The Role of Social and Socioemotional Language in Shaping Chatbot Competence and Relational Outcomes

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ABSTRACT

Chatbots are increasingly deployed in service encounters; yet little is known about how their language style influences consumer perceptions and outcomes. Building on the Stereotype Content Model (SCM) and Assemblage Theory, this research examines the effects of social versus socioemotional chatbot language across three studies. Study 1 clarifies the conceptual distinction between the two styles, showing that socioemotional language is not a separate category but rather an intensification of social cues through explicit emotional attributes. Studies 2 and 3 experimentally investigate how these language styles influence perceptions of chatbot competences—cognitive, social, and emotional—and their integration into global competence. Results demonstrate that socioemotional language enhances emotional competence, while social language more strongly predicts social competence; cognitive competence emerges as context-dependent. Global competence, in turn, drives downstream outcomes by fostering information sharing, which increases compliance with chatbot recommendations and enhances consumer wellbeing. Together, these findings advance theory by refining the conceptualization of chatbot language styles, extending SCM to language-mediated human–AI interactions, and integrating Assemblage Theory to explain how competence perceptions translate into relational outcomes. Managerially, the results guide firms in designing chatbot communication strategies that strengthen both competence perceptions and consumer benefits.

Keywords:

Chatbots, socioemotional communication, language style, competence, consumer interaction, artificial intelligence

1. Introduction

A chatbot is defined as a software application that engages in a conversation with a human using natural language to respond to a consumer's question in real-time (Rese et al., 2020). Chatbots are commonly employed by companies to interact with customers at various touchpoints throughout the customer journey, spanning different contexts such as travel, medical services, and retail (Crolic et al., 2022).

CASA (Computers Are Social Actors) paradigm (Nass et al., 1994) has been widely adopted in the field of Human-Computer Interaction (HCI), positing that users interact with machines as if they were social agents, attributing to them anthropomorphic traits and behaviors. This tendency, especially evident in the case of chatbots, highlights the importance of understanding how user perceptions towards these technologies are formed and influenced. This research specifically addresses calls from the literature to investigate how chatbots' languages styles can be calibrated to optimize customer service experiences (Bleier et al., 2019).

Within HCI, especially in communication context, task-oriented and socially oriented language has been addressed. Task-oriented style where chatbots prioritize task efficiency, diligently striving to achieve a successful outcome, conveying competence, and frequently utilizing formal conversational elements. Although there is consensus on task-oriented language, a research gap has been identified in social-oriented style that needs to be investigated. Social-oriented style aims to achieve social goals and involve informal and relational exchanges normally with positive expressions. However, some literature also includes recognition and response to emotional needs (Xu et al., 2022), and emotional support (Chattaraman et al., 2019) within this domain. Expressing emotional support can be considered emotional language because it involves recognizing the user's emotion or concern (Chandra et al., 2022). The integration of both social and emotional components in the same message leads to a mixed language style. In addition, Assemblage Theory (Hoffman & Novak, 2018) provides a complementary perspective by explaining how human and technological resources combine during interactions to produce emergent outcomes, offering a useful lens to analyze how competence perceptions translate into relational consequences. The integration of both social and emotional components in the same message leads to a mixed language style. This work aims to conduct a detailed examination of social language and socioemotional language and their distinct nature. Differentiating between social and emotional components in the communication of chatbots provides a more holistic perspective on how chatbots can facilitate more natural and meaningful interactions. This research aims to (1) conceptually differentiate social from socioemotional chatbot language by identifying their distinctive features, (2) examine how these two language styles differentially shape perceptions of cognitive, social, and emotional competences, (3) investigate how these competence dimensions integrate into chatbot global competence, and (4) assess the downstream effects of global competence on information sharing, compliance with chatbot recommendations, and consumer wellbeing.

2. Theoretical framework

The interaction style of service agents plays a key role in shaping consumers' service evaluations, often exerting more influence than other factors like service treatments or information. In this sense, it is crucial to emphasize that the chatbot language style acts as a key determinant in exploring chatbot's attitudes (Roy & Naidoo, 2021). Language style in chatbots involves using varied expressions and features to communicate.

Researchers have mainly addressed this issue by dividing the language style into two very distinct styles: *task-oriented* and *social-oriented.* As previously mentioned, although there is a consensus on task-oriented language, a research gap has been identified in social language. The language of a social chatbot aims to foster an interpersonal relationship with the user, facilitating more human-like interactions while addressing the user's requests. On the other hand, a socioemotional chatbot language incorporates additional elements, such as the ability to understand and respond to the user's emotions, demonstrate concern, and provide support. Specifically, the fundamental premise of socioemotional chatbot language is to prioritize the understanding and emotional well-being of the user. Therefore, it is important to study this distinction, as the literature on social features can be intermixed in the context of chatbots (See Table 1[1]).

The Stereotype Content Model (SCM) developed by Fiske et al. (2002) is a theoretical framework from social psychology, to explain social cognition in interpersonal interactions. This theory studies a psychological complex process, the social stereotyping through which individuals draw inferences about human or non-human objects. SCM posits that there are two principal dimensions to capture interpersonal judgments: competence and warmth, therefore, through theses dimensions, it is explained how people judge and stereotype other's (chatbots) impressions. Competence is relate to capacity, skillfulness where warmth is associated with friendliness, helpfulness, and trustworthiness (Cuddy et al., 2004). Considering the idea from CASA that humans tend to anthropomorphize computers, it implies that humans can potentially apply both dimensions – competence and warmth - to chatbots.

