether they are empirically separable and add explanatory value.

3.2. Participants and Procedure

We recruited an independent sample of consumers (Study 1a) through Credamo, a China-based online research platform widely used in consumer and behavioral research in China [46,47]. Credamo maintains a registered participant pool and supports screening, quota control, and multi-wave matching through unique respondent identifiers. Eligibility required current use of a conversational AI agent for shopping, product inquiry, or after-sales service. Participants named an agent they had used recently and evaluated that agent on all six constructs. Scale order was randomized across participants to limit order effects, and two attention-check items were embedded in the questionnaire. After attention checks and data-quality screening, 400 valid responses were retained (56.00% female; M_age = 31.79; 89.25% holding a bachelor's degree or above). No participant took part in both Study 1 and Study 2.

3.3. Measures

All constructs were measured on 7-point Likert scales (1 = strongly disagree, 7 = strongly agree). AH and CH were developed for the present study (see Supplementary Materials). Item development proceeded in three stages. *Item pool.* A review of adjacent

measures indicated that they capture friendliness, capability, or task performance rather than mind attribution to AI agents [18,19,21]. We therefore drafted six candidate items per dimension grounded in the experience–agency distinction in mind perception [34,35], which separates attributions of feeling from attributions of thinking and has been shown to hold for artificial agents in service settings [13,18]. Each item was worded so that endorsement required attributing human-like affective experience (AH) or human-like cognitive understanding (CH) to the agent, a judgment distinct from task competence. *Expert review.* Four researchers in consumer psychology and human–computer interaction reviewed the 12-item pool for correspondence with its intended dimension and distinctiveness from adjacent constructs, and four items per dimension were retained. *Pretest and item retention.* The eight items were pretested with 45 current conversational-AI users who did not take part in Study 1a, Study 1b, or Study 2. Participants rated a recently used agent and provided open-ended feedback on clarity and redundancy. In each dimension, the item with the lowest corrected item–total correlation (below 0.55, versus above 0.65 for the retained items) was dropped, yielding the final three-item AH and CH scales. Warmth and competence were adapted from the stereotype content model [36]. PEI and PCI were adapted from Kim and Im [37], whose instrument distinguishes emotional from cognitive intelligence in AI agents; PCI items were further informed by the perceived-intelligence scale of Moussawi and Koufaris [38].

3.4. Results

Descriptive statistics and correlations for the six focal constructs are reported in Supplementary Table S4. Competence (M = 5.960) and PCI (M = 5.965) received the highest mean ratings, whereas AH (M = 4.636) and CH (M = 5.111) were rated comparatively lower, suggesting that participants did not attribute correspondingly high human-likeness despite perceiving the agents as competent and cognitively capable. Discriminant validity was corroborated by the Fornell–Larcker criterion, as the square root of the average variance extracted (AVE) for each construct exceeded its interconstruct correlations. All standardized loadings exceeded 0.70, composite reliability ranged from 0.898 to 0.946, and Cronbach's alpha was adequate across constructs (α = 0.889–0.939). AVE exceeded 0.50 for every construct, confirming convergent and discriminant validity.

We then estimated a series of nested confirmatory factor analyses (CFAs), comparing a baseline six-factor model against six constrained alternatives: AH merged with warmth; AH merged with PEI; CH merged with competence; CH merged with PCI; AH merged with CH; and all six constructs collapsed into a single factor. Table 2 reports the comparisons. The six-factor model fit the data well and fit significantly better than every constrained alternative (all $\Delta\chi^2$ tests, $p < 0.001$), with uniformly superior fit on the comparative fit index (CFI), Tucker–Lewis index (TLI), root mean square error of approximation (RMSEA), and standardized root mean square residual (SRMR). Because $\Delta\chi^2$ is sensitive to sample size, we also evaluated ΔCFI against the conventional criterion of 0.01 [48]. Every constrained model lowered CFI by at least 0.027 (ΔCFI = 0.027–0.176), well above this criterion; the smallest decrements occurred when AH was merged with PEI (0.027) or with CH (0.035). Collapsing AH with either warmth or PEI produced a marked deterioration in fit, as did collapsing CH with either competence or PCI. The single-factor model fit worst, ruling out the possibility that all six measures reflect a single evaluative judgment.

Discriminant validity was corroborated at the construct-pair level. As shown in Table 3 (Panel A), all pairwise heterotrait–monotrait (HTMT) ratios fell below the conservative 0.85 threshold, including the ratios between AH and warmth, AH and PEI, CH and competence, and CH and PCI. The AH–CH ratio likewise fell below the threshold, indicating that the

two forms of human-likeness are separable and do not index a single human-likeness perception.

Table 2. Confirmatory factor models for AH/CH construct distinctiveness in the independent validation sample.

Model	χ^2	df	$\Delta\chi^2$	Δdf	CFI	ΔCFI	TLI	RMSEA	SRMR
Baseline 6-factor model	786.04	309	-	-	0.938	-	0.930	0.062	0.047
Constrained Model 1 (AH + Warmth)	1163.40	314	377.37 ***	5	0.890	0.048	0.877	0.082	0.077
Constrained Model 2 (AH + PEI)	997.28	314	211.24 ***	5	0.911	0.027	0.901	0.074	0.058
Constrained Model 3 (CH + Competence)	1235.22	314	449.18 ***	5	0.880	0.058	0.866	0.086	0.084
Constrained Model 4 (CH + PCI)	1238.07	314	452.04 ***	5	0.880	0.058	0.866	0.086	0.086
Constrained Model 5 (AH + CH)	1058.38	314	272.34 ***	5	0.903	0.035	0.892	0.077	0.056
Constrained Model 6 (Single factor)	2159.96	324	1373.92 ***	15	0.762	0.176	0.742	0.119	0.106

Note(s): N = 400. *** $p < 0.001$. ΔCFI = CFI of the baseline model minus CFI of the constrained model.

Table 3. HTMT ratios between AH/CH and related constructs in Study 1a (Panel **A**) and Study 1b (Panel **B**).

Panel A. Study 1a (N = 400)

	AH	CH	Warmth	Competence	PEI	PCI
AH						
CH	0.674 [0.599, 0.741]					
Warmth	0.690 [0.610, 0.764]	0.720 [0.596, 0.825]				
Competence	0.370 [0.271, 0.466]	0.497 [0.388, 0.597]	0.585 [0.434, 0.709]			
PEI	0.663 [0.583, 0.732]	0.674 [0.576, 0.759]	0.686 [0.594, 0.760]	0.479 [0.377, 0.577]		
PCI	0.320 [0.195, 0.433]	0.415 [0.262, 0.545]	0.505 [0.332, 0.660]	0.719 [0.611, 0.811]	0.425 [0.291, 0.548]	

Panel B. Study 1b (N = 500)

	AH	CH	Experience	Agency	Warmth	Competence	PEI	PCI
AH								
CH	0.454 [0.363, 0.538]							
Experience	0.699 [0.634, 0.754]	0.241 [0.147, 0.336]						
Agency	0.493 [0.409, 0.569]	0.630 [0.495, 0.754]	0.266 [0.178, 0.356]					
Warmth	0.441 [0.345, 0.525]	0.644 [0.491, 0.772]	0.276 [0.180, 0.371]	0.396 [0.285, 0.514]				
Competence	0.135 [0.064, 0.218]	0.598 [0.468, 0.715]	0.075 [0.025, 0.106]	0.352 [0.238, 0.468]	0.559 [0.441, 0.662]			
PEI	0.475 [0.398, 0.543]	0.713 [0.586, 0.827]	0.358 [0.279, 0.431]	0.381 [0.263, 0.509]	0.769 [0.684, 0.839]	0.421 [0.313, 0.522]		
PCI	0.204 [0.110, 0.291]	0.518 [0.364, 0.641]	0.113 [0.040, 0.206]	0.238 [0.127, 0.362]	0.366 [0.263, 0.455]	0.534 [0.427, 0.621]	0.416 [0.332, 0.493]	

(Panel **A**) Note(s): N = 400. Values in brackets represent bias-corrected 95% bootstrap confidence intervals. The upper bounds of all HTMT ratios are strictly below the 0.85 threshold. (Panel **B**) Note(s): N = 500. Values in brackets represent bias-corrected 95% bootstrap confidence intervals. The upper bounds of all HTMT ratios are strictly below the 0.85 threshold.

3.5. Study 1b: Distinguishing AH and CH from Experience and Agency

Sample and measures. We recruited an independent sample through Credamo using the eligibility criteria of Study 1a. Participants named an agent they had used recently and evaluated it on all constructs; scale order was randomized, and two attention-check items were embedded. After screening, 500 valid responses were retained (60.8% female; mean age = 30.7 years; 87% holding a bachelor's degree or above). Unique respondent identifiers confirmed that no participant took part in Study 1a or Study 2. AH, CH, warmth, competence, PEI, PCI, and consumer preference (CP) were measured with the scales used in Study 1a and Study 2. Experience and agency were each measured with three items. Controls were gender, age, education, profession, familiarity, and usage frequency. All constructs showed acceptable reliability and convergent validity (α = 0.765–0.931, composite reliability (CR) = 0.785–0.956, AVE = 0.551–0.878; Supplementary Table S5).

Construct distinctiveness. We estimated an eight-factor CFA including AH, CH, experience, agency, warmth, competence, PEI, and PCI. The baseline model fit well ($\chi^2(271) = 674.11$, CFI = 0.941, TLI = 0.930, RMSEA = 0.055, SRMR = 0.058). Merging AH with experience ($\Delta\chi^2(7) = 139.95$, $p < 0.001$) or CH with agency ($\Delta\chi^2(7) = 202.01$, $p < 0.001$) significantly worsened fit, as did the remaining merged and correlation-fixed models (Supplementary Table S6). Every constrained model also lowered CFI by at least 0.012 (ΔCFI = 0.012–0.115), above the 0.01 criterion. As Table 3 (Panel B) shows, all HTMT ratios were below 0.85, and the upper limits of their 95% bootstrap confidence intervals were also below 0.85. The pattern follows the nesting logic. AH was closest to experience (0.699) and less close to agency (0.493), whereas CH was closer to agency (0.630) than to experience (0.241). Experience and agency were themselves clearly separable (0.266). CH also showed higher ratios with PEI (0.713) and warmth (0.644) than with agency, which suggests that attributing cognitive understanding partly overlaps with judging that an agent understands and cares about the consumer. These ratios nevertheless remain below the threshold. Mean AH differed across samples (Study 1a: 4.64; Study 1b: 3.29; Study 2: 5.03), as did the AH–CH HTMT ratio (0.67, 0.45, and 0.67, respectively), plausibly because respondents named their own agents, whose types and usage contexts varied; we therefore rely on the consistent separability of AH and CH rather than on absolute levels.