Chatbot competence has traditionally been defined by their ability to successfully complete tasks, indicating skillfulness (Chattaraman et al., 2019). However, this paper adopts a holistic approach, inspired by Chandra et al. (2022), which considers how cognitive, social, and emotional human-like competencies impact user engagement with chatbots. Drawing an analogy between human and chatbot capabilities in interactions highlights the need to evaluate chatbot competence comprehensively. Success in task resolution (global competence) might be influenced by cognitive, social, and emotional competences. Specifically, cognitive competence is seen when chatbots process information creatively and adaptively (Shum et al., 2018), social competence is reflected in their ability to foster cooperative and harmonious interactions (Roy & Naidoo, 2021), and emotional competence is demonstrated through their empathetic engagement with users' moods and feelings (Chandra et al., 2022).

Beyond these specific dimensions, prior research highlights that competence perceptions trigger important downstream outcomes. When users perceive a chatbot as globally competent, they might be more willing to engage in information sharing, disclosing needs, preferences, and personal details that enrich the interaction (Jiménez-Barreto et al., 2021a). Such disclosure not only improves personalization and diagnostic accuracy of recommendations, but also strengthens relational trust, thereby increasing users' intention to follow chatbot recommendations (Flavián et al., 2023a; Rhee & Choi, 2020). Moreover, information sharing might foster consumer wellbeing, as voluntary self-disclosure not only reduces stress but also enhances perceived support, stability, and a sense of autonomy and competence, thereby improving psychological wellbeing and enriching the overall consumer experience (Lee et al., 2008; McLean et al., 2023; Prentice et al., 2023). Accordingly, global competence can be understood not only as a multidimensional construct integrating cognitive, social, and emotional capacities, but also as a relational resource that generates broader experiential and wellbeing benefits through the mediating role of information sharing. Thus:

H1a. Socioemotional language influences the perceived cognitive competence of the chatbot more positively than social language. **H1b**. Social language influences the perceived

[1] Tables and figures are presented at the end, consecutively.

social competence of the chatbot more positively than emotional language. **H1c.** Emotional language influences the perceived emotional competence of the chatbot more positively than social language. **H2a**. Perceived cognitive competence positively influences perceived social competence. **H2b**. Perceived emotional competence positively influences perceived social competence. **H3a**. Perceived cognitive competence positively influences perceived global competence. **H3b**. Perceived emotional competence positively influences perceived global competence. **H3c**. Perceived social competence positively influences perceived global competence. **H4**. Chatbot global competence positively influences information sharing. **H5**. Users' information sharing positively influences intention to follow chatbot recommendations. **H6**. Users' information sharing positively influences consumer wellbeing. By combining both perspectives, the model (Figure 1) captures how language style initiates a chain of evaluations and relational outcomes across Studies 1–3.

3. Studies overview

To examine the role of chatbot language styles in shaping competence perceptions and relational outcomes, we conducted three complementary studies. **Study 1** (88 participants) employed a qualitative and conceptual approach to clarify the distinction between social and socioemotional language. Using content analysis of chatbot interactions, we demonstrated that socioemotional style is best understood as an intensification of social cues through explicit emotional attributes, rather than a separate category. **Study 2** (420 participants) consisted of an online experiment (between-subjects design) that manipulated chatbot language style (social vs. socioemotional) to test its effects on perceived competences (cognitive, social, and emotional) and finally on global competence. This study followed three stages: a LIWC analysis to validate the linguistic manipulations, a pretest, and the main experiment. **Study 3** (561 participants) replicated this design in a different interaction context and extended the model by including downstream outcomes—information sharing, intention to follow recommendations, and consumer wellbeing—also conducted in three stages (LIWC analysis, pretest, and final experiment). Together, the multi-study design moves from conceptual clarification (Study 1) to causal testing (Studies 2 and 3), ensuring robustness and triangulation of evidence across qualitative and experimental methods. Participants were recruited from Prolific.

4. Method and results

Study 1

Study 1 (88 participants: 53% female; M = 35.7 years, SD = 12.87) examined how users conceptually differentiate chatbot language styles. Participants assigned 42 attributes to four clusters (social, emotional, socioemotional, and none) and then ranked attributes for social and emotional styles. Results revealed that the correspondence analysis (Guzzetti et al., 2024) distinguished emotional attributes (e.g., compassionate, empathetic, supportive) as a cohesive cluster, while social attributes (e.g., relational, engaging, responsive) overlapped with socioemotional ones. The ranking task further showed that top-ranked social attributes were often perceived as socioemotional, whereas emotional attributes were consistently categorized as emotional, suggesting that socioemotional language reflects higher emotional intensity rather than a separate category. Therefore, social language reflects low emotional intensity, whereas socioemotional language represents high emotional intensity through the addition of explicit emotional attributes. This provided the conceptual foundation for experimental studies 2 and 3.

Study 2

Study 2 employed a one-factor between-subjects experiment (language style: social vs. socioemotional) in the context of booking a leisure vacation, a scenario widely used in chatbot research (Carneiro & Eusébio, 2019; Yu & Zhao, 2024). Stimuli consisted of scripted chatbot dialogues structured into opening, query/response, and closing phases (Jiménez-Barreto et al., 2023), presented as short videos to simulate turn-taking and conversational flow (See Figure 2). The manipulations, grounded in attributes identified in Study 1, were validated through a LIWC analysis (Boyd et al., 2022) using two dimensions: social processes and emotional tone. Results confirmed that the social condition scored higher on social processes, while the socioemotional condition scored higher on emotional tone, indicating that the social scenario was perceived as more social and the socioemotional scenario as more emotional according to the LIWC dictionary. A pretest ($n = 129$: 66 vs 63) further verified realism and manipulation strength using established social and emotional scales (Svikhnushina & Pu, 2022; van Dolen et al., 2007; Yim, 2023). Results showed that the socioemotional condition was rated significantly higher on emotional expressiveness ($M = 4.86$ vs. 4.11, $p < .001$) and marginally higher on social orientation ($M = 5.06$ vs. 4.58, $p = .059$), while realism was rated significantly above the midpoint ($M = 5.25$, $p < .001$).

The main experiment recruited 350 participants (final $N = 291$ after checks; 61% female; $M = 36.98$ years, $SD = 12.48$), randomly assigned to conditions (145 vs 146). Manipulation checks confirmed that the socioemotional chatbot was perceived as both more emotional ($M = 4.62$ vs. 3.96, $p < .001$) and more social ($M = 4.70$ vs. 4.35, $p = .043$) than the social chatbot, with realism again validated ($M = 5.20$, $p < .001$). Dependent variables included cognitive, social, and emotional competences (Brown et al., 2016; Chandra et al., 2022) as well as global competence (Cuddy et al., 2004), with mood (Townsend & Sood, 2012), prior chatbot experience (Haupt et al., 2023), and age as controls (See Table 2 for measurement). The measurement model showed good reliability and convergent and discriminant validity (Fornell & Larcker, 1981; Kline, 2011), and all VIF values were below recommended thresholds (Hair et al., 2010), confirming the absence of collinearity. Data were analyzed with PLS-SEM (Hair et al., 2019). Results showed that socioemotional language enhanced emotional competence, while social language more strongly increased social competence; neither style significantly improved cognitive competence. Moreover, cognitive and emotional competences reinforced social competence, and global competence was shaped by cognitive and social dimensions, but not directly by emotional competence. The full structural model results are reported in Table 3.

Study 3

Study 3 replicated the design of Study 2 (Figure 3) in a different service context (hotel leisure activity booking; Mei et al., 2024) to test robustness across domains and extended the model with new dependent variables: information sharing, intention to follow chatbot recommendations, and consumer wellbeing. LIWC analysis confirmed that the social condition scored higher on social processes and the socioemotional condition on emotional tone, validating the manipulations. In the pretest ($n = 128$: 66 vs 62), the socioemotional chatbot was rated significantly higher on emotional expressiveness ($M = 5.04$ vs. 4.35, $p = .001$) and social orientation ($M = 5.26$ vs. 4.72, $p = .019$), with realism confirmed above the midpoint ($M = 5.71$, $p < .001$). The main experiment recruited 500 participants ($N = 433$ after checks), randomly assigned to social or socioemotional conditions (216 vs 217). Manipulation checks again confirmed that the socioemotional chatbot was perceived as both more emotional ($M = 4.84$ vs. 4.37, $p < .001$) and more social ($M = 4.94$ vs. 4.53, $p = .005$), with realism validated ($M = 5.68$, $p < .001$). The measurement model (See Table 4) showed good reliability, convergent and discriminant validity, and acceptable VIF values (Hair et al., 2010). Results replicated Study 2 by showing that socioemotional language enhanced emotional competence and social language enhanced social competence, but uniquely, socioemotional language also increased cognitive competence in this context (H1a supported). Cognitive and emotional competences reinforced social competence, while cognitive and social competences predicted global competence; emotional competence again showed no direct effect. Extending the model, global competence positively influenced information sharing, which in turn significantly increased both compliance with chatbot recommendations and consumer wellbeing. The full structural model results are reported in Table 5.

5. General discussion and conclusion

This research investigated how chatbot language style—social versus socioemotional—shapes competence perceptions and relational outcomes. Across three studies, the findings converge to clarify conceptual ambiguities, test competence formation mechanisms, and reveal downstream effects on user behavior and wellbeing. Study 1 demonstrated that consumers distinguish social from socioemotional chatbot language not categorically but by the intensity of emotional cues: social style reflects low-intensity relational traits (e.g., responsiveness, engagement), while socioemotional style builds on these by adding explicit affective markers such as empathy and compassion (Chandra et al., 2022; Kim & Hur, 2023). This nuance extends prior work that broadly subsumed both under social language (Bickmore & Cassell, 2001; De Cicco et al., 2021).

Studies 2 and 3 provided causal evidence of how these styles shape competence perceptions. Both studies showed that socioemotional language enhances emotional competence, whereas social language more strongly predicts social competence. Importantly, socioemotional language influenced cognitive competence only in Study 3, suggesting that this effect is context dependent. These results align with the SCM (Fiske et al., 2002), which emphasizes that distinct cues shape competence stereotypes, and with CASA (Nass & Moon, 2000) and Social Presence Theory (Gunawardena, 1995), which highlight empathy and adaptiveness as relational rather than capability cues. Moreover, across both experiments, cognitive and emotional competences consistently reinforced social competence, which in turn strongly predicted global competence—showing that consumers interpret adaptability and empathy as relational resources (De Cicco et al., 2020; Chandra et al., 2022). Yet emotional competence did not directly predict global competence in either study, replicating a slightly negative effect across contexts. This suggests that empathy, while relationally valued, is not decisive for overall competence judgments in leisure-oriented services (Pavone et al., 2023; Zhang et al., 2025).