Incremental validity. To test whether AH and CH carry explanatory value beyond adjacent constructs, we regressed CP on the constructs in three blocks (Supplementary Table S7): controls (gender, age, education, profession, familiarity, and usage frequency; Step 1, R^2 = 0.215), experience, agency, warmth, competence, PEI, and PCI (Step 2, R^2 = 0.395), and AH and CH (Step 3, R^2 = 0.465). Adding AH and CH raised R^2 by 0.070 ($p < 0.001$, f^2 = 0.131), a small-to-medium increment by conventional benchmarks. Both were positively associated with CP (AH: β = 0.18, $p < 0.001$; CH: β = 0.26, $p < 0.001$). Competence (β = 0.205), PEI (β = 0.171), and PCI (β = 0.086) remained significant, warmth was marginal (β = 0.055, $p < 0.10$), and experience and agency were not significant. In the reverse order, the six adjacent constructs added 0.123 to R^2 after AH and CH. AH and CH therefore explain preference beyond the adjacent constructs, although these constructs overlap substantially.

Interpretation and boundary. Study 1b indicates that AH and CH are separable from experience and agency and that, jointly, they explain additional variance in consumer preference beyond the six adjacent constructs. We therefore treat them as context-specific attributions nested within the experience–agency framework, which refine rather than replace its general dimensions. Two limits apply. Study 1b is cross-sectional and single-source, so shared method variance may affect the estimates, and no marker variable was collected in this sample. In addition, experience and agency were not measured in Study 2, so its indirect-association tests do not control for them.

3.6. Discussion of Study 1

Study 1 provides evidence that AH and CH are empirically distinguishable from social evaluation, capability appraisal, experience, agency, and each other. Attributing human-like affective experience is not equivalent to judging an agent as warm or emotionally intelligent, and attributing human-like cognitive understanding is not equivalent to judging it as competent or cognitively effective. These results support the proposed construct boundaries; they do not imply that AH and CH replace the broader experience and agency dimensions of mind perception. Study 1b indicates instead that AH and CH are context-specific attributions nested within that framework: within the experience–agency pair, AH is closest to experience and CH to agency, and each remains separable from its parent dimension. Together, they also explain additional variance in consumer preference beyond the six adjacent constructs. CH also overlaps partly with PEI and warmth, which suggests that attributing cognitive understanding draws in part on perceived responsiveness to the consumer (see Section 6.2). With this distinction in place, Study 2 examines the associations of SCS and TCS with AH and CH, the indirect associations with consumer preference, and the moderating role of perceived task demands.

4. Study 2: Materials and Methods

4.1. Purpose and Design of Study 2

Study 2 tests the full model. It examines whether SCS and TCS are associated with AH and CH (H1a, H2a), whether AH and CH carry indirect associations between communication style and consumer preference (H1b, H2b), and whether ST and AT condition these associations and their misalignment patterns (H3a–H4b). The study also compares the two opposite misalignment coefficients directly. The hypotheses are evaluated with a three-wave field survey of current users of conversational AI agents.

We used a three-wave time-lagged survey rather than a scenario experiment for two reasons. First, perceived communication style reflects repeated encounters with deployed agents, and a field survey preserves the heterogeneity of agents, tasks, and interfaces present in current use. Second, the framework concerns how consumers evaluate the task demands they actually face, not those assigned by the researcher in a single scenario. Temporal separation secures the ordering of predictors, attributions, and outcome and reduces same-occasion measurement concerns. Because baseline levels of AH and CH were not measured at Wave 1, nor a baseline level of CP at Wave 2, the time lag supports temporal ordering of the focal variables rather than a change-model interpretation.

4.2. Data Collection

Participants were recruited through Credamo, the online research platform described in Study 1. We initially recruited 500 consumers who currently used conversational AI agents. Eligible participants named a conversational AI agent they currently used and evaluated the same agent across all three waves; unique respondent identifiers were used to match responses over time. The three waves were spaced two weeks apart to improve temporal ordering and reduce common-method concerns [49,50]. Wave 1 assessed communication style, perceived task demands, and controls [51]; Wave 2 measured AH and CH; and Wave 3 measured consumer preference for the focal agent relative to other AI agents (CP).

Several screens protected data quality. We embedded attention traps and excluded respondents whose completion time fell below 40% of the median response time [52,53], since extremely rapid completion signals careless responding rather than genuine evaluation (results are unchanged when the threshold is set at 30% or 50% of the median). We further removed respondents who switched agents between waves or failed consistency

checks. The final matched sample comprised 415 responses; Figure S1 documents the full procedure.

4.3. Instruments and Measures

Participants first named a conversational AI agent they currently use and evaluated that agent throughout, which fixes a concrete referent for all subsequent items. SCS and TCS were measured with three-item scales adapted from Keeling et al. [5] and Chattaraman et al. [11]. Because SCS and TCS are continuous dimensions, a respondent could rate the same agent high or low on both. Task context was operationalized as perceived task demands—what consumers regarded the interaction as requiring, independent of its objective properties. ST and AT follow the social–analytical task distinction established in human–agent research [6,21]; items were written for the present shopping context and share a common stem directing respondents to the situations in which they typically use the focal agent. AH and CH used the measures developed in Study 1 (Section 3.3). CP was measured with a three-item scale assessing consumers' preference for the focal agent relative to other AI agents they could use (e.g., "Compared with other AI agents, I prefer this AI agent"), adapted from Castelo et al. [21] and Jin and Zhang [44].

Controls were selected on theoretical grounds. Demographic characteristics comprised gender (Gender), age (Age), education—college or below (Edu_CollegeBelow) and master's degree or above (Edu_Master), with bachelor's degree as the reference—and profession—private-sector employment (Profession_Private), state-owned-enterprise employment (Profession_STE), public-sector employment (Profession_PUB), civil service (Profession_GOV), and foreign-owned-enterprise employment (Profession_Foreign), with self-employment as the reference. These characteristics are plausibly related to prior exposure to AI, expectations of the interaction, and interpretation of communication cues [1,4]. Agent category was represented by generative AI chatbots (AI_Chatbot) and online service agents (AI_Service), with voice assistants as the reference category, to absorb systematic differences in communication modality and interface form. Usage frequency (Usage_frequency) [51] and technological familiarity (Familiarity) [54] were included because prior experience is related to how consumers perceive communication style and attribute mind. Digital literacy (Digital_literacy) [55] and personal innovativeness in information technology (PIIT) [56] were included as standing individual differences in receptiveness to AI. All controls were measured before the attributions and the outcome.

4.4. Common Method and Nonresponse Bias

Because the focal variables are self-reported perceptions from a single source, we took procedural and statistical steps to limit common method bias (CMB) [49,50]. Procedurally, the three-wave design, with waves spaced two weeks apart, separated the measurement of communication style and task demands (Wave 1), the attributions (Wave 2), and the outcome (Wave 3). This secures the temporal ordering of the main paths. The four interaction terms, however, combine variables measured together at Wave 1 (SCS, TCS, ST, and AT), so the tests of H3a–H4b rely on same-wave, same-source data. Statistically, Harman's single-factor test extracted 43.201% of the variance in the first factor, although this test has limited diagnostic value [49]. A marker-variable test using respondents' attitude toward the color blue [57,58] showed small and non-significant marker correlations with the core variables ($|r| \leq 0.077$, $p > 0.1$). Because this marker is conceptually distant from the perceptual constructs studied, we treat the result as limited evidence, even though the marker was developed for perceptual, Likert-type survey data [59] and performed well among the prospective markers evaluated in earlier work [60]. A CFA marker analysis [61] with a theoretically closer marker would be a stronger test, which the survey did not include.

Overall, the design and these checks give no indication that CMB is a dominant source of the focal associations.

For nonresponse bias, we followed the wave analysis of Armstrong and Overton [62], comparing early and late Wave 1 respondents on demographics and focal constructs. Chi-square and independent-samples t-tests indicated no significant differences ($p > 0.1$) in gender, education, age, perceived communication style, or perceived task demands. For attrition bias, we compared participants who completed all three waves with those who withdrew after the first or second wave and again found no significant demographic differences ($p > 0.1$). These analyses did not indicate substantial nonresponse or attrition bias.

4.5. Econometric Specification and Supplementary Endogeneity Assessments

We tested the hypotheses with multiple regression, operationalizing latent constructs as composite scores averaged across their items. This suits our purpose, which is parameter-level hypothesis testing—interaction effects, coefficient comparisons, and instrumental-variable estimation—rather than overall structural model evaluation [63,64]. The baseline specification is:

$$Y_i = \beta_0 + \beta_1 SCS_i + \beta_2 TCS_i + \sum \gamma_k Control_{ki} + \epsilon_i \quad (1)$$

where Y_i denotes *CP*, *SCS* and *TCS* denote social- and task-oriented communication styles respectively, and ϵ_i is the error term. To test the indirect associations through *AH* and *CH*, we estimated the following system:

$$AH_i = \alpha_0 + \alpha_1 SCS_i + \alpha_2 TCS_i + \sum \gamma_{1k} Control_{ki} + \epsilon_{1i} \quad (2)$$

$$CH_i = \beta_0 + \beta_1 SCS_i + \beta_2 TCS_i + \sum \gamma_{2k} Control_{ki} + \epsilon_{2i} \quad (3)$$

$$CP_i = \delta_0 + \delta_1 SCS_i + \delta_2 TCS_i + \delta_3 AH_i + \delta_4 CH_i + \sum \gamma_{3k} Control_{ki} + \epsilon_{3i} \quad (4)$$

where *AH* and *CH* denote affective and cognitive human-likeness respectively. Equation (4) corresponds to Model 6 in Tables 8 and 9; *ST* and *AT* enter only the moderation models (Equation (5)). Indirect associations were tested by bootstrapping. The moderation tests augment the baseline with interaction terms between the focal predictors and the two task-demand dimensions:

$$\begin{aligned} Y_i = \beta_0 + \beta_1 SCS_i + \beta_2 TCS_i + \beta_3 ST_i + \beta_4 AT_i + \beta_5 (SCS_i \times ST_i) + \beta_6 (SCS_i \times AT_i) + \beta_7 (TCS_i \times ST_i) + \beta_8 (TCS_i \times AT_i) \\ + \sum \gamma_k Control_{ki} + \epsilon_i \end{aligned} \quad (5)$$

where Y denotes *AH* or *CH*. Because the two equations share an identical set of regressors, the standard errors of any given interaction term are directly comparable across them, and we report them for all focal interaction terms. We tested differences between two interaction coefficients within the same equation with Wald restrictions and seemingly unrelated regression (SUR), our primary tests of asymmetry. As a descriptive supplement, we also report two one-sided tests (TOST). The equivalence bound comes from a sensitivity power analysis, not from convention; given the sample size and residual degrees of freedom, the standard errors of the interaction coefficients imply a minimum equivalence margin detectable at conventional power, and we adopt a bound at or above this margin. The bound therefore reflects estimation precision, not a substantively derived smallest effect size of interest, so equivalence means only that a coefficient lies within it, and the TOST results are illustrative rather than confirmatory. The same standard errors and degrees of freedom define the smallest interaction effects and within-equation coefficient differences that the design can detect at conventional power (two-sided); we report these alongside the corresponding results.

4.5.1. Agent-Level Instrumental-Variable Sensitivity Check

Endogeneity remains a concern because both communication-style variables and the attributions are perceptual. We therefore constructed agent-level communication-style benchmarks as instrumental variables (IV) for SCS and TCS. For each agent in the sample, we assembled standardized interaction samples from publicly accessible demonstrations and product documentation. Independent coders rated these samples with the same SCS and TCS items used in the survey, and the aggregated ratings served as agent-level benchmarks. The benchmarks vary across agents but not across consumers evaluating the same agent. They are derived independently of respondents' evaluations and capture provider-level communication-design tendencies that predate individual consumer judgments.

The relevance condition is testable, because an agent's default communication design should be associated with consumers' perceived communication style. The exclusion restriction, however, is doubtful and cannot be tested: agent-level communication design plausibly covaries with agent capability (for example, the quality of the underlying language model), which may affect consumers' attribution of cognitive understanding (CH) directly rather than through perceived communication style, and such a violation would tend to inflate the IV estimates. We therefore treat the IV estimates as a bounded sensitivity check, not as an assessment of endogeneity. Following the plausible-exogeneity approach [65], we relax strict exogeneity and allow each instrument a direct effect on the outcome of up to $\delta = \pm 0.20$, and we report union-of-confidence-interval (UCI) bounds for the main paths of SCS and TCS in the main-effect models. Because the identifying variation comes from only 14 agents, we read the results for the direction and approximate robustness of the focal paths rather than as precise estimates.

4.5.2. Gaussian Copula Sensitivity Analysis

To complement the agent-level instrumental-variable sensitivity check, we conducted an instrument-free Gaussian copula control-function sensitivity analysis of potential dependence between SCS/TCS and the structural errors [66]. Shapiro–Wilk tests rejected normality for both SCS and TCS, so we constructed inverse-normal control functions from their empirical cumulative distributions and entered both copula terms simultaneously into the AH and CH equations, retaining the original controls, ST, AT, and interaction terms. Standard errors came from 1000 bootstrap replications. Because Gaussian copula estimates can be sensitive to model and sample characteristics [67,68], we treat this analysis as a complementary sensitivity check.

5. Study 2: Results

5.1. Descriptive Statistics and Measurement Model

The sample spans three interface types: voice assistants (50.12%, N = 208), online service agents (25.06%, N = 104), and generative AI chatbots (24.82%, N = 103). They differ in how tightly they are coupled to purchase. Service agents on Tmall, Taobao, and JD.com operate inside the transaction itself, whereas voice assistants and generative chatbots serve broader purposes while increasingly supporting product search, comparison, and recommendation; one sampled device, Tmall Genie, was built by a commerce platform for that purpose [2]. We retained all three interface types for two reasons. First, the focal constructs concern attributions to the agent that consumers actually use for shopping-related tasks, and the ST and AT items direct respondents to shopping situations (Section 4.3), so every respondent evaluated the agent in a shopping context. Second, restricting the sample to transaction-embedded service agents would have narrowed the range of agents and interfaces the findings speak to. The cost is that half of the sample evaluated voice assistants, so

the findings describe conversational AI used for shopping-related tasks broadly and generalize less clearly to transaction-embedded service agents (Section 6.4). Communication modality did not moderate the two focal pathways (Section 5.7).

Table 4 reports the demographic profile. Table 5 reports descriptive statistics and correlations. TCS was rated higher than SCS on average (M_{TCS} = 5.593, SD = 1.210; M_{SCS} = 5.176, SD = 1.327; paired t(414) = 7.09, $p < 0.001$), indicating that consumers perceived the agents they used as more task-centered than socially oriented. This descriptive pattern is consistent with the functional orientation of many deployed commercial agents, including customer-service systems, product-search tools, and shopping assistants [26].

Table 4. Demographic statistics.

Items	Category	N = 415	Percent (%)
Gender	Male	203	48.92%
	Female	212	51.08%
Age	Less than 21	25	6.02%
	21 to 30	160	38.55%
	31 to 40	130	31.33%
	41 to 50	62	14.94%
	51 to 60	38	9.16%
Education	College or below	60	14.46%
	Bachelor's degree	260	62.65%
	Master's degree or above	95	22.89%
Profession	Private-sector employee	150	36.14%
	Public-sector employee	80	19.28%
	State-owned enterprise employee	60	14.46%
	Civil servant	50	12.05%
	Foreign-owned enterprise employee	33	7.95%
	Self-employed	42	10.12%

Table 5. Descriptive statistics and correlations.

	Mean	Std.Dev	SCS	TCS	ST	AT	AH	CH	CP
SCS	5.176	1.327	*0.857*						
TCS	5.593	1.210	0.557	*0.921*					
ST	5.188	1.344	0.497	0.505	*0.883*				
AT	5.451	1.256	0.547	0.621	0.599	*0.875*			
AH	5.030	1.417	0.562	0.551	0.614	0.524	*0.901*		
CH	5.232	1.250	0.552	0.624	0.551	0.554	0.613	*0.883*	
CP	5.237	1.227	0.537	0.567	0.385	0.305	0.593	0.616	*0.846*

Note(s): N = 415. Italicized diagonal elements are the square roots of average variance extracted (AVE); each should exceed the corresponding interconstruct correlations for adequate discriminant validity.

The measurement model performed well. As Table 6 shows, Cronbach's α exceeded 0.70 for every construct [69], composite reliability ranged from 0.883 to 0.944, all standardized loadings exceeded 0.70, and average variance extracted (AVE) exceeded 0.50 [70]. Confirmatory factor analysis indicated good fit: $\chi^2(188) = 480.075$, $p < 0.001$, $\chi^2/df = 2.554$, CFI = 0.956, TLI = 0.946, RMSEA = 0.061, SRMR = 0.035 [71]. Discriminant validity was assessed in two ways. The square root of AVE exceeded every inter-construct correlation (Table 5), and all HTMT ratios ranged from 0.337 to 0.686, below the conservative 0.85 threshold (Table 7) [72].

Table 6. Reliability and validity assessment of focal constructs.

Variable	Item	Loading	Cronbach's Alpha (α)	CR	AVE	Adapted From
SCS	SCS1 SCS2 SCS3	0.82 0.879 0.871	0.885	0.892	0.735	[5,11]
TCS	TCS1 TCS2 TCS3	0.941 0.938 0.884	0.938	0.944	0.849	[5,11]
ST	ST1 ST2 ST3	0.885 0.9 0.863	0.906	0.914	0.779	Self-developed, based on [6,21]
AT	AT1 AT2 AT3 AT4	0.844 0.883 0.885 0.889	0.922	0.929	0.766	Self-developed, based on [6,21]
AH	AH1 AH2 AH3	0.899 0.899 0.903	0.921	0.928	0.811	Self-developed
CH	CH1 CH2 CH3	0.873 0.889 0.885	0.905	0.913	0.779	Self-developed
CP	CP1 CP2 CP3	0.81 0.855 0.871	0.874	0.883	0.715	[21,44]

Table 7. Assessment results of discriminant validity (HTMT criterion).

	SCS	TCS	ST	AT	AH	CH	CP
SCS							
TCS	0.607						
ST	0.550	0.544					
AT	0.601	0.663	0.650				
AH	0.618	0.589	0.667	0.564			
CH	0.612	0.672	0.603	0.602	0.666		
CP	0.605	0.621	0.429	0.337	0.655	0.686	

Note(s): N = 415.

5.2. Main Effects

Diagnostics indicated no serious multicollinearity (maximum variance inflation factor (VIF) = 5.37; Supplementary Table S8), no influential observations (all Cook's distance < 1), and no substantial heteroscedasticity (Breusch–Pagan test). Models nonetheless used heteroskedasticity-robust standard errors, and focal variables were mean-centered before forming interaction terms. Table 8 reports the estimates, with Models 1–2, 3–4, and 5–6 taking AH, CH, and CP as dependent variables. Per-term VIFs were 2.17–3.00 for main-effect terms and 4.12–5.37 for interaction terms, all below 10; models without interaction terms had VIFs below 3.5.

SCS was positively associated with AH (β = 0.169, SE = 0.048, $p < 0.001$), whereas TCS was not (β = 0.081, SE = 0.050, $p = 0.106$), supporting H1a. For CH, both TCS (β = 0.220, SE = 0.051, $p < 0.001$) and SCS (β = 0.097, SE = 0.049, $p = 0.048$) were positively associated, supporting H2a. AH (β = 0.128, SE = 0.054, $p = 0.018$) and CH (β = 0.216, SE = 0.054, $p < 0.001$) were both positively associated with CP, and the two coefficients did not differ significantly (Δβ = 0.088, SE = 0.097, $p = 0.365$). These focal paths were small by conventional benchmarks [73] ($f^2 = 0.032$ for SCS→AH, 0.047 for TCS→CH, and 0.041 for CH→CP; 0.014 for AH→CP, below the 0.02 benchmark for a small effect).

Among the controls, familiarity predicted AH; usage frequency predicted CH and CP; and digital literacy and PIIT predicted AH, CH, and CP. For AH, digital literacy (β = 0.292) and PIIT (β = 0.210) exceeded SCS (β = 0.169) in magnitude, which suggests

that a stable technology disposition matters more than a single situational cue; this does not bear on H1a. The AH→CP coefficient in Table 8 (0.128) is smaller than the partial least squares structural equation modeling (PLS-SEM) estimate (0.399; Section 5.7) mainly because PLS-SEM includes no controls: without the control block (and with AH and CH as the only predictors), the ordinary least squares (OLS) coefficient rises to 0.345, which accounts for about 80% of the gap. The reduction is concentrated in digital literacy and PIIT (Supplementary Table S16), which are associated with both AH and CP (Table 8), so we regard the controlled estimate as the more conservative one.

Table 8. Ordinary least squares regression results.