Finally, Study 3 extended the model by linking global competence to downstream consequences. Perceiving the chatbot as globally competent increased information sharing, which in turn enhanced compliance with chatbot recommendations and boosted consumer wellbeing. These findings resonate with Assemblage Theory (Hoffman & Novak, 2018), showing how competent chatbots become relational resources that reduce uncertainty and expand consumers' perceived control (Jiménez-Barreto et al., 2021, 2023). Disclosure thereby serves a dual role: enabling personalization and trust (Flavián et al., 2023; Rhee & Choi, 2020), while also delivering affective benefits such as autonomy, support, and reduced stress (Lee et al., 2008; Prentice et al., 2023). Together, the three studies refine conceptual distinctions, demonstrate competence formation as an integrative process, and highlight the role of global competence as a driver of richer and more beneficial human–AI interactions.

This research refines the distinction between social and socioemotional language, models global competence as an integrative construct driving disclosure and relational outcomes, and suggests calibrating emotional intensity to context while testing the model across cultures and modalities.

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7. Tables and Figures

Figure 1. Conceptual relationships in the model and study phases.

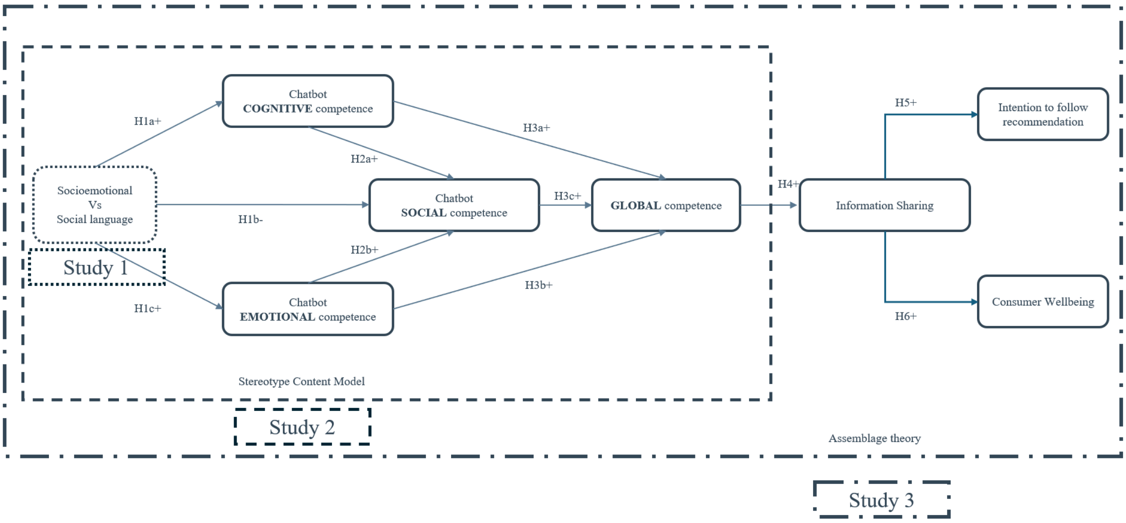


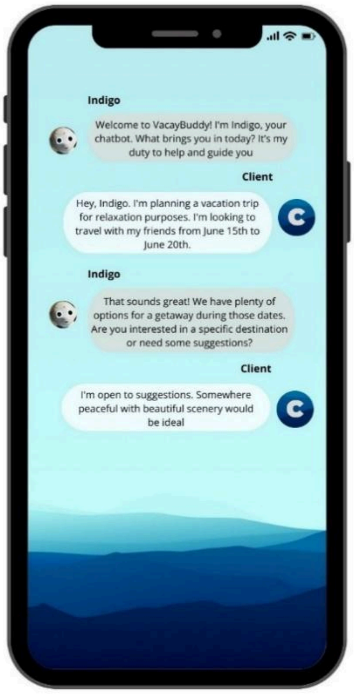
Table 1. Summary of definitions of social language in the chatbot context.

Source	Definition	Stimuli condition
Chattaraman et al., 2019, p. 317	Social language "involves informal, relational dialog with social interactions such as customary greetings, small talk, emotional support, and positive expressions to achieve socioemotional goals".	Informal, small talks, questions, exclamatory feedback, and encouragement
De Cicco et al., 2020, p. 1216	Social language "meets socio-emotional and relational goals through conversational cues that highlight empathy, personality, and friendliness".	Informal, small talks, jokes, exclamatory feedback, emoticons, and GIFs.
Maar et al., 2022, p. 211	A "language style with high social orientation aims to achieve socioemotional goals and involves informal and relational exchanges based on emotional support and positive expressions".	Informal, exclamatory feedback, and emojis.
Wang et al., 2023, p. 7	Social-oriented language "places greater emphasis on affective components, such as building emotional connections with consumers through customary greetings, small talk, and positive expressions".	Empathy, emotional expressions, exclamatory feedback, and emojis
Zhu et al., 2023, p. 644	Social language is oriented toward social values that focus on interpersonal relationships and meeting the emotional needs of the group, and better satisfies consumers' sense of enjoyment in the conversation process. The empathy, friendliness, and warmth of a social-oriented conversational style enhance people's perception of social values, meet the needs for socioemotional and relational goal attainment, and enhance social presence".	Informal, anthropomorphic character, "dear" or "honey".
Cheng et al., 2024, p. 2	Social language "achieves emotional and relational goals by demonstrating empathy, friendliness, and individual conversation clues".	Informal, emojis, exclamatory feedback, "Dear".
This paper	Social language is characterized by informal language that facilitates a harmonious relationship between the chatbot and the customer, involving relational dialogue with social interactions such as customary greetings, small talk, and positive expressions. On the other hand, socioemotional language also aims to facilitate a harmonious relationship but adds elements such as empathy, emotional expressions, and support, centering the interaction on the user's emotional state while the chatbot performs the task.	Social language: relational, engaging, and responsive. Socioemotional language adds supportive, empathetic, and compassionate.

Figure 2. Experimental stimuli of study 2.

Social-oriented chatbot language

Opening



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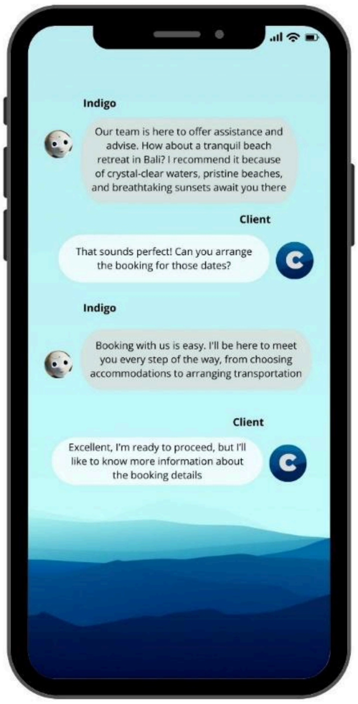

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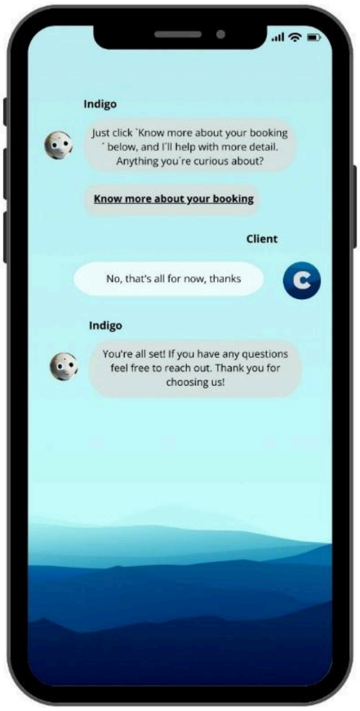
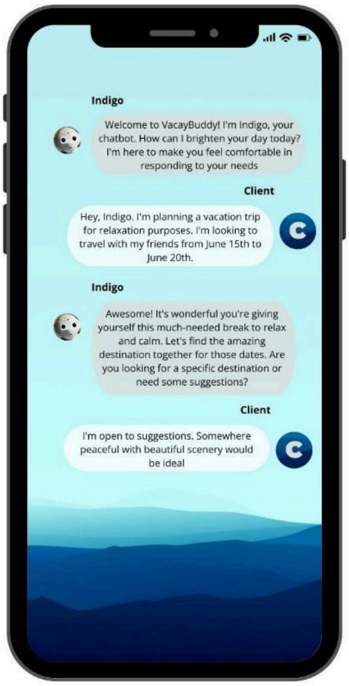


Socioemotional-oriented chatbot language

Opening



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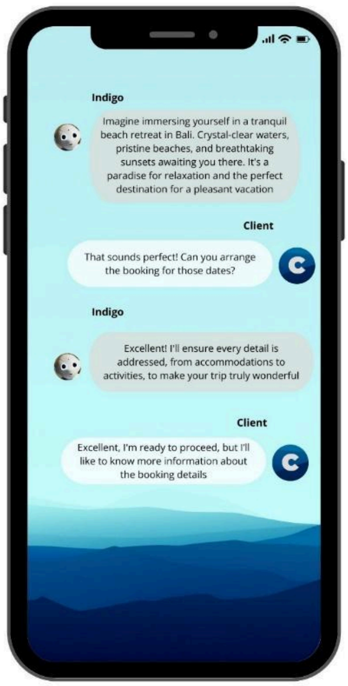

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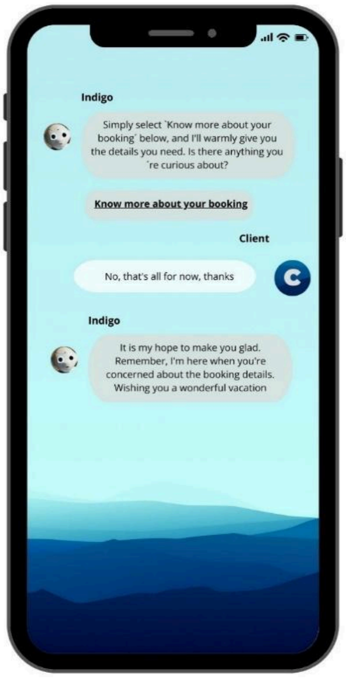


Table 2. Measurement scales, construct reliability, and convergent validity of study 2.