	AH	**AH**	**CH**	**CH**	**CP**	**CP**
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Control variable						
Gender	−0.027	−0.022	0.017	0.032	−0.030	−0.030
Age	−0.003	0.019	−0.021	−0.017	−0.035	−0.030
Edu_CollegeBelow	0.020	0.017	−0.004	−0.005	−0.032	−0.034
Edu_Master	−0.021	−0.015	−0.025	−0.014	−0.042	−0.034
Profession_Private	−0.077 †	−0.067	0.045	0.067	0.068	0.069
Profession_STE	0.005	0.008	0.038	0.042	−0.001	−0.010
Profession_PUB	−0.037	−0.029	0.029	0.043	−0.002	−0.004
Profession_GOV	−0.021	−0.022	0.000	0.009	0.026	0.029
Profession_Foreign	0.035	0.033	0.012	0.017	−0.069	−0.076 †
Usage_frequency	0.062	0.014	0.155 **	0.087 †	0.148 **	0.106 *
Familiarity	0.188 ***	0.198 ***	0.017	0.031	0.083 †	0.055
Digital_literacy	0.292 ***	0.264 ***	0.326 ***	0.288 ***	0.307 ***	0.199 ***
PIIT	0.210 ***	0.169 ***	0.152 ***	0.101 *	0.187 ***	0.125 **
AI_Chatbot	−0.022	−0.002	−0.004	0.004	0.003	0.007
AI_Service	0.059	0.055	−0.007	−0.025	0.067 †	0.061 †
Main Effect						
SCS	0.169 ***	0.102 *	0.097 *	0.045	0.108 *	0.066
TCS	0.081	0.031	0.220 ***	0.181 ***	0.115 *	0.057
Attributions						
AH						0.128 *
CH						0.216 ***
Contingent Effect						
ST		0.186 ***		0.204 ***		
AT		0.058		0.109 *		
SCS*ST		0.217 ***		0.077		
SCS*AT		−0.179 **		−0.171 **		
TCS*ST		0.002		−0.125 †		
TCS*AT		−0.005		0.230 ***		
Max VIF	3.40	5.37	3.40	5.37	3.40	3.44
R^2	0.653	0.687	0.635	0.679	0.632	0.661
Adjusted R^2	0.638	0.669	0.619	0.660	0.616	0.645
F	43.947 ***	37.313 ***	40.628 ***	35.960 ***	40.106 ***	40.536 ***

Note(s): N = 415; † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; VIF refers to the variance inflation factor. When the control block is excluded, the standardized OLS coefficient for AH→CP rises from 0.128 to 0.345 ($p < 0.001$; model with AH and CH as the only predictors), approaching the PLS-SEM coefficient (0.399); see Supplementary Table S16 for the decomposition. Source: Authors' own work

5.3. Indirect Associations

Bootstrapping with 5000 resamples supported both proposed indirect associations. The indirect association of SCS with CP through AH was positive (β = 0.022, 95% CI [0.006, 0.040]), a small effect by conventional benchmarks [73], and the indirect association of TCS with CP through CH was likewise positive and small (β = 0.048, 95% CI [0.022, 0.081]), supporting H1b and H2b. The results indicate that communication style is associated with consumer preference partly through attributed human-like affective experience and cognitive understanding. Because SCS is also positively associated with CH, we estimated the two cross-path indirect associations. The indirect association of SCS with CP through CH was positive (β = 0.021, 95% CI [0.005, 0.040]), whereas the indirect association of TCS with CP through AH was not distinguishable from zero (β = 0.010, 95% CI [−0.002, 0.026]). The four estimates account for the attenuation of the direct coefficients between Models

5 and 6 of Table 8. The indirect associations of SCS through AH and through CH were of similar size, whereas for TCS only the indirect association through CH was distinguishable from zero.

5.4. Moderating Effects

Both aligned associations varied with perceived task demands, as predicted. The SCS × ST interaction was positive and significant for AH (β = 0.217, SE = 0.063, t = 3.44, $p < 0.001$), indicating that the SCS–AH association is stronger at higher ST and supporting H3a. The TCS × AT interaction was positive and significant for CH (β = 0.230, SE = 0.066, t = 3.48, $p < 0.001$), indicating that the TCS–CH association is stronger at higher AT and supporting H3b. At this sample size, the design could detect a single interaction effect of about 0.176 to 0.185 at 80% power and about 0.204 to 0.214 at 90% power (α = 0.05, two-sided), so both significant interactions exceed this benchmark. Adding the four interaction terms increased explained variance from $R^2 = 0.653$ to 0.687 for AH ($\Delta R^2 = 0.034$) and from $R^2 = 0.635$ to 0.679 for CH ($\Delta R^2 = 0.044$), indicating that task demands account for a modest share of the explained variance.

Consistent with H4a, the SCS × AT interaction was negative and significant for both AH (β = −0.179, SE = 0.065, t = −2.75, $p = 0.006$) and CH (β = −0.171, SE = 0.065, t = −2.63, $p = 0.009$). For the reverse interaction, TCS × ST was unrelated to AH (β = 0.002, SE = 0.063, t = 0.03, $p = 0.975$) and marginally negative for CH (β = −0.125, SE = 0.064, t = −1.95, $p = 0.052$). Because non-significance alone does not establish equivalence, we assess equivalence directly in Section 5.5.

Figures 2–5 plot the unstandardized conditional associations across the observed range of the moderator, with 95% confidence bands and Johnson–Neyman boundaries [74] (Supplementary Table S17). Figures 2 and 3 enter one product term at a time, whereas Figures 4 and 5 are drawn from the simultaneous models in Table 8, so the slopes in Figures 2 and 3 differ in size from the standardized interaction coefficients in Table 8. The figures show where each association is distinguishable from zero, not the size of the interactions tested in H3 and H4. The SCS–AH association was distinguishable from zero only when ST exceeded 4.85 (Figure 2), and the TCS–CH association only when AT exceeded 4.16 (Figure 3). The SCS–AH association was distinguishable from zero only when AT was below 5.48 (Figure 4), and the SCS–CH association only when AT was below 4.98 (Figure 5). Both associations weaken as AT rises, consistent with H4a. Outside these regions, the confidence bands include zero, so the plots indicate direction only.

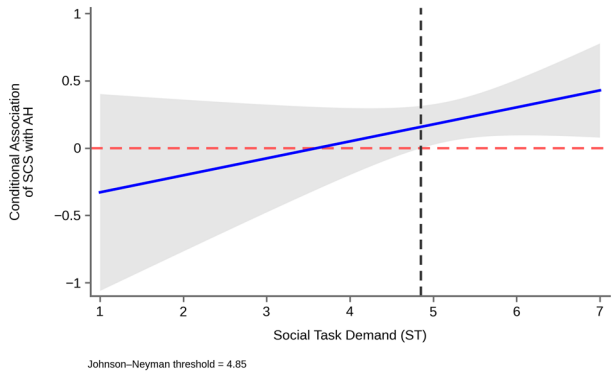


Figure 2. Conditional association of SCS with AH across ST. Note(s): The blue line shows the estimated unstandardized association, the gray band its 95% confidence band, the horizontal dashed line zero, and the vertical dashed line the Johnson-Neyman boundary. The same applies to the figures below.

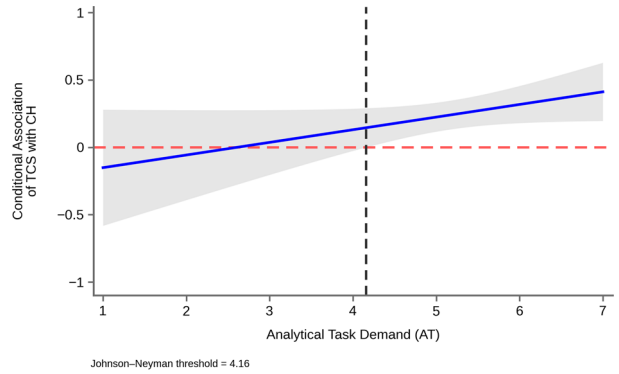


Figure 3. Conditional association of TCS with CH across AT.

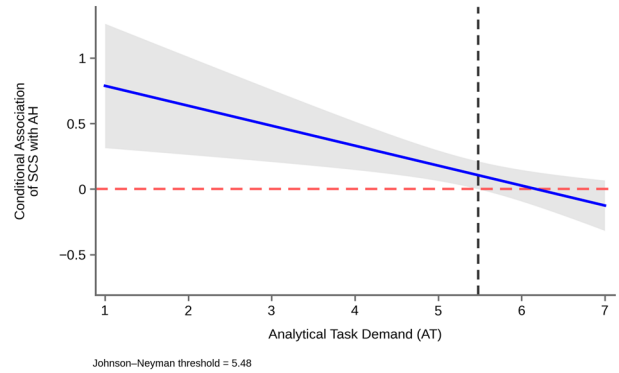


Figure 4. Conditional association of SCS with AH across AT.

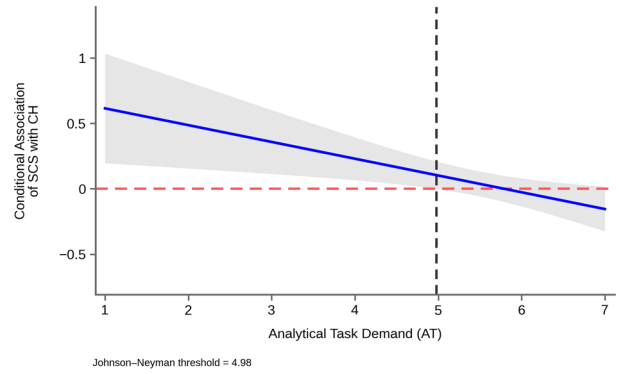


Figure 5. Conditional association of SCS with CH across AT.

The moderated indirect-association tests supported both aligned pathways. All estimates are standardized, with moderators mean-centered and indices obtained from PROCESS Model 7 (5000 bootstrap resamples). The index for SCS–AH–CP was positive and significant (index = 0.0278, bootstrap standard error (BootSE) = 0.0170, 95% CI [0.0011, 0.0651]), with the conditional indirect association rising from −0.0147 at low ST to 0.0131 at the mean and 0.0408 at high ST. The index for TCS–CH–CP was likewise significant (index = 0.0497, BootSE = 0.0225, 95% CI [0.0123, 0.0998]), rising from −0.0106 at low AT to 0.0391 at the mean and 0.0888 at high AT.

5.5. Tests of Asymmetry

The data are consistent with H4b for AH but not for CH. For AH, the Wald test ($\Delta\beta = -0.181$, SE = 0.085, $F(1, 391) = 4.52$, $p = 0.034$) and the SUR comparison ($p = 0.028$) indicate that the attenuation associated with SCS × AT was significantly greater than that associated with TCS × ST. The observed difference is smaller than the design's 80%

detection threshold for a within-equation comparison of this kind (about 0.24), so this significant result should be read with caution. For CH, neither the Wald test ($\Delta\beta = -0.046$, SE = 0.086, F(1, 391) = 0.29, $p = 0.592$) nor the SUR comparison ($p = 0.585$) showed a significant difference between the two misalignment coefficients. The equivalence bound was set with a sensitivity power analysis: given N = 415, the residual degrees of freedom of the moderation models (df = 391), and the standard errors of the focal interaction coefficients (SE $\approx$ 0.063–0.064), the design can detect an equivalence margin of about 0.157–0.159 at 80% power and 0.184–0.187 at 90% power ($\alpha = 0.05$, one-sided). We adopt ± 0.20 because it exceeds this margin, not because of the observed effects. For AH, the TCS $\times$ ST coefficient lies within this bound ($\beta = 0.002$, SE = 0.063, 90% CI [−0.102, 0.106], TOST $p = 0.001$), and equivalence holds for any bound of at least 0.11. Because the SCS $\times$ AT estimate ($\beta = -0.179$) also lies within ± 0.20, the bound does not indicate practical importance, and the asymmetry rests on the Wald and SUR comparisons. For CH, the corresponding interval extends beyond the lower bound ($\beta = -0.125$, SE = 0.064, 90% CI [−0.230, −0.020], TOST $p = 0.121$). Because TOST asks whether a single coefficient is negligibly small, not whether two coefficients differ, we treat these results as corroborating the Wald and SUR comparisons, not as an independent test of asymmetry.

5.6. Supplementary Endogeneity Assessments

5.6.1. Agent-Level Instrumental-Variable Sensitivity Results

We re-estimated the model by two-stage least squares using agent-level communication-style benchmarks as instruments (Table 9). The first stages indicated strong instrument relevance: SCS ($\beta = 0.415$, $p < 0.001$) and TCS ($\beta = 0.358$, $p < 0.001$) were strongly associated with their respective benchmarks, and the Cragg–Donald (53.268) and the cluster-robust Kleibergen–Paap (44.516) Wald F statistics exceeded the Stock–Yogo 10% critical value (7.03). The sample covers 14 distinct agents, the level at which the identifying variation arises, and all two-stage least squares standard errors are clustered by agent. Because 14 clusters are few for cluster-robust inference [75,76], we recomputed the p values of the focal second-stage coefficients with a wild cluster bootstrap using Webb weights (1000 replications); the inferences reported in Table 9 were unchanged. Even so, the cluster-robust Kleibergen–Paap statistic is unreliable with so few clusters. We therefore do not treat the IV p values as evidence of significance and read Table 9 for sign and relative magnitude. Several focal directions were broadly similar to the OLS results, although the magnitudes differed.

Table 9. Instrumental variable (IV) estimation results (bounded sensitivity check).

	AH	**AH**	**CH**	**CH**	**CP**	**CP**
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Main Effect						
SCS	0.404 ***	0.235 *	0.205 *	0.176 *	0.212 *	−0.006
TCS	0.196	0.079	0.489 ***	0.288 *	0.423 **	0.160
Attributions						
AH						0.281 ***
CH						0.361 ***
Contingent Effect						
ST		0.369 ***		0.312 ***		
AT		0.115		0.196 **		
SCS*ST		0.372 ***		−0.017		
SCS*AT		−0.298 **		−0.235 *		
TCS*ST		−0.061		−0.163 †		
TCS*AT		0.049		0.312 ***		
Control variables	YES	YES	YES	YES	YES	YES

Note(s): N = 415; † $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Models 1, 3 and 5 include 15 control variables plus SCS and TCS (k = 17); Models 2 and 4 add ST, AT and the four interaction terms (k = 23);

Model 6 adds AH and CH (k = 19). Interaction terms involving an endogenous regressor were instrumented by the corresponding products of the agent-level benchmarks and the moderators. R^2 is the second-stage R^2, and F is the model F statistic computed on the second-stage fit with the degrees of freedom implied by k. Identifying variation arises from 14 agents, so estimates are interpreted for sign and relative magnitude. Source: Authors' own work.

Table S9 reports the UCI bounds for the main-effect models (Models 1 and 3 of Table 9) as the allowed direct effect of the instruments increases from $\delta = 0$ to $\delta = 0.20$. The TCS→CH interval excluded zero throughout (lower bound 0.102 at $\delta = 0.20$). The SCS→AH interval excluded zero up to $\delta = 0.15$ (lower bound 0.018) and included zero at $\delta = 0.20$. The SCS→CH cross-path excluded zero under strict exogeneity (95% CI [0.047, 0.362]) but included zero from $\delta = 0.05$, so it is the most fragile of the paths. TCS→AH was not distinguishable from zero even under strict exogeneity (95% CI [−0.071, 0.463]). The aligned paths therefore keep their direction under moderate violations of the exclusion restriction, with TCS→CH the most robust and SCS→AH moderately so.

5.6.2. Gaussian Copula Sensitivity Results

To complement the IV sensitivity check, we conducted a Gaussian copula control-function sensitivity analysis [66]. After confirming that the endogenous variables deviate significantly from normality ($p < 0.001$), we generated inverse-normal copula terms via a semi-parametric approximation with continuous jittering. With these terms included in the structural equations (1000 bootstrap replications), the copula controls were not statistically significant in either the AH ($\beta_{SCS_copula} = 0.017$, $p = 0.939$; $\beta_{TCS_copula} = -0.281$, $p = 0.190$) or CH ($\beta_{SCS_copula} = 0.268$, $p = 0.229$; $\beta_{TCS_copula} = -0.169$, $p = 0.437$) models. The focal interactions were slightly attenuated but kept their sign and significance (SCS × ST on AH: $\beta = 0.198$, SE = 0.068, $p = 0.004$; TCS × AT on CH: $\beta = 0.207$, SE = 0.070, $p = 0.003$); the bootstrap standard errors are marginally larger than their OLS counterparts (0.063 and 0.066), as expected once two control functions are added. The analysis gives no sign that unobserved dependence between perceived communication style and the structural errors substantially biases the focal estimates, but we treat it as a sensitivity check, not a definitive test [67,68].

5.7. Robustness Checks

Six checks examined the robustness of the findings to estimation approach, model specification, outcome operationalization, and the way perceived task demands and communication modality enter the model, and assessed out-of-sample predictive power.

Alternative estimation. PLS-SEM reproduced the dual-pathway pattern. Because the PLS model estimates the structural paths without the control block used in Table 8 and additionally includes ST and AT as predictors of CP, the path magnitudes are not directly comparable with the OLS coefficients; the relevant comparison is the configuration of signs and significance (Table S10): SCS→AH ($\beta = 0.195$, $p < 0.01$), TCS→CH ($\beta = 0.318$, $p < 0.001$), AH→CP ($\beta = 0.399$, $p < 0.001$), CH→CP ($\beta = 0.351$, $p < 0.001$), with both aligned indirect associations significant (SCS→AH→CP: $\beta = 0.078$, $p < 0.01$; TCS→CH→CP: $\beta = 0.112$, $p < 0.001$). The two cross-path indirect associations reproduce the pattern of Section 5.3: SCS→CH→CP was significant ($\beta = 0.042$, $p < 0.05$), whereas TCS→AH→CP was not ($\beta = 0.045$, $p > 0.10$). Estimated without controls, the OLS and PLS-SEM coefficients for AH→CP are much closer (0.345 vs. 0.399, against 0.128 vs. 0.399 with controls; Supplementary Table S16).

Regional heterogeneity. Adding regional indicators for East, Central, Northwest, and Overseas, with Southwest China as the reference, left the focal coefficients stable in sign and significance (Table S11).

Alternative outcomes. Replacing CP with adoption intention [26] and recommendation intention [77] preserved the positive associations of AH and CH with both alternative outcomes (Table S12). SCS and TCS also remained positively associated with both outcomes, and their coefficients were smaller once AH and CH entered the equation: for adoption intention the SCS coefficient fell by 0.052 and the TCS coefficient by 0.060, and for recommendation intention by 0.051 and 0.064. AH and CH added a similar amount of explained variance across the three outcomes (0.029 for CP, 0.042 for adoption intention, and 0.039 for recommendation intention), so the pattern is not specific to the operationalization of CP.

Alternative operationalization of perceived task demands. To check that the alignment pattern is not an artifact of the continuous interaction specification, we divided the sample by dominant task demand. Participants whose mean ST exceeded their mean AT by at least half a scale point formed the social-demand group (N = 121), and those whose mean AT exceeded their mean ST by at least half a point formed the analytical-demand group (N = 190). The remaining 104 participants (25.1%), whose two ratings fell within half a point of each other, had no dominant demand and were not classified. We use a fixed cut-off rather than a within-person significance test because comparing three items with four provides no meaningful basis for such a test (Table S13). In the social-demand group, SCS predicted AH ($\beta = 0.341$, $p < 0.001$), whereas TCS did not ($\beta = 0.091$, $p > 0.10$). In the analytical-demand group, TCS predicted CH ($\beta = 0.323$, $p < 0.001$), whereas SCS was essentially unrelated to CH ($\beta = -0.0002$, $p > 0.10$); the within-equation difference was significant ($\Delta\beta = 0.323$, SE = 0.110, t = 2.935, $p = 0.004$). TCS was also associated with AH in this group ($\beta = 0.135$, $p = 0.032$), so the subsample patterns reflect differences in strength, not exclusive routes. Because the half-point cut-off excludes a quarter of the sample, we repeated the split with a looser cut-off (0.25) and stricter cut-offs (0.75, 1.00, and 1.25; Table S13), which yield social-demand and analytical-demand groups of N = 138 and 215, N = 88 and 157, N = 64 and 130, and N = 43 and 94, respectively. The SCS→AH coefficient in the social-demand group ($\beta = 0.318$, 0.371, 0.398, and 0.532) and the TCS→CH coefficient in the analytical-demand group ($\beta = 0.311$, 0.335, 0.406, and 0.420) remained positive and significant at every cut-off, whereas the cross-paths (TCS→AH in the social-demand group and SCS→CH in the analytical-demand group) remained non-significant.