Scale	Items	Loading
Cognitive competence adapted from Brown et al. (2016) and Chandra et al. (2022) *α= .919; CRpa=0.923; CRpc= .943; AVE= .805*		
During the interaction with the chatbot, I found the chatbot to be ….		
CC1	Visionary	.883
CC2	Spontaneous	.885
CC3	Creative	.932
CC4	Open-minded	.889
Social competence, adapted from Brown et al. (2016) and Chandra et al. (2022)**,** *α=.893; CRpa= .896; CRpc= .926; AVE=.758*		
During the interaction with the chatbot, I found the chatbot to be ….		
SC1	Cooperative	.821
SC2	Fair	.872
SC3	Sharing	.900
SC4	Considerate	.888
Emotional competence adapted from Chandra et al. (2022) and Ho & MacDorman (2017) *α= .912; CRpa= .926; CRpc= .944; AVE= .850*		
During the interaction with the chatbot, I found the chatbot to be ….		
EC1	Compassionate	.945
EC2	Emotional	.883
EC3	Empathetic	.936
Global competence adapted from Cuddy et al. (2004) *α= .907; CRpa= .949; CRpc= .962; AVE= .844*		
During the interaction with the chatbot, I found the chatbot to be ….		
GC1	Competent	.916
GC2	Capable	.948
GC3	Skillful	.890
Mood adapted from Lv et al. (2022) and Townsend & Sood (2012) α=*.946; CRpa=.949; CRpc=.961; AVE=.860*		
Please indicate your agreement with each of the following statements about your current mood. Use the scale from 1 to 7, where 1 means 'strongly disagree' and 7 means 'strongly agree'.		
MD1	Happy	.926
MD2	Good mood	.931
MD3	Pleased	.929
MD4	Cheerful	.924
Previous experience adapted from Haupt et al. (2023) and Maar et al. (2022) *α=.940; CRpa=.944; CRpc=.962; AVE=.893*		
PE1	Generally, I have found chatbots very useful this far	.932
PE2	I have benefited many times from using chatbots	.959
PE3	I have had numerous positive encounters with chatbots	.945

Table 3. Structural model results of Study 2

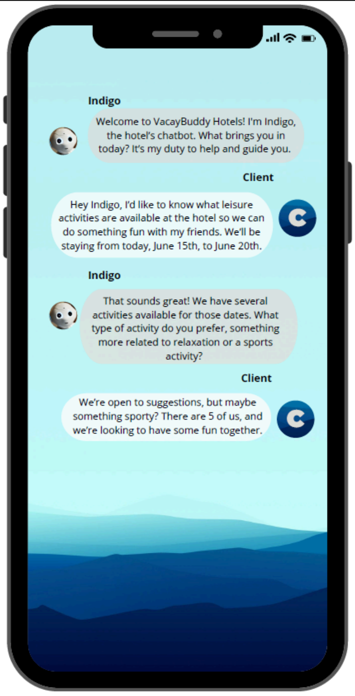
Relationship	Hypotheses		β	SD	*t*	*p*	2.5%	97.5%
Language -> Cognitive competence	H1a	Not supported	.179	.104	1.729	.084	-.023	.385
Language -> Social competence	H1b	Supported	-.238	.076	3.142	.002	-.387	-.092
Language -> Emotional competence	H1c	Supported	.474	.098	4.819	.000	.282	.668
Cognitive competence -> Social competence	H2a	Supported	.437	.046	9.530	.000	.345	.525
Emotional competence -> Social competence	H2b	Supported	.376	.050	7.559	.000	.273	.469
Cognitive competence -> Global competence	H3a	Supported	.209	.062	3.369	.001	.087	.326
Emotional competence -> Global competence	H3b	Not supported	-.112	.058	1.936	.053	-.226	.003
Social competence -> Global competence	H3c	Supported	.651	.064	10.124	.000	.521	.770
Age -> Cognitive competence	Control		-.090	.055	1.654	.098	-.195	.018
Age -> Emotional competence	Control		-.016	.051	.304	.761	-.117	.087
Age -> Global competence	Control		-.054	.040	1.358	.175	-.131	.024
Age -> Social competence	Control		-.045	.040	1.116	.264	-.124	.032
Mood -> Cognitive competence	Control		.098	.059	1.650	.099	-.020	.214
Mood -> Emotional competence	Control		.109	.054	2.025	.043	.007	.217
Mood -> Global competence	Control		.012	.044	.266	.790	-.077	.097
Mood -> Social competence	Control		.012	.038	.304	.761	-.062	.088
Previous experience -> Cognitive competence	Control		.421	.053	7.892	.000	.311	.521
Previous experience -> Emotional competence	Control		.437	.057	7.717	.000	.322	.542
Previous experience -> Global competence	Control		.060	.047	1.275	.202	-.031	.154
Previous experience -> Social competence	Control		.064	.046	1.408	.159	-.023	.154

Notes: 2.5% and 97.5% columns represent the lower and upper bounds of the 95% bias-corrected confidence intervals, estimated via bootstrapping.