Communication modality. Because the sample spans voice- and text-based agents, we tested whether the proposed relationships hold across communication modalities. Voice assistants (N = 208) were coded 1 and text-based agents—generative chatbots and online service agents—(N = 207) coded 0; the agent-category indicators were dropped to avoid collinearity with the modality variable. Neither focal pathway differed significantly by modality: modality did not moderate the SCS–AH association or the TCS–CH association (Table S14). Two non-focal cross-path interactions were significant at the 10% level: voice-based agents showed a stronger TCS–AH association ($\beta = 0.111$, SE = 0.063, $p = 0.080$) and a weaker SCS–CH association ($\beta = -0.118$, SE = 0.065, $p = 0.070$). Because these effects were not hypothesized, we report them as exploratory.

Out-of-sample predictive power. To assess predictive relevance beyond the estimation sample, we ran PLSpredict (10-fold cross-validation, 10 repetitions; Supplementary Table S15) [78]. Q^2predict was positive for all nine indicators of AH, CH, and CP (0.347–0.521), so the model predicts better than the indicator means. Relative to the linear-model benchmark, the PLS-SEM prediction error (root mean square error, RMSE) was lower for two of the three CP indicators (CP2 and CP3) and higher for CP1, which, under the guideline of Shmueli et al. [78], indicates medium predictive power for CP. For the six AH and CH indicators, the linear benchmark had the lower RMSE in every case, so the PLS model offers no advantage over a linear model for the two attributions, and it also had the lower mean absolute error (MAE) for all nine indicators. We therefore describe the out-of-sample

predictive power as modest. This analysis concerns the prediction of consumer preference; it does not show that AH and CH predict preference beyond warmth or PEI, which Study 1b addresses (Section 3.5).

6. General Discussion

6.1. Key Findings

This study examined how perceived communication style is associated with attributions of human-like affective experience and cognitive understanding to conversational AI agents, and whether perceived task demands condition those associations. Study 1 provided evidence that AH and CH are distinguishable from warmth, competence, PEI, PCI, experience, agency, and each other, and that, jointly, they explain additional variance in consumer preference beyond these constructs. Study 2 showed that SCS is positively associated with AH and TCS is positively associated with CH; SCS also has a positive cross-path association with CH. Both AH and CH are positively associated with CP. The SCS–AH association and the corresponding indirect association through AH are stronger when ST is higher, and the TCS–CH association and the corresponding indirect association through CH are stronger when AT is higher. SCS is indirectly associated with preference through both attributions, whereas only the indirect association of TCS through CH was distinguishable from zero; these indirect associations are small.

The two observed forms of misalignment were not equivalent. The estimated associations between SCS and both attributions were weaker at higher AT, whereas the TCS $\times$ ST coefficient fell within the equivalence bound only for AH. Direct coefficient comparisons are consistent with asymmetry for AH but not for CH. We did not test whether this asymmetry differs formally between AH and CH. The pattern does not imply that TCS is always inconsequential in socially demanding interactions, nor does it identify the unmeasured psychological process underlying the asymmetry. The agent-level IV analysis, a bounded sensitivity check and not a test of causal identification, yielded broadly similar directions for several focal estimates: the TCS→CH path was the most robust to relaxing the exclusion restriction, the SCS→AH path was moderately robust, and the SCS→CH cross-path was the most fragile.

6.2. Theoretical Contributions

First, the study contributes to AI communication-style research by shifting the explanatory focus from downstream evaluative and behavioral responses to the AH and CH attributions with which they are associated. Prior work has mainly examined trust, satisfaction, and use intentions, with the relative effectiveness of SCS and TCS varying across users, products, and task contexts [5,11,24,26]. We show that perceived communication style is associated with attributions of human-like mental qualities to an agent: SCS is positively associated with AH and CH, TCS is positively associated with CH but not distinguishably with AH, and both attributions are associated with consumer preference. This pattern may help explain why different communication styles are linked to favorable responses under different conditions, without assuming a universally superior style.

The positive SCS→CH cross-path, together with the non-significant TCS→AH cross-path, suggests that the two attributions may not be equally reachable through either style, although we did not test this difference directly. Two post hoc explanations are possible, neither tested here. First, producing contextually appropriate, well-timed social language requires interpreting the consumer's situation, so SCS may carry some evidence of understanding in addition to signaling warmth, whereas task-focused language can be generated from fixed templates without implying any inner experience and therefore offers little evidence of affect. Second, consumers may attribute agency to AI more readily than

experience [34,35], so weaker cues suffice to support CH while AH requires stronger and more specific evidence than TCS can offer. This pattern resembles that observed for AH in the misalignment tests (Section 5.5) and may reflect affective attributions requiring more evidence than cognitive attributions do, an interpretation that remains speculative. The partial overlap of CH with PEI and warmth in Study 1b (Section 3.5) is consistent with the first explanation: attributing understanding may rest partly on perceived responsiveness to the consumer.

Second, the study contributes to research on the correlates of AI mind perception by examining the two established dimensions of communication style. Existing research shows that mind perception of AI agents varies with functional role, behavioral style, and other interaction cues [13,14]. More recent work shows that anthropomorphic conversation styles, verbal embodiment, and affective speech are associated with perceived humanness or experience- and agency-related mind perception [4,15,16], while a systematic review identifies AI and human–AI interaction characteristics as broad antecedent classes [79]. Extending this literature, we show how established SCS and TCS communication styles are associated with affective and cognitive human-likeness (AH and CH). The contribution lies in specifying these associations; we do not propose a new affective–cognitive taxonomy.

Third, the study contributes to task-compatibility research by showing that perceived task demands condition the strength of the association between communication style and AI human-likeness attributions (AH and CH). Prior research demonstrates that consumers respond differently to algorithms and artificial agents across objective, subjective, social, and analytical tasks, and that design–task compatibility is associated with acceptance and task assignment [15,21–23]. Rather than treating tasks as mutually exclusive categories, we conceptualize ST and AT as continuous demands that can coexist within the same interaction. The SCS–AH association is stronger when ST is higher, whereas the TCS–CH association is stronger when AT is higher. The findings extend task-fit logic from matching an AI to a task category to understanding how the strength of specific communication–attribution links varies with task demands.

Fourth, the study contributes to communication–task misalignment research by showing that opposite forms of mismatch need not be associated with symmetric attributional consequences. Existing task-fit accounts primarily address whether an AI attribute matches task requirements, with less attention to whether different mismatches are penalized equally [15,21,25]. For AH, the TCS $\times$ ST coefficient fell within the equivalence bound, whereas Wald and SUR comparisons indicated significantly greater attenuation for SCS $\times$ AT. No corresponding asymmetry was found for CH, and the AH result rests on a single test that needs replication.

6.3. Practical Implications

Because the findings are associational and the indirect associations are small, we offer the implications below as heuristics for design and experimentation, not as fixed rules. The data show how SCS and TCS are associated with AH and CH under different perceived task demands; they do not evaluate the effectiveness of either style in any specific service scenario. The SCS–AH association was stronger when perceived social demands were higher (e.g., when consumers need their concerns acknowledged), and the TCS–CH association was stronger when perceived analytical demands were higher (e.g., when consumers need to compare options or check policy details). Managers of e-commerce conversational AI agents might therefore test whether matching agent communication to perceived task demands, rather than applying a single persona uniformly across a platform, alters these attributions. A simple starting point is to compare the relative levels of ST and

AT before leaning toward relational acknowledgment or task-focused explanation, treating this as a hypothesis to test.

The asymmetry findings suggest, as a working hypothesis, that social cues may need careful calibration. The associations of SCS with both AH and CH were weaker at higher AT, so relational content inserted indiscriminately into interactions with high analytical demands, such as comparing specifications or checking policy conditions, may be less likely to support these attributions. One approach is to keep a baseline of clarity in every exchange and vary social cues with the assessed task profile, updating that profile turn by turn rather than only at intake. Expressions of dissatisfaction could serve as a cue toward ST, and requests to compare options or specifications as a cue toward AT, with relational content scaled down as AT rises within a session. Developers could pilot this adjustment in A/B tests that evaluate AH, CH, and CP separately instead of relying on a single global human-likeness score, treating the switching logic as a proposition to test, not a specification.

A final implication concerns consumer welfare. Higher SCS may be associated with a greater tendency for consumers to attribute human-like affective experience, even though such attributions cannot be verified from observable system outputs. Consumers who infer concern may disclose more information, rely more readily on recommendations, or form expectations that the system cannot substantiate; we did not examine these possibilities. The findings do not argue against relational communication, which may be appropriate in interactions with high social demands. Proportionate and transparent use seems advisable, particularly when an e-commerce conversational AI agent moves from supportive dialogue to consequential advice involving price or policy conditions, as summarized in Figure 6.

General Implications	What the Results Suggest	Propositions for Future Validation
• Dimension-specific persona design may be worth testing against generic anthropomorphism. • AH and CH could be evaluated separately rather than as a single human-likeness score.	• SCS is more strongly associated with AH when social task demands are higher (e.g., when consumers need their concerns acknowledged). • TCS is more strongly associated with CH when analytical task demands are higher (e.g., when consumers need to compare options or check policy details).	• Developers could assess the relative social and analytical demands of an interaction before adjusting the balance of SCS and TCS. • Relational language may need careful calibration under high analytical demands. • These propositions should be piloted, for example in A/B tests, before adoption.

Figure 6. Recommendations and insights for e-commerce conversational AI agent developers.

6.4. Limitations and Future Research

This study has three main limitations. First, the sample comprised Chinese consumers, and half of the Study 2 respondents (50.1%) evaluated voice assistants, which are less tightly coupled to purchase than transaction-embedded service agents. CP also captures preference for the focal agent relative to other AI agents, not relative to human agents. The findings may therefore not generalize to other cultural settings, to transaction-embedded service agents, or to AI-versus-human substitution decisions.

Second, communication style was measured as a perception rather than manipulated, so the associations cannot be interpreted causally. All four interaction terms combine Wave 1 variables from the same respondents, so the moderation and misalignment tests rest on same-wave, same-source data, and the marker evidence is weak (Section 4.4).

TCS and AT are also conceptually close and correlated (r = 0.621; HTMT = 0.663), so TCS × AT may partly reflect a halo that the design cannot separate from agent–task fit; independent ratings of task demands would help. The endogeneity analyses are sensitivity checks, not tests of causal identification: the agent-level instruments probably violate the exclusion restriction because communication design covaries with agent capability, which may affect CH directly; the identifying variation comes from only 14 agents; and Gaussian copula estimates can be sensitive to model and sample characteristics [67,68]. The mechanism proposed for H4b, that a misplaced social cue loses credibility, was not measured (cue diagnosticity, authenticity, and expectancy violation were not assessed) and awaits direct tests. Future work should use experimental, behavioral, or field data and examine dynamic style adaptation across multi-turn recommendation, transaction support, and service-recovery encounters.

Third, experience and agency were measured only in Study 1b, a separate cross-sectional, single-source sample, so the Study 2 indirect-association tests do not control for them. Study 2 also did not measure warmth, competence, PEI, PCI, or dispositional anthropomorphism, so the associations of SCS and TCS with AH and CH may partly reflect these evaluations or traits, and the construct distinctiveness shown in Study 1 cannot establish that the Study 2 associations are specific to human-like mind attribution. AH and CH should accordingly be read as measured attributions, not as evidence of distinct underlying mind-perception processes. The evidence for the new AH and CH scales is also initial: content validation involved four experts, the pretest included 45 respondents, and measurement invariance across samples was not tested. The significant indirect associations (β = 0.021–0.048) and focal direct paths ($f^2 \leq 0.047$) are small, so the implications in Section 6.3 are hypotheses to test, not prescriptions. Future research should measure these constructs within a single longitudinal design and test the scales for measurement invariance across samples.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/jtaer21100371/s1, Figure S1: Sample recruitment, screening, and retention; Table S1: Prior research on communication style; Table S2: Research gaps in communication-style research on AI agents; Table S3: Constructs and measurement items; Table S4: Descriptive statistics and correlations; Table S5: Study 1b: Reliability, convergent validity, and descriptive statistics; Table S6: Confirmatory factor models for AH, CH, experience, agency, and adjacent constructs; Table S7: Hierarchical regression of consumer preference on adjacent constructs, AH, and CH; Table S8: Variance inflation factors for focal predictors in the moderated models; Table S9: Plausible Exogeneity Analysis Using the UCI Method; Table S10: PLS-SEM estimation results; Table S11: Regression results with additional regional control variables; Table S12: Regression estimates using alternative dependent measures; Table S13: Robustness checks with alternative sample-splitting cut-offs; Table S14: Exploratory post-hoc analysis: The moderating role of communication modality; Table S15: PLSpredict Assessment of Out-of-Sample Predictive Power; Table S16: Standardized focal-path estimates across estimators and control blocks; Table S17: Johnson–Neyman regions of significance for Figures 2–5.

Author Contributions: Conceptualization, J.W. and Y.L.; methodology, J.W. and X.Z.; software, J.W.; validation, J.W., X.Z. and L.Z.; formal analysis, X.Z.; investigation, J.W. and Y.Q.; data curation, X.Z. and Y.Q.; writing—original draft preparation, J.W.; writing—review and editing, Y.L. and L.Z.; visualization, Y.Q.; project administration, Y.L.; funding acquisition, J.W. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement: This study used anonymous survey responses containing no personally identifiable or sensitive data, and the risk to participants was no greater than minimal. The research was conducted in accordance with the Declaration of Helsinki, and the authors' institution confirmed that formal ethics-committee approval is not required for anonymous, minimal-risk consumer survey research.

Informed Consent Statement: Written informed consent was obtained from every participant prior to their inclusion in the study.

Data Availability Statement: The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Chen, Q.; Lu, Y.; Gong, Y.; Xiong, J. Can AI chatbots help retain customers? Impact of AI service quality on customer loyalty. *Internet Res.* **2023**, *33*, 2205–2243. [CrossRef]
2. Mari, A.; Mandelli, A.; Algesheimer, R. Empathic voice assistants: Enhancing consumer responses in voice commerce. *J. Bus. Res.* **2024**, *175*, 114566. [CrossRef]
3. Wang, L.; Bae, S. Encourage online consumers to embrace voice shopping: Roles of tasks, technology, and individual characteristics. *J. Theor. Appl. Electron. Commer. Res.* **2025**, *20*, 293. [CrossRef]
4. Bergner, A.S.; Hildebrand, C.; Häubl, G. Machine talk: How verbal embodiment in conversational AI shapes consumer–brand relationships. *J. Consum. Res.* **2023**, *50*, 742–764. [CrossRef]
5. Keeling, K.; McGoldrick, P.; Beatty, S. Avatars as salespeople: Communication style, trust, and intentions. *J. Bus. Res.* **2010**, *63*, 793–800. [CrossRef]
6. Hertz, N.; Wiese, E. Good advice is beyond all price, but what if it comes from a machine? *J. Exp. Psychol. Appl.* **2019**, *25*, 386–395. [CrossRef] [PubMed]
7. Pizzi, G.; Vannucci, V.; Mazzoli, V.; Donvito, R. I, chatbot! The impact of anthropomorphism and gaze direction on willingness to disclose personal information and behavioral intentions. *Psychol. Mark.* **2023**, *40*, 1372–1387. [CrossRef]
8. Williams, K.C.; Spiro, R.L. Communication style in the salesperson-customer dyad. *J. Mark. Res.* **1985**, *22*, 434–442. [CrossRef]
9. Tsai, W.-H.S.; Liu, Y.; Chuan, C.-H. How chatbots' social presence communication enhances consumer engagement: The mediating role of parasocial interaction and dialogue. *J. Res. Interact. Mark.* **2021**, *15*, 460–482. [CrossRef]
10. Liao, J.; Chen, K.; Qi, J.; Li, J.; Yu, I.Y. Creating immersive and parasocial live shopping experience for viewers: The role of streamers' interactional communication style. *J. Res. Interact. Mark.* **2023**, *17*, 140–155. [CrossRef]
11. Chattaraman, V.; Kwon, W.-S.; Gilbert, J.E.; Ross, K. Should AI-Based, conversational digital assistants employ social- or task-oriented interaction style? A task-competency and reciprocity perspective for older adults. *Comput. Hum. Behav.* **2019**, *90*, 315–330. [CrossRef]
12. Wright, J.L.; Lakhmani, S.G.; Chen, J.Y.C. Bidirectional communications in human-agent teaming: The effects of communication style and feedback. *Int. J. Hum.-Comput. Interact.* **2022**, *38*, 1972–1985. [CrossRef]
13. Wang, X.; Krumhuber, E.G. Mind perception of robots varies with their economic versus social function. *Front. Psychol.* **2018**, *9*, 1230. [CrossRef] [PubMed]
14. Cucciniello, I.; Sangiovanni, S.; Maggi, G.; Rossi, S. Mind perception in HRI: Exploring users' attribution of mental and emotional states to robots with different behavioural styles. *Int. J. Soc. Robot.* **2023**, *15*, 867–877. [CrossRef] [PubMed]
15. Li, B.; Yao, R.; Nan, Y. How does anthropomorphism promote consumer responses to social chatbots: Mind perception perspective. *Internet Res.* **2025**, *35*, 2471–2495. [CrossRef]
16. Klüber, K.; Schwaiger, K.; Onnasch, L. Affect-enhancing speech characteristics for robotic communication. *Int. J. Soc. Robot.* **2025**, *17*, 315–333. [CrossRef]
17. Kühne, R.; Peter, J. Anthropomorphism in human–robot interactions: A multidimensional conceptualization. *Commun. Theory* **2023**, *33*, 42–52. [CrossRef]
18. Li, Y.; Liang, Z.; Wang, Y.; Chang, Y. The negative effect of service robots' affective human-likeness on consumer satisfaction in frontline service encounters. *Int. J. Hosp. Manag.* **2023**, *115*, 103603. [CrossRef]
19. Kim, S.J.; Jin, S.J.; Chung, Y. The impact of perceived human likeness of ChatGPT on continuous use intention: The mediating effects of perceived benefits/risks and the moderated mediation effects of AI literacy. *SAGE Open* **2026**, *16*, 21582440261455627. [CrossRef]
20. Kim, T.H.; Im, H. Mental and physical humanlikeness in artificial intelligence influencers: Effects on humanness, eeriness, and consumer responses. *J. Consum. Behav.* **2026**, *25*, 102–117. [CrossRef]