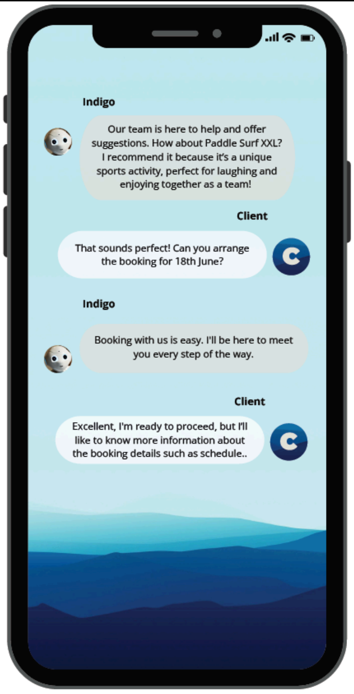
Figure 3. Experimental stimuli of study 3.

Social-oriented chatbot language

Opening



Query/Response



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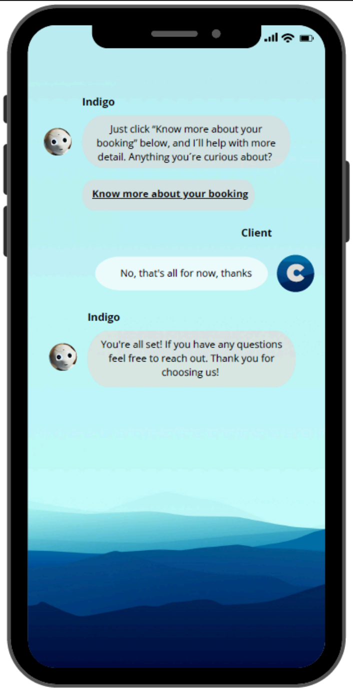
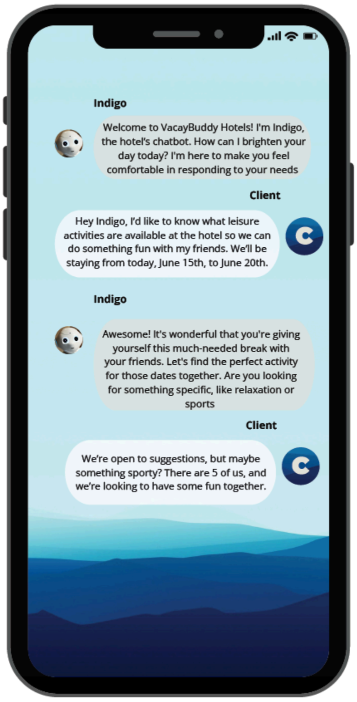


Socioemotional-oriented chatbot language

Opening



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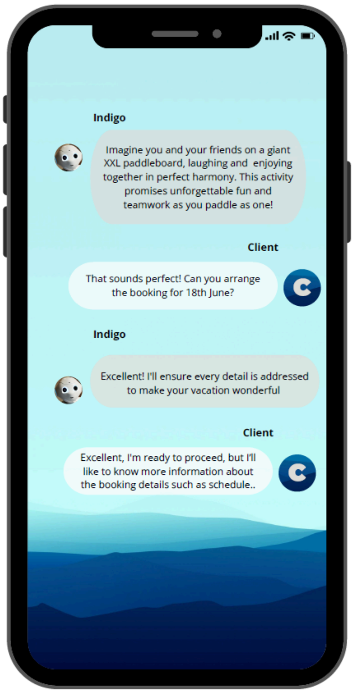

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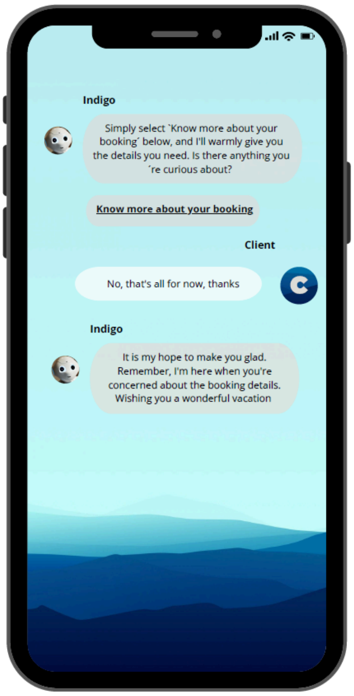

Table 4. Measurement scales, construct reliability, and convergent validity of study 3.