21. Castelo, N.; Bos, M.W.; Lehmann, D.R. Task-dependent algorithm aversion. *J. Mark. Res.* **2019**, *56*, 809–825. [CrossRef]
22. Longoni, C.; Cian, L. Artificial intelligence in utilitarian vs. hedonic contexts: The "word-of-machine" effect. *J. Mark.* **2022**, *86*, 91–108. [CrossRef]
23. Wiese, E.; Weis, P.P.; Bigman, Y.E.; Kapsaskis, K.; Gray, K. It's a match: Task assignment in human–robot collaboration depends on mind perception. *Int. J. Soc. Robot.* **2022**, *14*, 141–148. [CrossRef]
24. Xu, Y.; Zhang, J.Y.; Deng, G.K. Enhancing customer satisfaction with chatbots: The influence of communication styles and consumer attachment anxiety. *Front. Psychol.* **2022**, *13*, 902782. [CrossRef] [PubMed]
25. Karahanna, E.; Agarwal, R.; Angst, C.M. Reconceptualizing compatibility beliefs in technology acceptance research. *MIS Q.* **2006**, *30*, 781–804. [CrossRef]
26. Murtaza, Z.; Sharma, I.; Carbonell, P. Examining chatbot usage intention in a service encounter: Role of task complexity, communication style, and brand personality. *Technol. Forecast. Soc. Change* **2024**, *209*, 123806. [CrossRef]
27. Zhang, D.; Fu, L.; Ma, J.; Chen, C. Social-oriented versus task-oriented streamer interaction styles on live streaming e-commerce: Empirical research in China. *J. Consum. Behav.* **2024**, *23*, 1995–2008. [CrossRef]
28. Liu, Y.; Huang, Y.; Fan, H. Influence tactics, relational conditions, and key account managers' performance. *Ind. Mark. Manag.* **2018**, *73*, 220–231. [CrossRef]
29. Packard, G.; Li, Y.; Berger, J. When language matters. *J. Consum. Res.* **2024**, *51*, 634–653. [CrossRef]
30. Mori, M.; MacDorman, K.F.; Kageki, N. The uncanny valley. *IEEE Robot. Autom. Mag.* **2012**, *19*, 98–100. [CrossRef]
31. Riek, L.D.; Rabinowitch, T.-C.; Chakrabarti, B.; Robinson, P. How anthropomorphism affects empathy toward robots. In Proceedings of the 4th ACM/IEEE International Conference on Human Robot Interaction, La Jolla, CA, USA, 9–13 March 2009; pp. 245–246. [CrossRef]
32. Mende, M.; Scott, M.L.; van Doorn, J.; Grewal, D.; Shanks, I. Service robots rising: How humanoid robots influence service experiences and elicit compensatory consumer responses. *J. Mark. Res.* **2019**, *56*, 535–556. [CrossRef]
33. Zhang, L.; Mo, L.; Sun, X.; Zhou, Z.; Ren, J. How visual and mental human-likeness of virtual influencers affects customer–brand relationship on e-commerce platform. *J. Theor. Appl. Electron. Commer. Res.* **2025**, *20*, 200. [CrossRef]
34. Gray, H.M.; Gray, K.; Wegner, D.M. Dimensions of mind perception. *Science* **2007**, *315*, 619. [CrossRef] [PubMed]
35. Gray, K.; Wegner, D.M. Feeling robots and human zombies: Mind perception and the uncanny valley. *Cognition* **2012**, *125*, 125–130. [CrossRef] [PubMed]
36. Cuddy, A.J.C.; Fiske, S.T.; Glick, P. Warmth and competence as universal dimensions of social perception: The stereotype content model and the BIAS map. *Adv. Exp. Soc. Psychol.* **2008**, *40*, 61–149. [CrossRef]
37. Kim, J.; Im, I. Anthropomorphic response: Understanding interactions between humans and artificial intelligence agents. *Comput. Hum. Behav.* **2023**, *139*, 107512. [CrossRef]
38. Moussawi, S.; Koufaris, M. Perceived intelligence and perceived anthropomorphism of personal intelligent agents: Scale development and validation. In *Proceedings of the 52nd Hawaii International Conference on System Sciences, Maui, HI, USA, 8–11 January 2019*; University of Hawai'i at Mānoa: Honolulu, HI, USA, 2019; pp. 115–124. Available online: https://hdl.handle.net/10125/59452 (accessed on 12 October 2026).
39. Feldman, J.M.; Lynch, J.G., Jr. Self-generated validity and other effects of measurement on belief, attitude, intention, and behavior. *J. Appl. Psychol.* **1988**, *73*, 421–435. [CrossRef]
40. Purohit, D.; Srivastava, J. Effect of manufacturer reputation, retailer reputation, and product warranty on consumer judgments of product quality: A cue diagnosticity framework. *J. Consum. Psychol.* **2001**, *10*, 123–134. [CrossRef] [PubMed]
41. Epley, N.; Waytz, A.; Cacioppo, J.T. On seeing human: A three-factor theory of anthropomorphism. *Psychol. Rev.* **2007**, *114*, 864–886. [CrossRef] [PubMed]
42. Guo, Y.; Zhang, K.; Wang, C. Way to success: Understanding top streamer's popularity and influence from the perspective of source characteristics. *J. Retail. Consum. Serv.* **2022**, *64*, 102786. [CrossRef]
43. Huang, M.H.; Rust, R.T. The caring machine: Feeling AI for customer care. *J. Mark.* **2024**, *88*, 1–23. [CrossRef]
44. Jin, F.; Zhang, X.D. Artificial intelligence or human: When and why consumers prefer AI recommendations. *Inf. Technol. People* **2025**, *38*, 279–303. [CrossRef]
45. Riva, P.; Aureli, N.; Silvestrini, F. Social influences in the digital era: When do people conform more to a human being or an artificial intelligence? *Acta Psychol.* **2022**, *229*, 103681. [CrossRef] [PubMed]
46. Liang, Y.; Huang, Z.; Su, L. Too time-crunched to seek variety: The influence of parenting motivation on consumer variety seeking. *J. Mark. Res.* **2023**, *60*, 812–833. [CrossRef]
47. Huang, J.; Zhu, G.; Luo, Y.; Lu, J.; Wang, Q. Algorithm appreciation in privacy disclosure: How do the agent types (AI vs. human) affect privacy disclosure? *Inf. Technol. People* **2026**, *ahead of print*. [CrossRef]
48. Cheung, G.W.; Rensvold, R.B. Evaluating goodness-of-fit indexes for testing measurement invariance. *Struct. Equ. Model.* **2002**, *9*, 233–255. [CrossRef] [PubMed]

49. Podsakoff, P.M.; MacKenzie, S.B.; Lee, J.-Y.; Podsakoff, N.P. Common method biases in behavioral research: A critical review of the literature and recommended remedies. *J. Appl. Psychol.* **2003**, *88*, 879–903. [CrossRef] [PubMed]
50. Hulland, J.; Baumgartner, H.; Smith, K.M. Marketing survey research best practices: Evidence and recommendations from a review of JAMS articles. *J. Acad. Mark. Sci.* **2018**, *46*, 92–108. [CrossRef]
51. Chen, S.; Li, X.; Liu, K.; Wang, X. Chatbot or human? The impact of online customer service on consumers' purchase intentions. *Psychol. Mark.* **2023**, *40*, 2186–2200. [CrossRef]
52. Cornesse, C.; Blom, A.G. Response quality in nonprobability and probability-based online panels. *Sociol. Methods Res.* **2023**, *52*, 879–908. [CrossRef]
53. Greszki, R.; Meyer, M.; Schoen, H. Exploring the effects of removing "too fast" responses and respondents from web surveys. *Public Opin. Q.* **2015**, *79*, 471–503. [CrossRef]
54. Yu, R.; Xu, X.; Peng, S. The impact of individual AI proficiency on human-agent collaboration: Higher sensitivity to discern the comprehension ability of intelligent agents for users with higher AI proficiency levels. *Int. J. Ind. Ergon.* **2025**, *107*, 103745. [CrossRef]
55. Qadri, U.A.; Moustafa, A.M.A.; Abd Ghani, M. They misused me! Digital literacy's dual role in AI marketing manipulation and unethical young consumer behavior. *Young Consum.* **2025**, *26*, 744–764. [CrossRef]
56. Zhang, H.; Li, B.; Hu, B.; Ai, P. Exploring the role of personal innovativeness on purchase intention of artificial intelligence products: An investigation using social influence theory and value-based adoption model. *Int. J. Hum.-Comput. Interact.* **2026**, *42*, 752–766. [CrossRef]
57. Lindell, M.K.; Whitney, D.J. Accounting for common method variance in cross-sectional research designs. *J. Appl. Psychol.* **2001**, *86*, 114–121. [CrossRef] [PubMed]
58. Malhotra, N.K.; Kim, S.S.; Patil, A. Common method variance in IS research: A comparison of alternative approaches and a reanalysis of past studies. *Manag. Sci.* **2006**, *52*, 1865–1883. [CrossRef]
59. Miller, B.K.; Simmering, M.J. Attitude toward the color blue: An ideal marker variable. *Organ. Res. Methods* **2023**, *26*, 409–440. [CrossRef]
60. Simmering, M.J.; Fuller, C.M.; Richardson, H.A.; Ocal, Y.; Atinc, G.M. Marker variable choice, reporting, and interpretation in the detection of common method variance: A review and demonstration. *Organ. Res. Methods* **2015**, *18*, 473–511. [CrossRef]
61. Williams, L.J.; Hartman, N.; Cavazotte, F. Method variance and marker variables: A review and comprehensive CFA marker technique. *Organ. Res. Methods* **2010**, *13*, 477–514. [CrossRef]
62. Armstrong, J.S.; Overton, T.S. Estimating nonresponse bias in mail surveys. *J. Mark. Res.* **1977**, *14*, 396–402. [CrossRef]
63. Angrist, J.D.; Pischke, J.-S. *Mostly Harmless Econometrics: An Empiricist's Companion*; Princeton University Press: Princeton, NJ, USA, 2009. [CrossRef]
64. Hayes, A.F. *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach*, 3rd ed.; Guilford Press: New York, NY, USA, 2022. Available online: https://www.guilford.com/books/Introduction-to-Mediation-Moderation-and-Conditional-Process-Analysis/Andrew-Hayes/9781462549030 (accessed on 12 October 2026).
65. Conley, T.G.; Hansen, C.B.; Rossi, P.E. Plausibly exogenous. *Rev. Econ. Stat.* **2012**, *94*, 260–272. [CrossRef]
66. Park, S.; Gupta, S. Handling endogenous regressors by joint estimation using copulas. *Mark. Sci.* **2012**, *31*, 567–586. [CrossRef]
67. Becker, J.-M.; Proksch, D.; Ringle, C.M. Revisiting Gaussian copulas to handle endogenous regressors. *J. Acad. Mark. Sci.* **2022**, *50*, 46–66. [CrossRef]
68. Liengaard, B.D.; Becker, J.-M.; Bennedsen, M.; Heiler, P.; Taylor, L.N.; Ringle, C.M. Dealing with regression models' endogeneity by means of an adjusted estimator for the Gaussian copula approach. *J. Acad. Mark. Sci.* **2025**, *53*, 279–299. [CrossRef]
69. Nunnally, J.C.; Bernstein, I.H. *Psychometric Theory*, 3rd ed.; McGraw-Hill: New York, NY, USA, 1994.
70. Fornell, C.; Larcker, D.F. Evaluating structural equation models with unobservable variables and measurement error. *J. Mark. Res.* **1981**, *18*, 39–50. [CrossRef]
71. Hu, L.; Bentler, P.M. Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Struct. Equ. Model.* **1999**, *6*, 1–55. [CrossRef]
72. Henseler, J.; Ringle, C.M.; Sarstedt, M. A new criterion for assessing discriminant validity in variance-based structural equation modeling. *J. Acad. Mark. Sci.* **2015**, *43*, 115–135. [CrossRef]
73. Cohen, J. *Statistical Power Analysis for the Behavioral Sciences*, 2nd ed.; Lawrence Erlbaum Associates: Hillsdale, NJ, USA, 1988.
74. Busenbark, J.R.; Graffin, S.D.; Campbell, R.J.; Lee, E.Y. A marginal effects approach to interpreting main effects and moderation. *Organ. Res. Methods* **2022**, *25*, 147–169. [CrossRef]
75. Cameron, A.C.; Gelbach, J.B.; Miller, D.L. Bootstrap-based improvements for inference with clustered errors. *Rev. Econ. Stat.* **2008**, *90*, 414–427. [CrossRef]
76. Webb, M.D. Reworking wild bootstrap-based inference for clustered errors. *Can. J. Econ.* **2023**, *56*, 839–858. [CrossRef]
77. Lee, K.Y.; Sheehan, L.; Lee, K.; Chang, Y. The continuation and recommendation intention of artificial intelligence-based voice assistant systems (AIVAS): The influence of personal traits. *Internet Res.* **2021**, *31*, 1899–1939. [CrossRef]

78. Shmueli, G.; Sarstedt, M.; Hair, J.F.; Cheah, J.-H.; Ting, H.; Vaithilingam, S.; Ringle, C.M. Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict. *Eur. J. Mark.* **2019**, *53*, 2322–2347. [CrossRef]
79. Li, Y.; Qin, X.; Yam, K.C.; Gray, K.; Cheng, X.; Wen, J.; Lai, X. Mind perception of artificial intelligence: A systematic review. *Inf. Process. Manag.* **2026**, *63*, 104820. [CrossRef]

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