Scale	Items	Loading
Cognitive competence adapted from Brown et al. (2016) and Chandra et al. (2022) *α= .919; CRpa= .924; CRpc= .943; AVE= .804*		
During the interaction with the chatbot, I found the chatbot to be ….		
CC1	Visionary	.900
CC2	Spontaneous	.869
CC3	Creative	.925
CC4	Open-minded	.892
Social competence adapted from Brown et al. (2016) and Chandra et al. (2022)**,** *α=.870; CRpa= .875; CRpc= .911; AVE=.720*		
During the interaction with the chatbot, I found the chatbot to be ….		
SC1	Cooperative	.811
SC2	Fair	.830
SC3	Sharing	.861
SC4	Considerate	.889
Emotional competence adapted from Chandra et al. (2022) and Ho & MacDorman (2017) *α= .907; CRpa= .912; CRpc= .942; AVE= .844*		
During the interaction with the chatbot, I found the chatbot to be ….		
EC1	Compassionate	.931
EC2	Emotional	.895
EC3	Empathetic	.930
Global competence adapted from Cuddy et al. (2004) *α= .885; CRpa= .887; CRpc= .929; AVE= .813*		
During the interaction with the chatbot, I found the chatbot to be ….		
GC1	Competent	.908
GC2	Capable	.923
GC3	Skillful	.873
Mood adapted from Lv et al. (2022) and Townsend & Sood (2012) α=*.955; CRpa=.957; CRpc=.967; AVE=.880*		
Please indicate your agreement with each of the following statements about your current mood. Use the scale from 1 to 7, where 1 means 'strongly disagree' and 7 means 'strongly agree'.		
MD1	Happy	.952
MD2	Good mood	.938
MD3	Pleased	.932
MD4	Cheerful	.932
Previous experience adapted from Haupt et al. (2023) and Maar et al. (2022) *α=.943; CRpa=.944; CRpc=.964; AVE=.898*		
PE1	Generally, I have found chatbots very useful this far	.932
PE2	I have benefited many times from using chatbots	.954
PE3	I have had numerous positive encounters with chatbots	.957
Information sharing adapted from (Jiménez-Barreto et al., 2021b) *α=.839; CRpa=.847; CRpc=.903; AVE= .756*		
During the interaction, the chatbot encouraged me to…		
IS1	continue developing conversation	.895
IS2	ask for more questions for additional queries	.841
IS3	spend more time in the conversation	.873
Intention to follow the recommendation adapted from **(Flavián et al., 2023b)** *α=.906; CRpa=.915; CRpc=.935; AVE=.782*		
IFR1	I would feel comfortable behaving according to the recommendation I obtained from the chatbot	.870
IFR2	I would do NOT hesitate to take into account the recommendation obtained from the chatbot	.823
IFR3	I would feel secure in following the recommendation obtained from chatbot	.922
IFR4	I would definitely follow the recommendation obtained from the chatbot	.918
Consumer wellbeing, adapted from **(Jamil et al., 2023)** *α=.951; CRpa=.952; CRpc=.969; AVE=.912*		
CB1	The chatbot plays an important role in tourist overall social well-being at the resort	.948
CB2	The chatbot plays an important role in tourist experience well-being at the resort	.970
CB3	The chatbot plays an important role in enhancing the quality of tourist experience at the resort	.946

Table 5. Structural model results of Study 3

Relationship	Hypotheses		β	SD	*t*	*p*	2.5%	97.5%
Language -> Cognitive competence	H1a	Supported	.213	.077	2.761	.006	.056	.364
Language -> Social competence	H1b	Supported	-.189	.066	2.855	.004	-.316	-.058
Language -> Emotional competence	H1c	Supported	.295	.081	3.642	.000	.136	.453
Cognitive competence -> Social competence	H2a	Supported	.310	.062	4.968	.000	.190	.434
Emotional competence -> Social competence	H2b	Supported	.352	.053	6.635	.000	.246	.450
Cognitive competence -> Global competence	H3a	Supported	.157	.051	3.060	.002	.059	.260
Emotional competence -> Global competence	H3b	Not supported	-.076	.061	1.234	.217	-.192	.046
Social competence -> Global competence	H3c	Supported	.499	.075	6.693	.000	.348	.642
Global competence -> Information sharing	H4	Supported	.254	.061	4.140	.000	.133	.370
Information sharing -> Intention to follow recommendation	H5	Supported	.346	.049	6.995	.000	.253	.446
Information sharing -> Consumer wellbeing	H6	Supported	.264	.052	5.077	.000	.162	.365
Age -> Consumer wellbeing	Control		.038	.039	.992	.321	-.039	.114
Age -> Cognitive competence	Control		-.027	.041	.661	.509	-.108	.053
Age -> Emotional competence	Control		-.085	.038	2.255	.024	-.158	-.010
Age -> Global competence	Control		.101	.034	2.996	.003	.034	.166
Age -> Intention to follow recommendation	Control		-.031	.036	.850	.396	-.102	.039
Age -> Information sharing	Control		-.010	.042	.226	.821	-.091	.075
Age -> Social competence	Control		-.061	.034	1.777	.076	-.129	.008
Mood -> Consumer wellbeing	Control		.064	.038	1.706	.088	-.011	.137
Mood -> Cognitive competence	Control		.148	.045	3.267	.001	.060	.238
Mood -> Emotional competence	Control		.114	.046	2.471	.013	.026	.206
Mood -> Global competence	Control		.032	.038	.854	.393	-.042	.107
Mood -> Intention to follow recommendation	Control		.031	.040	.779	.436	-.047	.109
Mood -> Information sharing	Control		.032	.049	.644	.519	-.068	.127
Mood -> Social competence	Control		.021	.040	.540	.589	-.054	.101
Previous experience -> Consumer wellbeing	Control		.491	.048	10.255	.000	.394	.580
Previous experience -> Cognitive competence	Control		.535	.041	12.916	.000	.451	.612

Previous experience -> Emotional competence	Control	.466	.038	12.205	.000	.388	.540
Previous experience -> Global competence	Control	.233	.056	4.155	.000	.119	.339
Previous experience -> Intention to follow recommendation	Control	.456	.049	9.325	.000	.354	.546
Previous experience -> Information sharing	Control	.294	.055	5.346	.000	.186	.401
Previous experience -> Social competence	Control	.182	.048	3.753	.000	.086	.276

Notes: 2.5% and 97.5% columns represent the lower and upper bounds of the 95% bias-corrected confidence intervals, estimated via bootstrapping.